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ENERGY SAVING METHODS FOR INTELLIGENT BUILDINGS BASED ON B-RNN FUSION PARTICLE SWARM MODEL

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Abstract. In order to effectively reduce the energy consumption of air conditioning systems in smart buildings, a B-RNN fusion particle swarm optimization model energy-saving control method is proposed. This method uses particle swarm optimization as a framework to map different air conditioning terminals into different particles. Optimize the fitness function trained by B-RNN deep learning network for particle position and velocity. The implementation process of structural design and attention mechanism embedding for B-RNN deep network is provided. We conducted integrated optimization experiments on complex systems with multiple air conditioning terminals, and the results showed that our method can place each air conditioning terminal in a more fully loaded operating power range, with an energy-saving effect 3-4% higher than the PSO method.

1. Introduction

With the rapid development of science and technology, traditional buildings are gradually transitioning towards intelligent buildings [13, 15, 16]. Intelligent buildings combine the structure, systems, services, and management of buildings, and optimize them according to user needs, providing users with an efficient, comfortable, and convenient humanized building environment [3, 12, 14]. From a functional perspective, intelligent buildings automate the management of drainage, power distribution, lighting, ventilation, and other systems, maximizing their management efficiency and reducing their energy consumption. Energy conservation is an important goal in the control process of intelligent buildings.

The energy consumption of smart buildings is influenced by various factors, with internal factors mainly being the building's own influence and external factors mainly being geographical environment, climate conditions, indoor personnel flow, and air conditioning system form [2]. Taking public buildings as an example, the energy consumption of electrical equipment such as central air conditioning alone accounts for over 50% of the total energy consumption. Therefore, building energy conservation should first consider the control methods for central air conditioning energy conservation [4]. As one of the main sources of building energy consumption, energy-saving control of central air conditioning systems can effectively reduce building energy consumption and achieve the goal of sustainable development of green buildings. In the era of traditional architecture, central air conditioning was generally operated based on the maximum power required by the building. However, in reality, the power of the air conditioning system when it

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reaches the appropriate temperature required by the human body is much lower than the maximum power [1]. This results in energy consumption of air conditioning systems, especially central air conditioning systems. In the case of high energy consumption, not only does it require more electricity bills, but it also fails to achieve the optimal suitable temperature for human needs. Especially, the service life of air conditioning systems is prone to decrease during long-term overload operation. In the context of the era of intelligent buildings, automatic control and adjustment of central air conditioning to achieve energy-saving goals is a very important issue [9]. The air conditioning control system was initially switch controlled, and later gradually replaced by PID control and adaptive control [5]. PID control and adaptive control have also preliminarily achieved the intelligent control properties of the air conditioning system. With the increasing complexity of air conditioning systems, the nonlinear characteristics of their control process are becoming more and more apparent [7]. PID control, as a linear control method, is no longer sufficient for controlling air conditioning systems. Fuzzy control describes the fuzziness between different systems by selecting membership functions, mimicking human control experience to control the system [11]. Fuzzy control is essentially a nonlinear controller that can be applied to various nonlinear control objects and does not require an accurate mathematical model of the controlled object. Fuzzy control has strong anti-interference ability and has minimal impact on external dynamic disturbances, making it a modern controller with autonomous reasoning and decision-making capabilities. Rogers proposed a fuzzy PID control method for central air conditioning water systems based on a model, and demonstrated through simulation experiments that the method has good anti-interference ability [10]. Liu proposed a fuzzy self-tuning PID control system to address the nonlinearity, large lag, and strong coupling characteristics of central air conditioning systems, and introduced the principle and model of temperature control systems for central air conditioning systems. Good control performance was obtained through simulation [8]. In order to better control air conditioning equipment, building automation control systems have been designed [6]. The building automation control system establishes a unified interface protocol, reducing the integration difficulty between various systems and achieving multi system coordination and linkage. Combining traditional control with building automation control is an effective approach in the design of intelligent buildings.

In summary, scholars have conducted certain research on energy-saving control in intelligent buildings, and different control methods have been applied. In recent years, the rise of deep learning has greatly improved its nonlinear approximation ability and learning performance, and has also gained better adaptability for solving complex control problems. Therefore, this article focuses on the energy-saving of air conditioning in intelligent buildings, constructs a deep learning method based on B-RNN network, and verifies it through experiments.

2. Design of energy-saving methods for intelligent building air conditioning

Through the overall configuration of hardware systems and the rational design of intelligent methods, intelligent buildings can achieve automatic control of controlled variables, thereby achieving the goal of energy conservation. For large buildings, air conditioning systems have become the main equipment for energy consumption, accounting for over 50% of all energy consumption. Therefore, we take air conditioning energy-saving control as the core research objective of intelligent building energy-saving control.

2.1. **Design of Energy saving Framework Based on Particle Swarm Optimization Model.** In this article, the energy-saving control scheme for the intelligent building air conditioning system we constructed is shown in Figure 1.

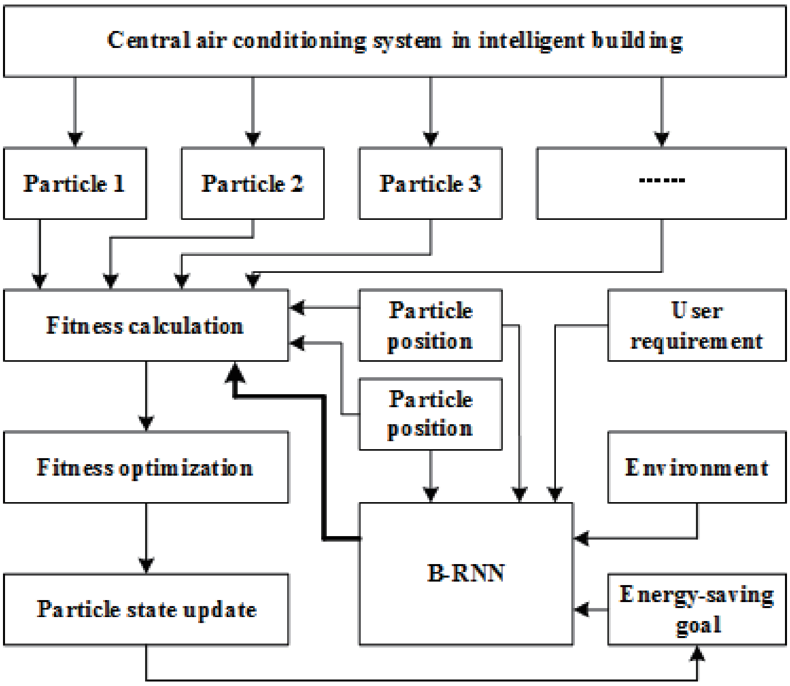

FIGURE 1. Framework of Energy saving Control Method for Intelligent Buildings Based on PSO Model

In Figure 1, each particle corresponds to an air conditioning terminal in a room. The position of the particles corresponds to the current air conditioning energy consumption, and the velocity of the particles corresponds to the adjustment speed of the air conditioning energy consumption. These pieces of information will be fed into the fitness function for calculation and optimization, thereby completing the update of particle position and velocity. It should be pointed out that if this method is used, it forms a conventional particle swarm optimization method. However, the requirements for smart buildings cannot be solely focused on energy-saving control. In the control process of intelligent buildings, it is necessary to fully consider the changes in environmental information and the different temperature requirements of users in each room, and combine these factors with the overall goal of energy-saving control to provide the best control plan. Considering the complexity of these factors, a B-RNN deep learning network is introduced within the overall framework of particle swarm control to participate in the calculation and optimization of the fitness function. It is this change that has led to the formation of a new energy-saving control method.

2.2. **Embedding B-RNN in Energy saving Methods.** CNN and RNN networks are typical forms of deep learning. RNN, with its cyclic convolution learning method, has better memory performance and parameter sharing performance. In this article, RNN is used as the basic structure of deep learning to handle the fitness function and fitness optimization process of particle swarm optimization algorithm. Meanwhile, considering that the process of deep learning involves not only variables such as particle position and velocity, but also environmental information, user requirements, energy-saving goals, etc., a BERT module has been added to the structure of RNN. The BERT module can perform better filtering and processing on different data types, enabling them to be unified into subsequent deep processing processes. In addition, a multi head attention mechanism has been added between the RNN hidden layer and output layer, which is also necessary for comprehensively processing various factors and better achieving fitness optimization. Based on this, the deep learning framework adopted is shown in Figure 2.

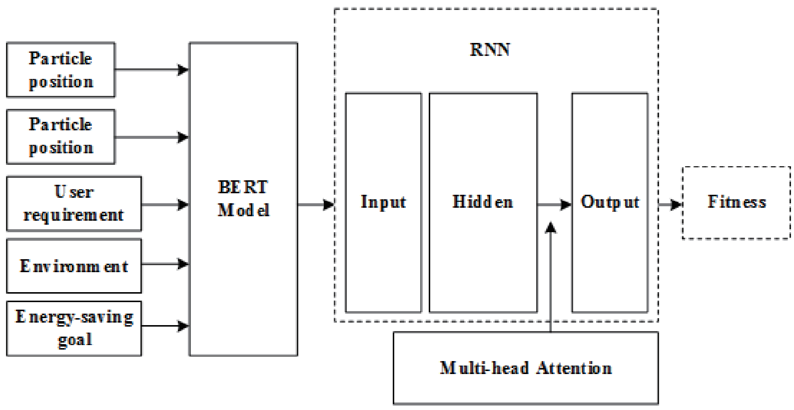

FIGURE 2. Basic framework of B-RNN method

From the B-RNN method framework shown in Figure 2, it can be seen that multiple types of data are used as input, first processed by the BERT module for simplification and classification, and then sent to the input layer of the RNN network. Here, the BERT module can further streamline the input dataset, thereby improving the efficiency of RNN learning. After iterative training and processing in the hidden layer of the RNN network, they are then incorporated into the Attention module for redundancy removal, obtaining accurate correspondence relationships before reaching the output layer of the RNN network and ultimately obtaining optimized fitness results. This result will also be applied to the particle swarm model to achieve energy-saving control of intelligent building air conditioning systems. The multi head attention mechanism module plays a role between the hidden layer and output layer of RNN, which can make the deep learning process more focused on key points and remove invalid or redundant information. The final output obtained by the B-RNN network is the fitness required by the particle swarm algorithm. After deep learning processing by B-RNN network, the fitness function is more accurate than the general particle swarm algorithm, and plays a better control role in the overall optimization of particle swarm.

2.3. **Structural Design of RNN.** Based on the B-RNN method framework presented in Figure 2, it can be seen that RNN plays a multi-layered role in the fitness optimization process. So, in order to achieve detailed design at the algorithm level, it is necessary to design the structure of the RNN network.

Assume x_m represent the status data of energy-saving control of the air conditioning systems in intelligent building, with the serial number m. Assume y_m represent the optimized state data of the air conditioning system in intelligent building, with the serial number m. Assume H_{mn} represent the neurons involved in the iterative training process of the RNN network, with number (m, n). The relationship between the input hidden layer neurons in the RNN network structure can be characterized by Equation (2.1) and Equation (2.2):

$$H_m = f\left(w_x x_m + w_h H_{m-1}\right) \tag{2.1}$$

$$y_m = g\left(w_y H_m\right) \tag{2.2}$$

In the above two Equations, $f()$ represents the nonlinear activation function in energy-saving control of air conditioning systems in intelligent building, $g()$ represents the activation function of energy-saving control of air conditioning systems in intelligent building, w_x represents the weight of various input variables in energy-saving control of air conditioning systems in intelligent building, w_h represents the implicit weight in energy-saving control of air conditioning systems in intelligent building, and w_y represents the weight of various output variables in energy-saving control of air conditioning systems in intelligent building.

2.4. **Attention mechanism embedding.** From the structural design of B-RNN shown in Figure 2, it can be seen that an Attention module, also known as the Attention Mechanism module, is configured between the hidden layer and the output layer of the RNN network. The reason for adding this module is that the energy-saving control data of intelligent building air conditioning systems is too large, and there is a large amount of invalid information in it. The Attention module can more accurately locate the iterative process on the problem to be studied, effectively removing the influence of invalid information and improving the accuracy of the final detection results. Based on this consideration, the Attention module was introduced.

The data in energy-saving control of intelligent building air conditioning systems forms a vector T, which is then divided into three sub vectors VT, KT, and QT. The decomposition process is shown in Equation (2.3):

$$\left\{\begin{array}{l} Q_T = T w^Q \\ K_T = T w^K \\ V_T = T w^V \end{array}\right. \tag{2.3}$$

In the above Equation, T represents the eigenvectors in energy-saving control of air conditioning systems in intelligent building, Q_T represents the query matrix in energy-saving control of air conditioning systems in intelligent building, K_T

represents the key matrix in energy-saving control of air conditioning systems in intelligent building, w^Q represents the value matrix in energy-saving control of air conditioning systems in intelligent building, represents the query weights in energy-saving control of intelligent building air conditioning systems, w^K represents the key weights in energy-saving control of air conditioning systems in intelligent building, and w^V represents the value weights in energy-saving control of air conditioning systems in intelligent building.

After splitting the state data into three sub vectors, further calculate the values head_i of each sub vector by Equation (2.4).

$$\begin{aligned} \text{head}_i &= \text{Attention}\ (Q_T, K_T, V_T) \\ &= \text{Same}\ \left(\frac{Q_T K_T}{\sqrt{D_K}}\right) V_T \end{aligned} \tag{2.4}$$

In the above Equation, Attention() represents the attention mechanism function in energy-saving control of air conditioning systems in intelligent building, Same() represents the normalization function in energy-saving control of air conditioning systems in intelligent building, and D_K is the dimension of the matrix K_T.

In order to obtain more accurate results, it is necessary to perform multiple repeated calculations on head_i, hence it is called multi head attention mechanism.

After obtaining final determinations of multiple head_i, they are merged to obtain a semantic expression model for energy-saving control of air conditioning systems in intelligent building, as shown in Equation (2.5):

$$\text{Multihead\_}Y\,(Q_T, K_T, V_T) = \text{Fusion}\ (\text{head}_1, \text{head}_2, \cdots, \text{head}_i)\, w_0 \tag{2.5}$$

In the above Equation, Multihead_Y represents the feature semantic vector in energy-saving control of air conditioning systems in intelligent building. Fusion() represents the fusion function in energy-saving control of air conditioning systems in intelligent building, and w_0 represents the linear transformation matrix in energy-saving control of air conditioning systems in intelligent building.

3. Experimental results and analysis of energy-saving control in intelligent buildings

In the previous research, we proposed an energy-saving control method based on particle swarm optimization model for the energy-saving control of air conditioning systems in intelligent buildings. In this energy-saving control method, B-RNN deep learning network is used for adjusting the fitness function. In the following work, in order to verify the effectiveness of the proposed method, a simulation model of a multi air conditioning terminal system in a complex building structure is first constructed, and the results are shown in Figure 3.

In Figure 3, the intelligent building model includes multiple rooms, and air conditioning terminals have been installed in 6 of them according to user needs. These air conditioning terminals are controlled by the central air conditioning control system. In order to achieve energy-saving control of the entire intelligent building, the proposed method is adopted to control the energy-saving of these six air conditioning terminals.

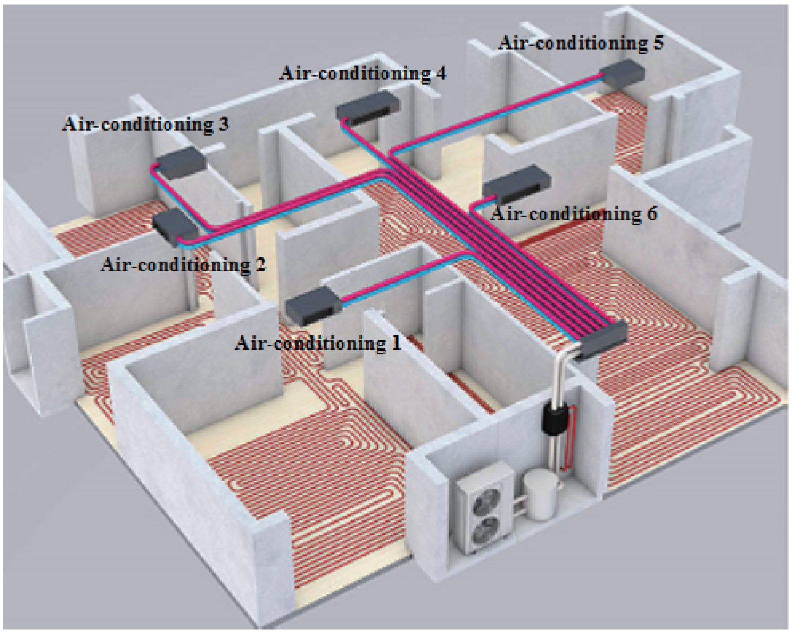

FIGURE 3. Simulation model of multi air conditioning terminal system in complex building structures

Corresponding to the proposed method, each air conditioning terminal is configured with one particle. The state of each air conditioning terminal is expressed by corresponding particles. The sequence data of particle position and velocity will be continuously fed into the proposed method. Based on this data, as well as information on the environment, users, and energy-saving goals, B-RNN is iteratively trained to obtain the optimal fitness function for energy-saving control processing in particle swarm optimization algorithm. While intelligent buildings are achieving energy-saving control, the energy consumption of each particle representing the air conditioning terminal is also constantly being optimized.

Next, the air conditioning operation status of each room will be monitored. Considering the homogeneity of changes in each air conditioner and the limitations of space, only two sets of air conditioners are presented here as representatives of all six sets of air conditioners. Among them, the percentage change rate of the operating power of the air conditioning terminals in room 3 and room 6 relative to the full load power is shown in Figure 4 and Figure 5, respectively.

In Figure 4, the horizontal axis represents the operating time of the air conditioning terminal, measured in hours, from 9am to 6pm. The vertical axis represents the proportion of the actual operating power of the air conditioning terminal relative to the full load power, in%. Based on experience, it is ideal for the power ratio of air conditioning equipment to be between 80% and 100%. From the curve changes in Figure 4, it can be seen that the power proportion of air conditioner 3 is mostly above 80%, with only two places below 80% at 11-12 o'clock and 14:00. This indicates that under the control of the proposed method, the air conditioning equipment in room 3 has achieved a relatively ideal energy-saving effect while

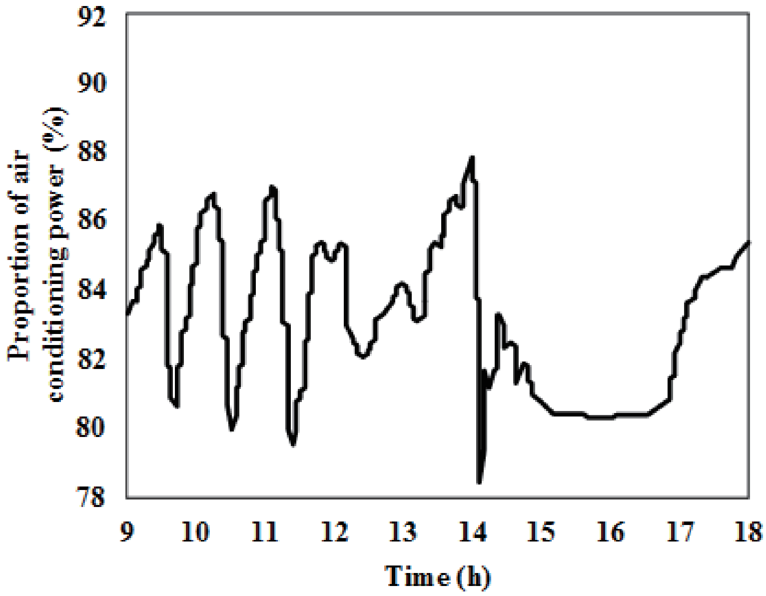

FIGURE 4. Change rate of the proportion of operating power of air conditioner 3 relative to full load power

meeting the overall energy-saving requirements of the air conditioning system. The ideal aspect of the proposed method is that it effectively saves energy while meeting user needs through deep learning networks and their processing. Through this method of processing, changes in the air conditioning in the room can be tracked and continuously adjusted and optimized.

In Figure 5, the horizontal axis represents the operating time of the air conditioning terminal, measured in hours, from 9am to 6pm. The vertical axis represents the proportion of the actual operating power of the air conditioning terminal relative to the full load power, in%. Based on experience, it is ideal for the power ratio of air conditioning equipment to be between 80% and 100%. From the curve changes in Figure 5, it can be seen that the power ratio of air conditioner 6 remained above 80% throughout the testing time. This indicates that under the control of the proposed method, the air conditioning equipment in room 6 has achieved a very ideal energy-saving effect while meeting the overall energy-saving requirements of the air conditioning system.

4. Conclusions

Intelligent buildings are an important technological revolution in the field of architecture, which can utilize information technology, Internet of Things technology, and artificial intelligence technology to integrate and optimize various subsystems of complex buildings. Energy saving is one of the important advantages of smart buildings. A B-RNN fusion particle swarm optimization model energy-saving control method is proposed to address the issue of high energy consumption in air conditioning systems in smart buildings. Firstly, the framework of the entire method

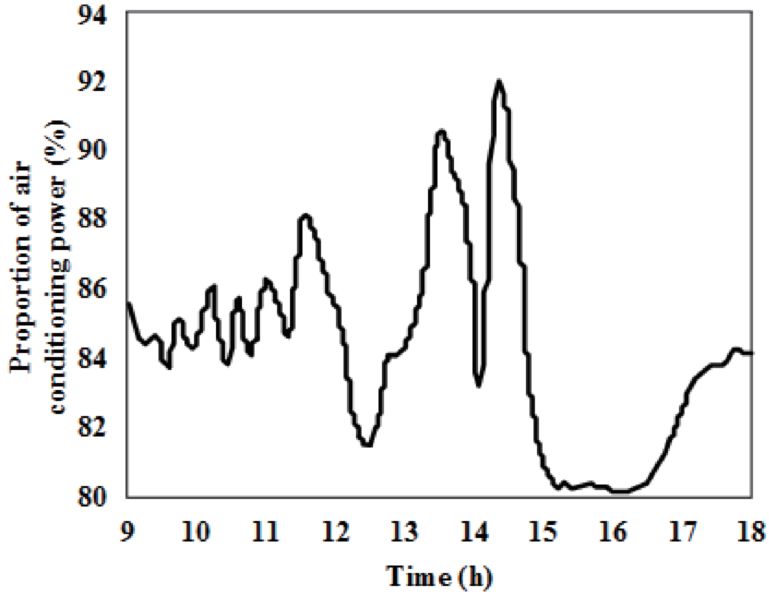

Figure 5. Proportion change rate of operating power of air conditioner 6 relative to full load power

was constructed based on the particle swarm model, which corresponded different particles to various air conditioning terminals. Secondly, using B-RNN deep network to train the fitness function improves the performance of particle swarm optimization. Finally, a scene model consisting of six air conditioners was constructed for experimental research. The experimental results show that our method can place each air conditioning terminal in a more full load operating power range, and the energy-saving effect is significantly better than the PSO method.

References

[1] S. Abdul-Rauf, H. Schwenk, P. Lambert and M. Nawaz, *Empirical use of information retrieval to build synthetic data for SMT domain adaptation*, IEEE/ACM Transactions on Speech and Language Processing **24** (2016), 745–754.

[2] J. Chen, Y.-C. Liou and C.-F. Wen, *Bilevel vector pseudomonotone equilibrium problems: duality and existence*, Journal of Nonlinear and Convex Analysis **16** (2015), 1293–1303.

[3] Y. Djenouri, D. Djenouri, A. Belhadi, G. Srivastava and J. C.-W. Lin, *Emergent deep learning for anomaly detection in internet of everything*, IEEE Internet of Things Journal **10** (2023), 3206–3214.

[4] Y. Fang and S. T. Ng, *Applying activity based costing approach for construction logistics cost analysis*, Construction Innovation **11** (2021), 259–281.

[5] V. Jamshidi, V. Nekoukar and M. H. Refan, *Implementation of UAV smooth path planning by improved parallel genetic algorithm on controller area network*, Journal of Aerospace Engineering **35** (2022), 135–148.

[6] D. P. Kuttichira, S. Gupta, D. Nguyen, S. Rana and S. Venkatesh, *Verification of integrity of deployed deep learning models using Bayesian optimization*, Knowledge-Based Systems **241** (2022): 108238.

[7] R. Liu, T. Zhang and F. Chen, *Deep convolutional neural networks for pareto optimal front of multi objective optimization problem*, Journal of Nonlinear and Convex Analysis **23** (2022), 833–846.

[8] Y. Liu, S. Jafari and T. Nikolaidis, *Advanced optimization of gas turbine aero engine transient performance using linkage learning genetic algorithm: Part II, optimization in flight mission and controller gains correlation development*, Chinese Journal of Aeronautics **34** (2021), 568–588.

[9] P. V. Ramamurthi, M. C. Fernandes, P. S. Nielsen and C. P. Nunes, *Logistics cost analysis of rice residues for second generation bioenergy production in Ghana*, Bioresource Technology **173** (2014), 429–438.

[10] A. Rogers, C. Manes and T. Tsuzaki, *Measuring the geometry of a developing scour hole in clear water conditions using underwater sonar scanning*, International Journal of Sediment Research **35** (2020), 105–114.

[11] D. K. Sharma, A. Singh, S. K. Sharma, G. Srivastava and J. C.-W. Lin, *Task specific image summaries using semantic information and self-supervision*, Soft Computing **26** (2022), 7581–7594.

[12] M. Shahbazi, G. Sohn and J. Th 卒 eau, *High density stereo image matching using intrinsic curves*, Journal of Photo Grammetry and Remote Sensing, **146** (2018), 373–388.

[13] M. Tinhinane, D. Youcef, B. Asma, G. Srivastava and J. C.-W. Lin, *A sustainable deep learning framework for fault detection in 6G Industry 4.0 heterogeneous data environments*, Computer Communications **187** (2022), 164–171.

[14] P. Tueller, R. Kastner and R. Diamant, *Target detection using features for sonar images*, IET Radar, Sonar and Navigation **14** (2020), 1940–1949.

[15] D. Walker, J. D. Shutler, D. M. Harper, J. C. B. Hoedjes and C. G. Laing, *Quantifying water storage within the north of Lake Naivasha using sonar remote sensing and Landsat satellite data*, Ecohydrology and Hydrobiology **22** (2021), 12–20.

[16] I. G. Widagda, N. P. Sastra, D. M. Wiharta and R. S. Hartati, *Invariant moment and learning vector quantization for images classifification*, Journal of Physics: Conference Series **1722** (2021): 012003.

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