Scalable Computing: Practice and Experience, ISSN 1895-1767, http://www.scpe.org
© 2024 SCPE. Volume 25, Issues 3, pp. 1499–1507, DOI 10.12694/scpe.v25i3.2661

APPLICATION OF DEEP LEARNING ALGORITHM IN OPTIMIZATION OF ENGINEERING INTELLIGENT MANAGEMENT CONTROL

SHUAI ZHOU*AND JING GUO†

Abstract. Currently, there are a series of problems in the management of the construction industry, such as resource waste, substandard quality, and low construction efficiency. In response to this phenomenon, the author proposes a multi-objective optimization control method for construction engineering management projects using deep learning algorithms. This method analyzes the relationship between cost, duration, and quality, and constructs an optimization management model for these three factors. At the same time, the improved SULSTM neural network algorithm is used to optimize the model parameters. The experimental results indicate that, when the value coefficient is 0.2211, the total investment cost and quality coefficient are 412700 yuan and 0.99496 yuan, respectively. When the value coefficient is 0.1976, the total cost and quality coefficient are 456300 yuan and 0.98798 yuan, respectively. When the value coefficient is 0.1990, the total cost and quality coefficient are 456300 yuan and 0.99496 yuan, respectively. Proved that the SUSTM neural network algorithm has faster convergence speed and lower loss values compared to the improved LSTM neural network algorithm. The cost of improving quality has a greater impact on the quality coefficient than the duration, and the total investment cost has a greater impact on the value coefficient than the quality coefficient.

Key words: Construction engineering, Multi objective optimization, Management efficiency, SUSTM neural network structure

1. Introduction. At present, due to the influence of market environment and national control measures, the construction industry has encountered some problems in construction project management. After the country issued a series of market control measures, it is difficult for construction enterprises to grasp the latest national control policies and industry management decisions under the influence of market environment. It is difficult for enterprises to adjust in real-time according to national policies and changes in market environment during development, this leads to a mismatch between the company's own goal control and management level and socio-economic development, and a lack of timely response to market cyclical changes [16]. In fact, how construction enterprises improve management efficiency in the current market environment, and how to optimize management efficiency under multi-objective conditions will be important means to improve the overall efficiency of the enterprise, quickly adapt to external changes from within, and promote the healthy and stable development of the industry.

For a long time, homeowners have often established a temporary organization to carry out the design, procurement, construction, and daily quality and progress management of construction projects. If the owner has rich experience in engineering management, or if the project size is not large and the technical requirements are relatively simple, under such conditions, the traditional construction project management can achieve good results. However, in recent years, with the continuous improvement of the national economy and the continuous construction and development of municipal supporting facilities and public infrastructure, the number of large-scale engineering projects in related fields such as architecture, energy, and municipal highways has gradually increased, which has prompted homeowners to have higher requirements for various professional goals [3]. There are also higher expectations for the environment, quality costs, and progress. Corresponding construction project managers need to have richer management experience and more advanced construction techniques in order to keep up with the speed of industry development and meet the needs of industry development. Therefore, accurately grasping the overall goal of the project from the source, reasonably allocating various resources in the early stage of construction, promoting the improvement of project engineering quality, reducing construction investment to a certain extent, and shortening the construction period. The handling and decision-making of all these issues are of great significance for the entire construction project.

*Hebei Vocational University of Industry and Technology, Shijiazhuang, Hebei, 050091, China
†Hebei Vocational University of Industry and Technology, Shijiazhuang, Hebei, 050091, China (Corresponding Author)

Construction project management refers to the systematic regulation and management of projects based on management theories and methods, and the reasonable allocation of costs and construction periods while ensuring the expected functions of construction projects, ensuring quality assurance, and the healthy operation of daily project work. The management of construction projects has very obvious characteristics, which are particularity, one-time, strong constraint, and full lifecycle. For each construction project, the control of quality, cost, and progress is very important. By comprehensively controlling these issues, the expected management goals can be achieved. The regulation of these stages is comprehensive and holistic, with the goal of overall benefits. The allocation of various resources, reasonable construction period, cost investment, and guaranteed quality goals all comprehensively determine the accurate control of limited resources in the early stages of the project [8]. The construction unit, general contractor, and each construction unit have all undertaken corresponding tasks in each stage, and although there may be differences in tasks in each stage, the overall goal remains the same. Generally speaking, cost, schedule, and quality are the three basic objectives of project management. In the project management knowledge system PMBOK, the American Project Management Association has extended the project objective system to a certain extent after in-depth research and analysis, adding four additional contents, namely procurement, risk, communication, and integration. Based on these nine objectives, the basic framework of PMBOK has been formed. At present, research on construction project management is mostly based on this framework as the research premise. In future research and development, regardless of how the number of management objectives increases, progress, cost, and quality are still the three most important basic goals that have the greatest impact on the overall goal throughout the entire life cycle of the construction project. How to find a balance among the three, obtaining the optimal project execution effect remains the fundamental goal of construction project management.

2. Literature Review. At present, there are not many research results on the efficiency of construction project management in the country, and most of them are focused on a single goal. The author's research on the efficiency of construction project management starts from three aspects: progress, cost, and quality. Considering that these three goals have the greatest impact on the overall goals of the project, so through comprehensive optimization of this aspect, the overall level of construction project management can be improved. Moreover, the author's reasonable quantification of quality parameters has greatly improved the effectiveness of quality objective research. Through the construction of a comprehensive analysis model of progress cost quality, the current insufficient research on management efficiency under multi-objective construction engineering has been effectively improved, which can enrich the existing management efficiency optimization theory [1]. When evaluating the optimization effect of management efficiency, the author introduced value engineering as a measurement indicator and reasonably transformed the cost and quality objectives in construction engineering into value engineering, using the idea of high or low value to reflect the advantages and disadvantages of project multi-objective regulation. Not only does it provide an effective tool for optimizing the efficiency of construction project management, but it also facilitates the integration of management research with other disciplines. There are reference examples in the process of setting goals for construction project management. At present, the common problem in construction projects is that project managers do not attach importance to management objectives, and the allocation of various resources is not scientific and systematic enough [15]. Through the author's research, it can provide a certain reference for the implementation of construction project management. Construction project managers do not attach great importance to management efficiency from an ideological perspective. They often only focus on whether their management methods have been implemented in actual construction, and do not intuitively realize the effectiveness of improving management efficiency in improving the overall efficiency of the enterprise. The author's research can make up for this deficiency and effectively strengthen the importance of management efficiency by managers, furthermore, it ensures that the management costs invested in the implementation of construction projects can achieve maximum benefits.

Regarding the optimization of management efficiency in construction projects, foreign scholars have continuously increased their attention in recent years. Through the application of different research methods and theories, as well as attempts at various research objectives, a large amount of research has been conducted on the overall optimization of construction industry and construction project management efficiency, which has been continuously promoted and developed on the basis of previous research [7, 6].

With the continuous improvement of living standards and the increasing electricity load, the number of power transmission and transformation equipment is also rapidly increasing. The original maintenance mode is insufficient to ensure the safe operation of the huge power grid. This article mainly studies the research and application of machine learning based optimization technology for substation equipment maintenance decision-making. Liu, Z, based on the technical principles of online monitoring and status maintenance of substation equipment, combined with deep learning models, implemented an intelligent monitoring and maintenance early warning system. The main functions of this system include monitoring equipment management, operation monitoring, and comprehensive display, which can effectively carry out online monitoring and status warning for substation equipment [11]. Whale Optimization Algorithm (WOA) is a relatively novel algorithm in the field of meta heuristic algorithms. Compared with other mature optimization algorithms, WOA can demonstrate efficient performance, but there are still problems of premature convergence and easy falling into local optima in complex multimodal functions. Therefore, Guo, Y. K. Z proposed an improved WOA and proposed a new strategy of random jump change and a random control parameter strategy to improve the exploration and utilization ability of WOA. This article uses 24 well-known benchmark functions to test the algorithm, including 10 unimodal functions and 14 multimodal functions. The experimental results show that the convergence accuracy of this algorithm is better than the original algorithm on 21 functions, and better than the other 5 algorithms on 23 functions [5]. We combine Deep Gaussian Process (DGP) with multitasking and transfer learning for performance modeling and optimization of HPC applications. The deep Gaussian process combines the uncertainty quantification advantages of Gaussian processes with the predictive ability of deep learning. Multi task and transfer learning allow for improved learning efficiency when learning several similar tasks simultaneously, as well as when seeking models from previous learning to assist in learning new tasks separately. The comparison with state-of-the-art automatic tuners shows the advantages of our method in two application problems. In this article, Dongarra, J. combines DGP with multitasking and transfer learning, which can improve the adjustment of application parameters for problems of interest and predict parameters for any potential problems that the application may encounter [13].

In summary, domestic and foreign scholars have conducted research and analysis on the efficiency of construction project management from different perspectives, realizing the importance of optimizing management efficiency, and using various methods to establish systematic analysis models to improve the management effectiveness of construction projects. The proposed improvement measures also have practical guiding significance. Although current management efficiency has gradually been integrated into construction project management, the existing research literature mainly studies a single or two elements in the construction management process, and the essence of its research is still linear. From the perspective of managers, there is not much research on multi-objective comprehensive control in the construction process. Therefore, based on the dependency deep learning algorithm, the author establishes a multi-objective comprehensive analysis model to optimize the management efficiency of construction projects, and calculates and verifies it through examples, providing a new approach for subsequent research.

3. Methods.

3.1. Optimization Control Model for Construction Engineering Management Oriented to SUSTM. The optimal control model for construction project management is a management behavior that involves the entire production process of construction products, with characteristics such as one-time, comprehensive, and strong constraints. Construction project management includes quality management, schedule management, cost management, contract management, safety management, risk management, communication management, human resource management, information management, and environmental protection. The management project needs to ensure efficient management efficiency, and the recognized influencing factors at home and abroad include four aspects: Management process, management methods, manager quality, property rights, and responsibility system. Research the introduction of value engineering for multi-objective control optimization analysis of construction project management, replacing product functionality with quality, treating cost as contracting cost, and value coefficient as the ratio of quality to cost [14].

The flow chart of optimization control for construction projects is shown in Figure 3.1. Before the project officially starts, the first step is to establish a comprehensive model of schedule cost quality optimization for construction project management based on reasonable quantification of construction project quality. The second step is to optimize the three objectives and obtain corresponding target values, and then use the obtained target

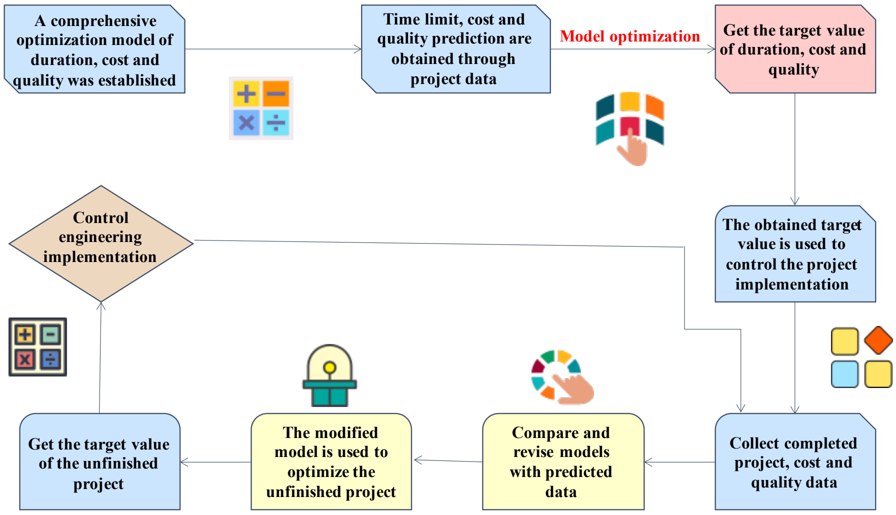


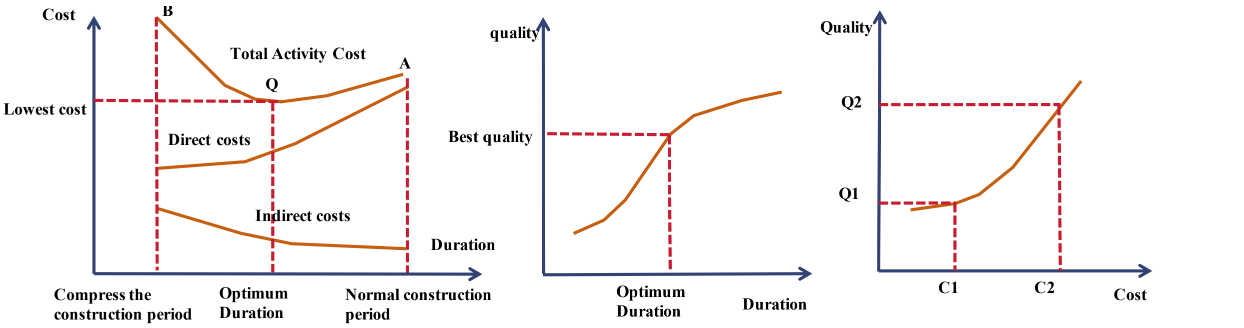
Fig. 3.1: Optimization control flow chart of the construction project

values to control the construction project [2]. After the project has been put into construction, data information on time, quality, and completed project costs is first collected. Then, these data are used to modify and optimize the comprehensive model. The next step is to use the modified model to optimize the unfinished projects and obtain three target values. Repeat the above steps until the optimal solution is obtained and the optimization process is completed.

The study introduces a quality coefficient for quantification, and the relationship between the quality coefficient and the six major quality characteristics can be expressed through calculation expressions. The method for determining quantitative quality based on the following characteristics of engineering projects, including applicability, safety, economy, safety and environmental protection, durability, and reliability, is represented by the letters a1-a6 [18]. Quality quantification can control the quality of construction projects during the construction process through quality coefficients. Different quality coefficients indicate inconsistent quality quantification values. When the quality coefficient is about 1, the minimum values of a1-a6 are 0.8, 0.9, 0.9, 0.8, and 0.9, respectively. When the quality coefficient is about 0.9983, the minimum values of a1-a6 are 0.6, 0.7, 0.6, 0.6, 0.7, and 0.7, respectively. When the quality coefficient is about 0.97, the minimum values of a1-a6 are 0.5, 0.5, 0.3, 0.3, 0.5, and 0.5, respectively. When the quality coefficient is about 0.85, the minimum values of a1-a6 are 0.3, 0.3, 0.2, 0.2, 0.3, and 0.3, respectively. When the quality coefficient is about 0.47, the minimum values of a1-a6 are 0.1, 0.1, 0.1, 0.1, 0.1, and 0.1, respectively [21]. At the same time, the degree of satisfaction of the six quality characteristics of a1-a6 is as follows. In the case of slight satisfaction, the value range of a3-a4 is 0.1∼0.2, while the rest are 0.1∼0.3. Under basic conditions, the value ranges of a3-a4 are 0.2-0.4 and 0.2-0.3, respectively, while the other quality characteristic ranges are 0.3-0.5. In the case of satisfaction, the value ranges of a3-a4 are 0.4-0.6 and 0.3-0.6 respectively, while the other quality characteristic ranges are 0.5-0.6. In very satisfactory cases, the range of values for a3-a4 is 0.6-0.9, while the rest are 0.6-0.8. Under very satisfactory conditions, the range of values for a3-a4 is 0.9-1, while the rest are 0.8-1.

If the construction project includes a unit project with a total quantity of w, and there is a unit project involving a sub project with a quantity of r in the unit project, and the construction project also includes a sub project with a quantity of k. When the quality coefficient of the sub item is set, the corresponding satisfaction level value is set to 0. The calculation formula for the quality coefficient of construction engineering is:

$$\left\{\begin{array}{l} q^0 = 1 - \prod^0 (1 - a_m) \\ q^1 = 1 - \prod^k \left(1 - q^0 i\right) \\ q^2 = 1 - \prod^r \left(1 - q^1 i\right) \\ q = 1 - \prod^w \left(1 - q^2 i\right) \end{array}\right. \tag{3.1}$$



(a) The relationship between direct costs, indirect costs, and construction period(b) Relationship between construction period and quality(c) Relationship between cost and quality

Fig. 3.2: Progress cost quality relationship

In equation (3.1), $i = 1, 2, K$, q^0 refer to the quality coefficient of sub projects, q^1 and q^2 represent sub projects and unit projects, respectively, q is the quality coefficient of construction engineering. On this basis, the study establishes a quality cost schedule model and obtains the optimal quality coefficient, which is then compared and analyzed with the aforementioned quality characteristics and satisfaction level. Figure 3.2 shows the relationship between progress cost quality [12].

This includes both direct and indirect costs. The directly incurred expenses include the costs of raw materials, labor, and equipment. If there is a compression of the construction period, the direct costs incurred will also increase accordingly. Indirect costs mainly include enterprise management fees and training fees, which will continue to decrease with the acceleration of project progress, mainly manifested as the shortened usage time of leased equipment and prefabricated houses. Therefore, the optimal completion time can be determined by combining two types of costs. Figure 3.2 (b) refers to the relationship between project progress and quality. There is an opposing and unified relationship between progress and quality. The acceleration of progress is likely to cause a decrease in the overall quality level of construction projects [17]. If the balance and continuity of progress can be ensured, quality can meet the standards as much as possible. At the same time, the introduction of science and technology and the improvement of management level will also improve the overall progress and quality. Figure 3.2 (c) shows the relationship between cost and quality. Introducing advanced technology and equipment not only increases costs, but also increases the quality of construction projects. When the cost is higher than C1, the quality meets the minimum quality standard. When the cost is higher than C2, the quality level does not improve significantly, but the cost increases faster. Therefore, in the actual management process, it is advisable to choose a cost range of C1-C2 and a construction quality range of Q1-Q2.

C_1 and c_2 represent the cost of investment under the conditions of qualified quality and improvement, respectively. Before establishing a comprehensive model, the following conditions need to be established. C_1 and time t are inversely linearly correlated, with q_0 increasing with the increase of c_2 and q_0 decreasing with the decrease of t. The calculation expression for the decision variables of the model is equation (3.2).

$$\begin{cases} c_{1i} = \frac{\left(c_{1i}^C - c_{1i}^N\right)(t_i - t^c)}{t^C - t^N} + c_{1i}^C \\ c_i = c_{1i} + c_{2i} \\ q_i^0 = Ac_{2i}^2 + Bt_i \end{cases} \tag{3.2}$$

In equation (3.2), $A = \frac{t^N q^c - t^c q^N}{\left(c_2^N\right)^2 t^N - \left(c_2^c\right)^2 t^C}$, $B = \frac{\left(c_2^N\right)^2 q^N - (c_2^c)^2 q^C}{\left(c_2^N\right)^2 t^N - \left(c_2^c\right)^2 t^C}$, t_i^N and t_i^C refer to the normal and minimum durations of sub item i, respectively, c_{1i}^N and c_{1i}^C respectively refer to the lowest and highest costs after the building is qualified, c_{2i}^N and c_{2i}^C refer to the lowest and highest costs after improving quality, q_i^N and q_i^C refer to the minimum and maximum quality coefficients, and t_i refers to the actual duration. The constraint conditions are as follows: firstly, $\sum t_i \leq T_c$, where T_c is the calculated duration. Secondly, the minimum cost is less than or equal to the construction project cost, while the project cost is less than or equal to the project contract price. Thirdly, the quality coefficient is equal to or greater than the minimum qualification coefficient [10].

3.2. Selective Update Neural Network Structure Solving Model. The LSTM neural network structure is based on the classical recurrent neural network, introducing three logical structures: Input gate, output gate, and forgetting gate. Forgetting gate is the process of clearing all unimportant information in the unit state. Its input includes a specific time step x^t and the unit state of the previous hidden layer $h^{(t-1)}$. The control function determines whether the information is cleared or retained. The value interval of the vector $f^{(t)}$ for the final output unit state is $[0, 1]$. If the value is 1, then the input value is retained as a whole. If the value is 0, then the value is deleted as a whole. Input refers to determining whether information is added to the unit state for data update, using the Sigmad function to delete the information of x^t and $h^{(t-1)}$, and then calculating the current input unit state. After establishing the Tach function, a vector is selected with a value range of [-1,1], and finally calculating the unit state $c^{(t)}$ at the current time, this value is first multiplied by the previous unit state $c^{(t-1)}$ and the forgetting gate, then added to $c'(t)$, and multiplied by the input gate $i^{(t)}$ to obtain the final result. The output gate selects the valuable unit states that need to be presented for output, and its specific implementation process includes two steps, firstly, a filter $o^{(t)}$ is obtained by using x^t and $h^{(t-1)}$, and then the Tach function is selected to compress the values of the unit state vector into an interval of [-1,1]. At the same time, the result obtained by multiplying the vector and $o^{(t)}$ is used as the basis for determining the hidden information $h^{(t)}$. The selectively updated long-term and short-term memory neural network structure is based on the LSTM neural network structure, combining the forgetting gate and output gate as update gates, greatly reducing the training time of the neural network model and improving the learning efficiency of the algorithm. The update formula for the improved SUSTM neural network structure is equation (3.3).

$$\begin{cases} f^{(t)} = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_t\right) \\ o^{(t)} = \sigma\left(W_o \cdot [c_t, h_{t-1}, x_t] + b_o\right) \\ c'_t = \tanh\left(W_c \cdot [c_t, h_{t-1}, x_t] + b_c\right) \\ c_t = f_t \cdot c_{t-1} + (1 - f_t) \cdot c'_t \\ h_t = o_t \cdot \tanh\left(c_t\right) \end{cases} \tag{3.3}$$

W_f, W_c, W_o respectively represent the weights of the update gate, calculation input unit, and output gate, while b_t, b_c and b_o respectively refer to the biases of the update gate, calculation input unit, and output gate.

4. Analysis of the Optimal Control Model for Construction Engineering Management.

4.1. Model Optimal Parameters. The author takes the construction project undertaken by a certain construction company as an example. The project covers an area of 145.53 acres, has a plot ratio of 2.5, a total land cost of 470 million yuan, a floor price of 2114 yuan/m^2, and a building density of 30%. The experimental analysis includes a sales area with a building area of 1650m^2, a floor height of 8.6m, a contract period of 150 days, and a contract cost of 2.68 million yuan, the lowest quality coefficient is 0.8, and the lowest enterprise cost is 2.2 million yuan [20]. The maximum value coefficient calculated through the composition and parameters of the engineering project is 0.2375. The optimal parameters of the corresponding optimization control model for construction project management are shown in Table 4.1, and the quality qualification cost, improvement quality cost, quality coefficient, and duration of 11 sub projects are obtained. The experiment utilized a progress quality coefficient cost optimization model for data analysis, with an optimized cost of 2.2919 million yuan and a quality coefficient of 0.8325. Therefore, this optimization model can bring more economic profits to the enterprise while ensuring quality.

Figure 4.1 shows the model training loss results of deep learning neural networks before and after improvement. It can be seen from the figure that the training loss values of the two network structures continue to decrease with the increase of iteration times. Both LSTM and SUSTM neural network algorithms converge quickly at around 20 iterations, and the difference between the two algorithms is not particularly significant [9]. However, when the number of iterations ranges from 20 to 100, compared to the LSTM neural network algorithm, the convergence speed of the SUSTM neural network algorithm is faster, and the loss value tends to be more stable.

Table 4.1: Optimum parameters for optimal control of construction engineering management

Distribution entry	Distribution entry	Quality qualified fee / ten thousand yuan	Quality improvement cost / ten thousand yuan	Mass coefficient	Duration days / day
Foundation and foundation sub project	Earthwork project	10.48	7.46	0.832	8.12
	Reinforcement project	3.56	4.45	0.781	4.06
	Template Project	1.14	1.43	0.765	1.01
	Brick building project	7.25	9.32	0.833	6.11
Main structure sub projects	Waterproof project	2.39	4.22	0.791	18.26
	Template Project	22.87	27.31	0,761	6.12
	concrete	7.41	9.35	0.811	24.45
	Construction projects	30.5	35.61	0.801	12.11
Construction wall sub items from	Wall project	15.36	18.41	0.765	15.23
Decoration sub project	External wall plastering project	3.55	2.81	0.732	3.11
	Ground projects	9.75	12.56	0.912	8.05

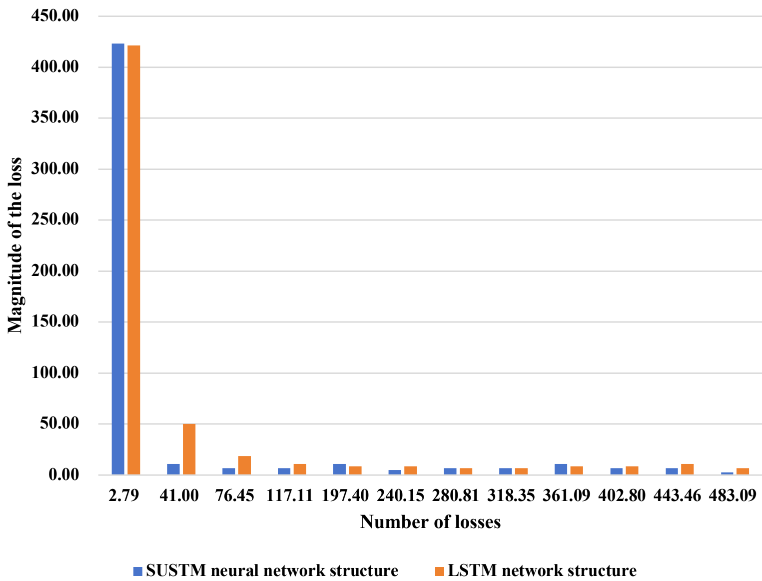


Fig. 4.1: Model training loss results

4.2. Sensitivity Analysis. The study further utilizes sensitivity analysis theory to determine the most important factors affecting the economic interests of enterprises, while verifying the correctness and rationality of the proposed model.

Based on the aforementioned content, the cost and duration of improving quality jointly determine the quality coefficient. The quality sensitivity analysis of the cost and duration of improving quality is shown in Figure 4.2. When the quality coefficient is 0.609, the duration and cost of improving quality are 8 days and 144000 yuan, respectively. When the quality coefficient is 0.7007, the duration and cost of improving quality are 7.2 days and 160000 yuan, respectively [19]. When the quality coefficient is 0.0716, the duration and cost of improving quality are 8 days and 160000 yuan, respectively. When the quality coefficient is 0.8343, the duration and cost of improving quality are 8 days and 176000 yuan, respectively. Therefore, the cost of improving quality has a greater impact on the quality coefficient of sub projects than the duration, which is consistent with the actual situation.

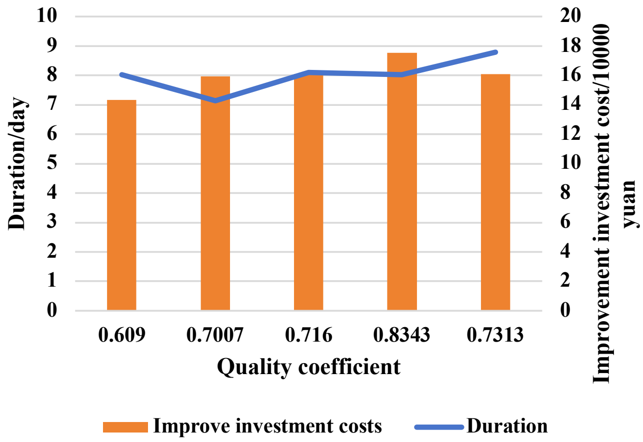


Fig. 4.2: Quality sensitivity analysis of improvement costs and duration

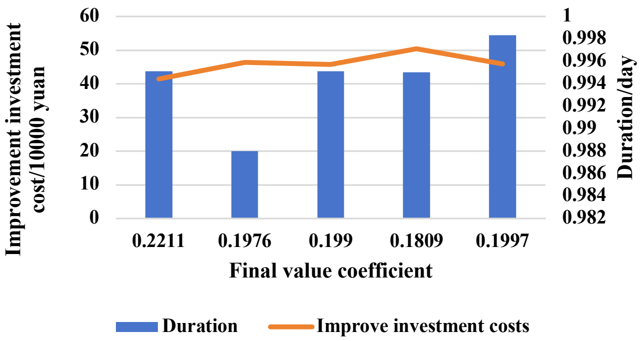


Fig. 4.3: Sensitivity analysis of total expenditure and quality coefficient

The sensitivity results of the total expenditure and quality coefficient to the value coefficient are shown in Figure 4.3 when selecting the projects of the foundation and foundation construction parts. When the value coefficient is 0.2211, the total investment cost and quality coefficient are 412700 yuan and 0.99496 yuan, respectively. When the value coefficient is 0.1976, the total cost and quality coefficient are 456300 yuan and 0.98798 yuan, respectively [4]. When the value coefficient is 0.1990, the total cost and quality coefficient are 456300 yuan and 0.99496 yuan, respectively. Therefore, compared to the coefficient of quality, cost has a greater impact on the value of buildings.

5. Conclusion. The optimization and control of construction project management is currently a topic of common concern among relevant experts and scholars. This study utilizes deep learning algorithms to achieve multi-objective optimization control, this method introduces quality coefficient and value engineering to quantify quality and construct an optimization control model, which is solved using the SULSTM neural network algorithm. The algorithm solving model results show that this method can obtain the optimal parameters for optimal control of construction project management. The loss values of LSTM and two neural network algorithms have the same trend in the first 20 iterations, but within the range of 20-100 iterations, the SUSTM neural network algorithm has faster convergence speed and more stable loss values. Sensitivity analysis shows that the cost of improving quality has a more significant impact on the quality coefficient, and the total investment cost has a more significant impact on the value coefficient. Therefore, the established optimization control model is feasible and practical.

REFERENCES

[1] R. M. Buvanesvari and K. S. Joseph, *An efficient secured pit management and attack detection strategy enhanced by csoa-dcnn algorithm in a named data networking (ndn).*, International Journal of Intelligent Engineering & Systems, 14 (2021).

[2] Y. J. Chen, J.-T. Tsai, W.-T. Huang, and W.-H. Ho, *Intelligent optimization in model-predictive control with risk-sensitive filtering*, Journal of Intelligent & Fuzzy Systems, 40 (2021), pp. 7863–7873.

[3] J. Du, Y. Xue, V. Sugumaran, M. Hu, and P. Dong, *Improved biogeography-based optimization algorithm for lean production scheduling of prefabricated components*, Engineering, Construction and Architectural Management, 30 (2023), pp. 1601–1635.

[4] A. Guo and C. Yuan, *Network intelligent control and traffic optimization based on sdn and artificial intelligence*, Electronics, 10 (2021), p. 700.

[5] Y. Guo, H. Shen, L. Chen, Y. Liu, and Z. Kang, *Improved whale optimization algorithm based on random hopping update and random control parameter*, Journal of Intelligent & Fuzzy Systems, 40 (2021), pp. 363–379.

[6] L. He, Z. Gu, Y. Zhang, H. Jing, and P. Li, *Review on thermal management of lithium-ion batteries for electric vehicles: Advances, challenges, and outlook*, Energy & Fuels, 37 (2023), pp. 4835–4857.

[7] Z. Hou, J. Guo, J. Xing, C. Guo, and Y. Zhang, *Machine learning and whale optimization algorithm based design of energy management strategy for plug-in hybrid electric vehicle*, IET Intelligent Transport Systems, 15 (2021), pp. 1076–1091.

[8] J. Jia, S. Yuan, Y. Shi, J. Wen, X. Pang, and J. Zeng, *Improved sparrow search algorithm optimization deep extreme learning machine for lithium-ion battery state-of-health prediction*, Iscience, 25 (2022).

[9] W. Li, G. Feng, and S. Jia, *Research on multi-energy management system of fuel cell vehicle based on fuzzy control*, Journal of Intelligent & Fuzzy Systems, 40 (2021), pp. 6205–6217.

[10] D. Lin, M. Li, Q. Zhan, X. Song, Y. Yang, and H. Li, *Application of intelligent logistics inventory optimization algorithm based on digital supply chain*, International Journal of Emerging Electric Power Systems, 24 (2022), pp. 61–72.

[11] Z. Liu, X. Zhu, J. Ma, C. Hu, H. Fu, and K. Zhao, *Application of optimization technology for overhaul decision of substation equipment based on machine learning*, in Journal of Physics: Conference Series, vol. 2066, Hangzhou, China, 2021, IOP Publishing, p. 012095.

[12] B. Luo et al., *A method for enterprise network innovation performance management based on deep learning and internet of things*, Mathematical Problems in Engineering, 2022 (2022).

[13] P. Luszczek, W. M. Sid-Lakhdar, and J. Dongarra, *Combining multitask and transfer learning with deep gaussian processes for autotuning-based performance engineering*, The International Journal of High Performance Computing Applications, 37 (2023), p. 10943420231166365.

[14] S. R. Nekoo, J. Á. Acosta, and A. Ollero, *A search algorithm for constrained engineering optimization and tuning the gains of controllers*, Expert Systems with Applications, 206 (2022), p. 117866.

[15] R. K. Prasad and T. Jaya, *Intelligent spectrum sharing and sensing in cognitive radio network by using aroa (adaptive rider optimization algorithm)*, International Journal of Computational Intelligence and Applications, 22 (2023), p. 2341007.

[16] G. Saravanan and N. Yuvaraj, *Cloud resource optimization based on poisson linear deep gradient learning for mobile cloud computing*, Journal of Intelligent & Fuzzy Systems, 40 (2021), pp. 787–797.

[17] H. Tian, C. Tian, C. Yuan, and K. Li, *Dynamic operation optimization based on improved dynamic multi-objective dragonfly algorithm in continuous annealing process*, Journal of Industrial and Management Optimization, 19 (2023), pp. 6159–6181.

[18] Y. Wang, R. Xie, W. Liu, G. Yang, and X. Li, *Modeling and optimization of nox emission from a 660 mw coal-fired boiler based on the deep learning algorithm*, Journal of Chemical Engineering of Japan, 54 (2021), pp. 566–575.

[19] S. Xiong, Y. Zhang, C. Wu, Z. Chen, J. Peng, and M. Zhang, *Energy management strategy of intelligent plug-in split hybrid electric vehicle based on deep reinforcement learning with optimized path planning algorithm*, Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering, 235 (2021), pp. 3287–3298.

[20] C. Yang, K. Liu, X. Jiao, W. Wang, R. Chen, and S. You, *An adaptive firework algorithm optimization-based intelligent energy management strategy for plug-in hybrid electric vehicles*, Energy, 239 (2022), p. 122120.

[21] D. Zhang, J. Zhao, Y. Zhang, and Q. Zhang, *Intelligent train control for cooperative train formation: A deep reinforcement learning approach*, Proceedings of the Institution of Mechanical Engineers, Part I: Journal of Systems and Control Engineering, 236 (2022), pp. 975–988.

Edited by: B. Nagaraj M.E.
Special issue on: Deep Learning-Based Advanced Research Trends in Scalable Computing
Received: Oct 5, 2023
Accepted: Nov 14, 2023