International Journal for Housing Science and Its Applications
Publish August 6, 2025. Volume 46, Issue 3 Pages 8019-8028

https://doi.org/10.70517/ijhsa463685

A study on optimizing library space management effectiveness using support vector regression

Xiyuan Yang[1,*]
[1] Changchun University of Technology, Changchun, Jilin, 130000, China
Corresponding authors: (e-mail: Young.a_a@163.com).

Abstract In recent years, with the increasing demand for self-study space in college libraries, traditional space management methods often rely on experience and manual intervention, which lack scientificity and precision. In this paper, a method for optimizing the effectiveness of library space management based on the Improved Gray Wolf Optimization (IGWO) algorithm and Support Vector Regression (SVR) model is proposed. First, the key parameters of SVR are optimized using the gray wolf optimization algorithm to improve the prediction accuracy of the regression model. Then, it is experimentally verified that the improved Gray Wolf algorithm has superior accuracy and convergence speed compared with the traditional GWO algorithm. In the experiment, the root mean square error (RMSE) of the IGWO-SVR model is 0.0008, the mean absolute error (MAE) is 0.0057, and the coefficient of determination (R^2) reaches 99.95%. In addition, the maximum absolute error (MAE) of the IGWO-SVR model in predicting the spatial effectiveness of libraries is 0.0057, which is significantly lower than the errors of the BPNN model and the traditional SVR model. The experimental results show that the improved SVR model can not only accurately predict library space management effectiveness, but also provide theoretical support and practical basis for optimizing resource allocation and enhancing management services.

Index Terms improved gray wolf optimization algorithm, support vector regression, library space management, performance optimization, machine learning, model prediction

I. Introduction

As a storehouse of knowledge and an important place for academic research, libraries play an important role in modern society [1]. With the continuous investment in library construction, as well as the continuous evolution of the demand for library use, the spatial layout of libraries has been gradually rationalized [2], [3]. Among them, the concept of people-oriented management occupies an increasingly important position in the spatial layout of libraries [4]. In order to better meet the needs of readers, the optimization of library space management has become particularly important [5].

In the past, traditional libraries tend to be more conservative in architectural design, mostly adopting regular shapes such as rectangle or square, and their internal design focuses more on creating local independent spaces, such as study rooms of different sizes, research rooms, rest areas and reading areas [6]-[8]. Although these functional partitions are clear, the spaces are often relatively closed. However, with the in-depth development of concepts such as information sharing and space sharing, the functional layout of libraries has been constantly innovated [9]. Libraries have not only become a centralized place for cultural sharing, but also broken the boundaries of traditional space management and transformed into an open communication space [10], [11]. In the new spatial layout, the library is meticulously partitioned into functional zones according to the time and frequency of use [12], [13]. These areas include consultation, lending, book collection, study, sharing, display and integrated office, etc. Some libraries have even set up a special “daze area”, which effectively improves the spatial management efficiency of libraries [14]-[16].

With the rapid development of information technology, traditional library space management is facing more and more challenges. Library space not only needs to meet the basic needs of users, but also to provide a more flexible and efficient learning and research environment. However, there are many shortcomings in traditional space management methods, such as uneven resource distribution and low space utilization. Therefore, how to optimize library space management scientifically and efficiently has become one of the hot issues in current research.

Studies have shown that machine learning models, especially support vector regression (SVR), have better performance in space management prediction. However, the performance of SVR depends on suitable parameter selection, and traditional methods have local optimum problems in the optimization process. To address this problem, the Gray Wolf Optimization (GWO) algorithm, as an emerging global optimization algorithm, has become an effective tool to solve this problem by virtue of its strong global search capability. In this paper, SVR is combined with GWO to propose the improved gray wolf optimization algorithm (IGWO), through which the parameters of SVR model are optimized so as to improve the prediction accuracy of the model. The core idea of the research is to enhance the parameter selection ability of SVR model through the improved Gray Wolf Optimization Algorithm, and to verify its application effect in optimizing the effectiveness of library space management through experiments. The experimental results will demonstrate the advantages of the IGWO-SVR model in dealing with space management data and compare it with traditional methods to provide library managers with feasible optimization solutions.

II. Improving Support Vector Regression for Predicting Library Space Management Effectiveness

II. A. Introduction to support vector regression machines

Support Vector Machine (SVM) [17] is developed based on statistical theory, based on the principle of structural risk minimization, has a fast convergence speed and strong generalization ability, and has good performance in dealing with classification and regression problems. Support vector regression machine is a new method to solve the regression fitting problem based on support vector machine, whose basic idea is no longer to find an optimal classification surface to separate the two types of samples, but to find an optimal classification surface so that the training samples minimize the error away from the optimal classification surface.

Support vector regression machine at the same time consider the empirical risk and confidence range, to minimize the structural risk as the principle, so that the algorithm can achieve the global optimum.SVR can deal with linear regression and nonlinear regression problems, this paper studies the effectiveness of the evaluation of the problem belongs to the latter. For the nonlinear case, the nonlinear samples in the low-dimensional space are converted to linear samples in the high-dimensional space by using nonlinear mapping, and then solved by using the method of processing linear regression. The linear regression function is established in the high-dimensional feature space as:

$$f(x)=\omega\cdot\varphi(x)+b \tag{1}$$

where $f(x)$ is the regression function, $\varphi(x)$ is the nonlinear mapping function, and ω and b are the coefficients and constant terms, respectively.

The standard support vector machine uses the $\varepsilon-$ insensitive loss function, and ε specifies the error allowed for the regression function, and the following fits are obtained:

$$\begin{cases} y_i-f(x_i)\leq\varepsilon+\xi_i \\ f(x_i)-y_i\leq\varepsilon+\xi_i^* \quad i=1,2,\cdots,n \\ \xi_i,\xi_i^*\geq 0 \end{cases} \tag{2}$$

where ξ_i,ξ_i^* is the relaxation factor, when the regression has an error, ξ_i,ξ_i^* are both greater than 0, the error does not exist, and is taken to be 0. The larger the value of ε, the wider the width of the sensitivity band will be, the model's complexity is reduced, and the generalization is enhanced. The problem is transformed into a problem of minimizing the optimization objective function:

$$R(\omega,\xi,\xi^*)=\frac{1}{2}\omega^T\cdot\omega+C\sum_{i=1}^{n}(\xi_i+\xi_i^*) \tag{3}$$

In Eq. (1), the first term makes the fitting function flatter, thus improving the generalization ability; the second term is to reduce the error, in which the constant C indicates the degree of punishment for exceeding the error sample, which is used to weigh the confidence range and the empirical risk in the training process of the support vector machine, and if the value of the parameter is set appropriately, it enables the learning machine to enhance its generalization while improving the prediction accuracy.

The Lagrange function is introduced to Eq. (2) and Eq. (3) and minimized, and the pairwise form is constructed and solved to obtain the saddle point of the convex function. The nonlinear regression function is obtained:

$$f(x)=\sum_{i=1}^{n}(\alpha_i-\alpha_i^*)(\varphi(x_i).\varphi(x))+b \tag{4}$$

In Eq. (4), α_i and α_i^* are Lagrange multipliers, and it can be seen from Eq. (4) that the support vector regression machine only carries out the inner product operation and operation in high-dimensional space, and it does not involve complex high-dimensional operations. Therefore, the introduction of appropriate kernel functions can greatly simplify the vector operations of the original problem in high-dimensional space. Equation (4) can be transformed into the following equation after introducing the kernel function:

$$f(x)=\sum_{i=1}^{n}(\alpha_i-\alpha_i^*)K(x,x_i)+b \tag{5}$$

In this paper, the radial basis kernel function with strong generalization ability is used as shown in the following equation:

$$K(x,x_i)=\exp(-\frac{\|x-x_i\|^2}{2\sigma^2}) \tag{6}$$

Among them, the radius parameter σ of the kernel function has a great influence on the learning performance of the RBF kernel SVR, and how to choose the appropriate radius parameter is a key issue in the selection of the RBF kernel SVR model.

II. B. The Gray Wolf Algorithm

Gray Wolf Optimization (GWO) [18], as a pack-based algorithm, GWO simulates the hunting and social processes of gray wolves in nature. Gray wolves are divided into α, β, δ, and ω wolves according to the hierarchy. α wolves are the leaders of the pack, β wolves are subordinate to α wolves and are located in the second tier of the pack hierarchy, they usually assist α wolves in decision making, and they are the best candidates to be the next leader. δ wolves are located in the third tier of the pack, and they are usually the pack's "workers" who receive orders from the upper tier of wolves in the pack. Finally, ω wolves are at the lowest level of the pack and assist the other members of the pack.GWO achieves the optimization goal based on the mechanism of wolf pack cooperation. The algorithm effectively solves the shortcomings of the grid search method with an uncomplicated algorithmic structure and without overly cumbersome tuning parameters.

II. B. 1) Surrounding prey

In GWO wolves surround their prey foraging before attacking, this process determines the distance between the predator and the prey, the following mathematical model equation represents this behavior well:

$$\vec{D}=|\vec{C}\cdot\vec{X}_p(t)-\vec{X}(t)| \tag{7}$$

$$\vec{X}(t+1)=\vec{X}_p(t)-\vec{A}\cdot\vec{D} \tag{8}$$

Here t is the number of iterations, $\vec{X},\vec{X}_p$ are the position vectors of the prey and the gray wolf, and $\vec{D}$ is the distance between the gray wolf and the individual $\vec{A}$ and $\vec{C}$ are the coefficient vectors. To wit:

$$\vec{A}=2\vec{a}\cdot\vec{r}_1-a \tag{9}$$

$$\vec{C}=2\cdot\vec{r}_2 \tag{10}$$

where $\vec{a}$ is the convergence factor in the iterative process, and $\vec{r}_1$ and $\vec{r}_2$ are random numbers between [0, 1].

II. B. 2) Hunting behavior

Gray wolves can find prey to hunt after surrounding them, which is smart hunting behavior of gray wolves. According to the social hierarchy of gray wolf characteristics, the charm hunting behavior is monitored by α wolves, β wolves, δ wolves, ω wolves searching for α wolves, β wolves, δ wolves in position $\vec{X}_\alpha,\vec{X}_\beta,\vec{X}_\delta$ to mathematically model the hunting behavior of gray wolves, the optimal solution is α wolf, the second best solution is β wolf, the third best solution is δ wolf, and the rest of gray wolves according to the location of the $\vec{X}_\alpha,\vec{X}_\beta,\vec{X}_\delta$ position information to update their own position, the mathematical expression corresponding to this process is as follows:

$$\begin{cases} \vec{D}_\alpha = |\vec{C}_1 \cdot \vec{X}_\alpha - \vec{X}| \\ \vec{D}_\beta = |\vec{C}_2 \cdot \vec{X}_\beta - \vec{X}| \\ \vec{D}_\delta = |\vec{C}_3 \cdot \vec{X}_\delta - \vec{X}| \end{cases} \tag{11}$$

where $\vec{X}$ is the current position of the gray wolf, $\vec{D}_\alpha, \vec{D}_\beta, \vec{D}_\delta$ represents the distance between the remaining individual ω wolves of the pack and the α, β, δ wolves, respectively, $\vec{X}_\alpha, \vec{X}_\beta, \vec{X}_\delta$ represents the current position of α, β, δ, respectively, and $\vec{C}_1, \vec{C}_2, \vec{C}_3$ is a random vector. Namely:

$$\begin{cases} \vec{X}_l = \vec{X}_\alpha - A_l \cdot (\vec{D}_\alpha) \\ \vec{X}_2 = \vec{X}_\beta - A_2 \cdot (\vec{D}_\beta) \\ \vec{X}_3 = \vec{X}_\delta - A_3 \cdot (\vec{D}_\delta) \end{cases} \tag{12}$$

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \tag{13}$$

The gray wolf ω updates the step size and direction of its own position and determines the final position of ω.

The core phase of GWO is to attack the prey, which means to find the best solution, this process is realized mainly through the change of A and a decreasing in the equation, after that follow the process of Eq. continuously approaching the prey for attacking the prey to forage until the end of the iteration, completing the optimality seeking process of GWO.

II. B. 3) Improved Gray Wolf Algorithm

The traditional GWO algorithm also has some drawbacks, such as the local extreme value problem and the convergence speed problem. When $|A|>1$, the gray wolf pack searches for the best solution in the global range, and when $|A|<1$, the pack searches for the search in a certain local range. Therefore, if you want to improve the performance of the algorithm's search and evaluation, the value of $\vec{A}$ is extremely important, and it can be seen that there is a great correlation between the relationship between $\vec{A}$ and the convergence factor a, so the value of a is a key element to ensure the performance of the algorithm's evaluation.

(1) Convergence factor

In practice, the iteration of the algorithm does not necessarily behave as a linear change, therefore, this paper proposes a tangent convergence factor, which can be expressed as:

$$a = a_{\max} - (a_{\max} - a_{\min}) \tan(\frac{\pi}{4} \cdot \frac{t}{t_{\max}}) \tag{14}$$

where t is the current iteration number and $t_{\max}$ is the maximum iteration number. The strategy by nonlinearly adjusting the value of itself, in the algorithm for optimization search, the first period of the larger value of itself, to ensure that the algorithm in the search of the first period of the global estimation ability, to provide a good convergence speed; the later period of time and the ability to smaller value of itself to enhance the algorithm in the search of the later period of the local estimation ability, so as to improve the accuracy of the solution.

(2) Levy flight strategy

In the standard GWO, the best three wolves are selected, and the other individuals update their positions according to the α, β, δ wolves, however, when the positions of the three α, β, δ wolves are close to a certain local optimum, these wolves will also converge to the local optimum. Therefore, this paper chooses to introduce the Levy flight strategy [19], which changes the random walk boundary of the algorithm in different iterations due to its random walk property, thus improving the global estimation ability and local estimation ability of the algorithm. Its mathematical model is as follows:

$$\begin{aligned} &X_\alpha(t+1) = X_\alpha(t) - a \oplus Levy(\beta) \\ &a = random(size(\alpha\_popsition)) \\ &levy(\beta) \sim 0.01 \frac{u}{|v|^{1/\beta}} (X_\alpha(t) - X_{\alpha best}) \end{aligned} \tag{15}$$

The location of the new generation of α wolves is computed by Levy flights; $X(t)$ is the location of the α wolf at the t th generation; $\oplus$ is a point-to-point multiplication; a denotes the random number of individual α wolves, and $levy(\beta)$ is the random search path. The value interval of β is generally $1<\beta<3$, and $X_{\alpha best}$ is the historically optimal position of the α wolf.

II. C.IGWO-SVR modeling

The improved Gray Wolf algorithm can greatly improve the generalization ability of the regression model, and has a good solution for the problem of difficult parameter selection, and the prediction accuracy of the SVR regression model has been greatly improved. The specific steps of the algorithm can be described as follows:

Step1: Data preprocessing, importing the library space management sample set, normalizing, and dividing the processed data into training set and test set;

Step2: model parameter setting, this model sets the population size to 25 and the function dimension to 2;

Step3: traversing all wolves,through the calculation of fitness value, according to the fitness value from the best to the worst into α wolves, β wolves, δ and ω wolves;

Step4: Perform a global search for the wolves to update the wolf positions and update the convergence factor, expand the search range and update the wolf positions;

Step5: Calculate again the fitness of each wolf in the new position, compare the fitness of the old and new individuals, and select the better individual for retention;

Step6: If the number of iterations reaches the set condition, the next step is executed, and vice versa, return to step 3;

Step7: Construct the SVR model using the optimal parameters obtained from the optimization search, and train the training set;

Step8: Use the final trained IGWO-SVR model for prediction on the test set, and inverse normalization to get the final output.

III. Analysis of library space management effectiveness and optimization effect

III. A. Performance test of improved gray wolf algorithm

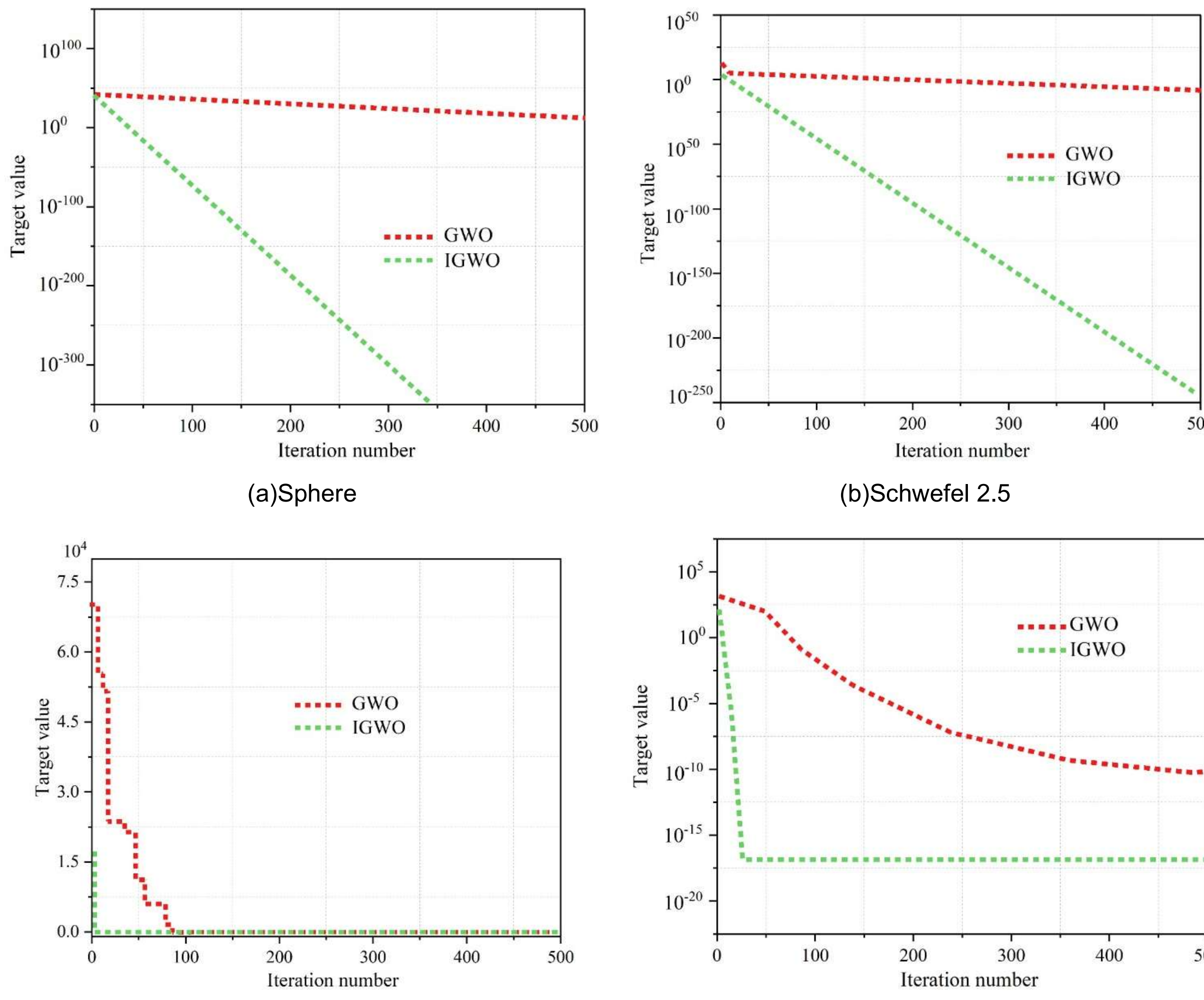
In order to verify the optimization performance of IGWO, it is applied to four generic standard test functions for solving. The information of the standard test functions when the dimension is 30 and the optimal value is 0 is shown in Table 1.

Table 1: Information of standard test functions

Serial number	Function name	expression	Search space
1	Sphere	$f_1(x)=\sum_{i=1}^{d} x_i^2$	[-50,50]
2	Schweel 2.5	$f_2(x)=\sum_{i=1}^{d} \lvert x_i \rvert+\prod_{i=1}^{d} \lvert x_i \rvert$	[-20,20]
3	Schwefel 1.5	$f_3(x)=\sum_{i=1}^{d}\left(\sum_{j=1}^{i} x_j\right)^2$	[-50,50]
4	Ackley	$f_4(x)=-20\exp\left(-0.2\sqrt{\frac{1}{d}\sum_{i=1}^{d} x_i^2}\right) -\exp\frac{1}{d}\sum_{i=1}^{d}\cos(2\pi x_i)+20+e$	[-25,25]

In order to verify the performance of IGWO, it is compared with the GWO algorithm, the initial number of populations are all set to 30, the maximum number of iterations is set to 500, and the parameter is set to $\zeta=0.65, a_{initial}=2.0, \lambda=0.3, b_1=0.6, b_2=0.6$. Fig. 1 shows the specific performance of IGWO and GWO algorithms respectively for four functions, (a) ~ (d) are Sphere, Schweel 2.5, Schwefel 1.5 and Ackley.As can be seen from the figure, compared to GWO, IGWO performs better under the standard test functions, with better solution accuracy and convergence speed than the original algorithm.

The improved Gray Wolf algorithm is able to achieve a balance between local optimization and global search, and has outstanding advantages in both solution accuracy and convergence speed. Therefore, in order to further improve the accuracy of SVR prediction, this paper uses IGWO to optimize the values of these three parameters.IGWO is fused with SVR through the fitness function, and this paper adopts the mean square error as the fitness function. During the optimization process, the ωwolf position is updated iteratively, which makes the fitness function decrease gradually until the iteration termination condition is reached and the optimization is completed. At this point, the establishment of the spatial management effectiveness prediction model based on IGWO's SVR is completed.



(a)Sphere (b)Schwefel 2.5

(c)Schwefel 1.5 (d)Ackley

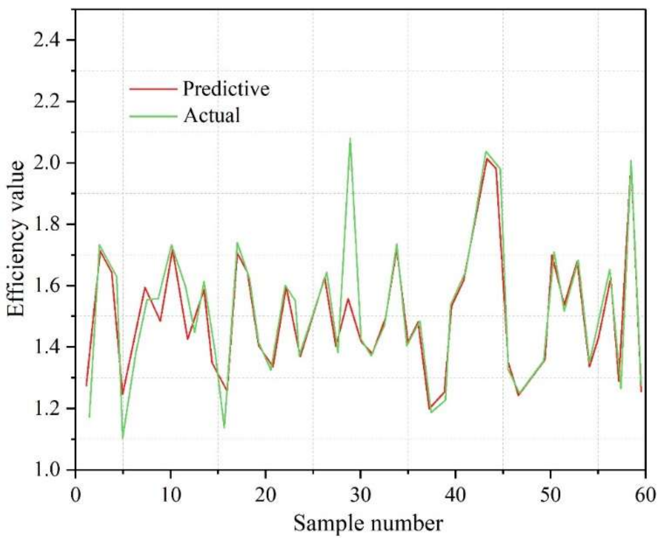
Figure 1: The test function precision is compared with the convergence speed

III. B. Prediction results of the IGWO-SVR model

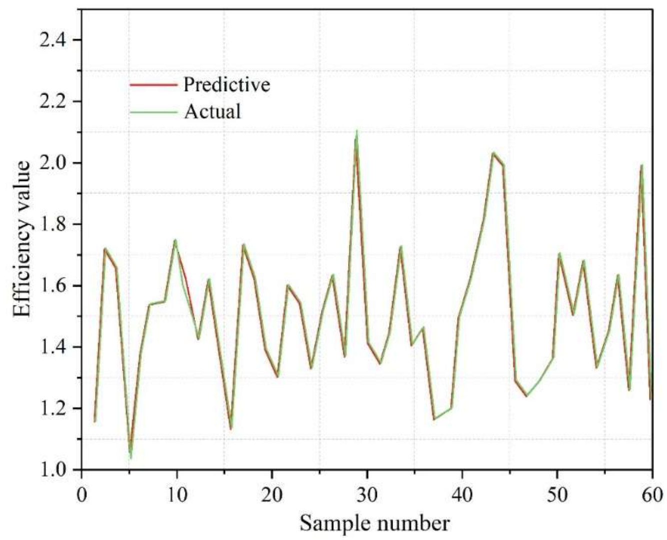
Firstly, the SVR model parameters are optimized using the IGWO algorithm, and the parameter optimization intervals are as follows: penalty parameter $c \in [1e-4, 100]$ insensitive loss function $\varepsilon \in [0,1]$; Gaussian kernel function parameter $\sigma \in [1e-4, 50]$. The maximum number of iterations max is 500, and the population size N is 60. The maximum number of iterations max is 500 and the population size N is 60. SVR parameter optimization results $(C, \varepsilon, \sigma) = (50, 0.113, 2.5035)$ are obtained by learning from the training dataset.

The SVR prediction model is established based on the parameters obtained from the optimization search, and the normalized sample data are trained and tested. To verify the effectiveness of the model proposed in this paper, the test results are compared with the GWO-SVR model, the default parameter SVR model and the BPNN model. Among them, the number of neurons in the input and output layers of BPNN is 5 and 2, respectively; the number of hidden layers is 2, the number of neurons is 12, the learning efficiency is 0.01, the number of training times is 600, which is equivalent to the maximum number of iterations of the GWO series of algorithms, and the error limit is 0.005.

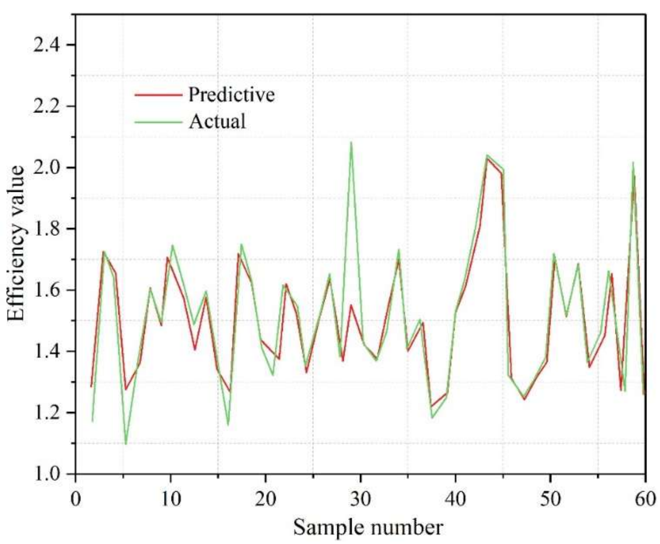
The IGWO-SVR, the SVR model optimized by the GWO algorithm (GWO-SVR), the default parameter SVR model, and the BPNN model were trained and tested under the condition of using the exact same training and test sets, respectively.The prediction results and absolute errors of the test sets for the four model evaluations are shown in Figs. 2 and 3, and Figs. 2(a) to (d) show the Basic SVR, respectively, IGWO-SVR, BPNN and GWO-SVR.It can be seen that the absolute error values evaluated by the IGWO-SVR model are smoother and have relatively small errors.



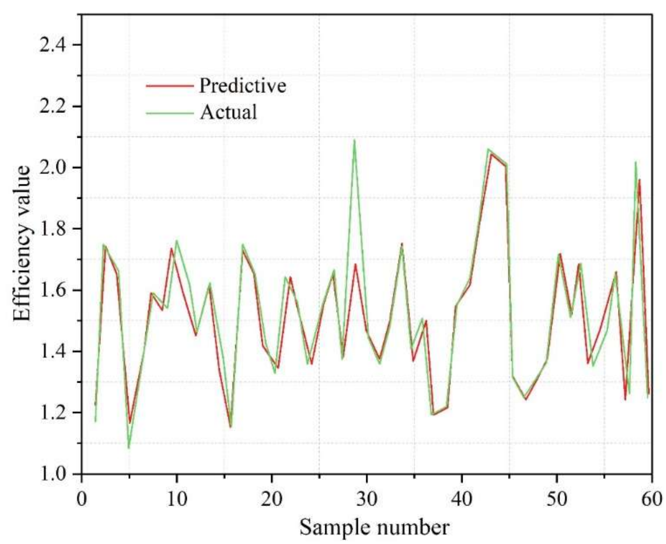
(a)Basic SVR



(b) IGWO-SVR



(c)BPNN



(d)GWO-SVR

Figure 2: Effectiveness evaluation curve

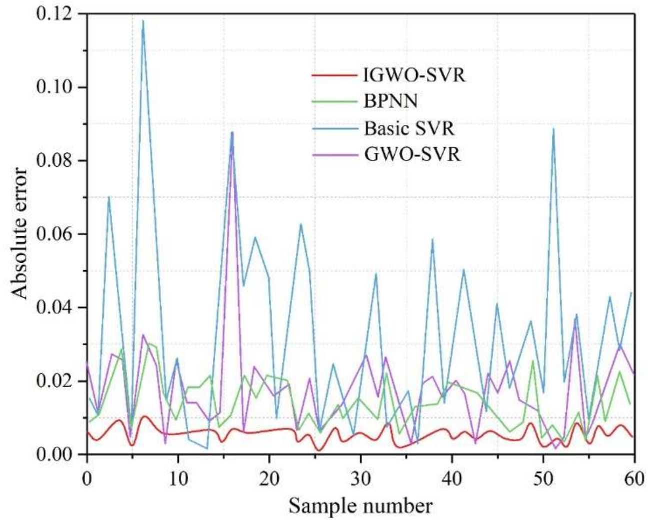


Figure 3: The absolute error diagram corresponding to the algorithm

In order to better reflect the actual situation of the prediction value error, the root mean square error RMSE, the mean absolute error MAE, and the coefficient of determination R^2 are calculated for the four methods.RMSE is the root of the expectation of the square of the difference between the evaluated value of the efficacy and the actual value obtained by inputting the data of each sample into the model, and the formula is as follows:

$$RMSE=\sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y_i-\hat{Y}_i)^2} \tag{16}$$

where, $Y_i, \hat{Y}_i$ denote the actual value of the i th sample and the evaluation value, respectively; n is the number of samples.The smaller the value of RMSE, the higher the prediction accuracy of the effectiveness evaluation model.

MAE is the degree of difference between the predicted value and the actual value obtained by inputting each sample into the model, and MAE does not have the problem of error offset, thus it can accurately reflect the size of the actual error, the formula is as follows:

$$MAE=\frac{1}{n}\sum_{i=1}^{n}|Y_i-\hat{Y}_i| \tag{17}$$

The R^2 reflects how well the model fits the actual values with the following formula:

$$R^2=1-\sum_{i=1}^{n}(Y_i-\hat{Y}_i)^2 \Big/ \sum_{i=1}^{n}(Y_i-\overline{Y})^2 \tag{18}$$

where, $\overline{Y}=1/n\sum_{i=1}^{n}Y_i$ is the average of the predicted values of n samples.

The error values of the evaluation results of IGWO-SVR, default parameter SVR model and BPNN model are shown in Table 2. It can be seen that the accuracy of the IGWO-SVR model reaches 0.001, and the fit of the predicted values to the true values reaches more than 99.95%. The maximum absolute error of the optimized model performance prediction is 0.0057, while the maximum absolute error of the default parameter SVR model is 0.0233, the maximum absolute error of the BPNN model is 0.0381, and the maximum absolute error of the GWO-SVR model is 0.0221. Comparison of the experimental results leads to the conclusion that the improved SVR model based on the GWO algorithm studied in this paper performs better than the default parameter SVR model, BPNN model. Among them, the performance of IGWO-SVR model improved on GWO algorithm is further improved than that of GWO-SVR model with strong generalization ability.

Table 2: Experimental comparison

Model	RMSE	MAE	R^2
Default parameter SVR	0.0331	0.0233	0.8602
IGWO-SVR	0.0008	0.0057	0.9995
BPNN	0.0363	0.0381	0.8778
GWO-SVR	0.0188	0.0221	0.9208

III. C. Innovative Measures for Management and Service of Self-study Space in Higher Education Libraries

III. C. 1) Increasing the supply of seating resources

The reason for the insufficient resources for study seats in the libraries of higher education institutions is that the space of the libraries' premises is unable to accommodate the size of the enrolled students. Therefore, to solve this problem fundamentally, it is necessary to expand the area of library premises. However, from a general point of view, the trend of change in the area of college libraries has been in a steady and slow growth. Individually, the actual situation of college libraries is more likely to be that after the school has constructed an independent building, it is not possible to invest in it again in a short period of time, i.e., it is difficult to expand the area of libraries and then increase the study space and study seats.

III. C. 2) Increased effectiveness of management and technical services

(1) Innovative seat management mode

The tightness of self-study seat resources in college libraries is due to the insufficient number of seats on the one hand, and the failure to fully and reasonably utilize the seat resources on the other. Manual management and automated management need to complement each other in order to achieve the purpose of orderly and reasonable use of library resources. Libraries should innovate the management and service mode, build seat reservation system, and refine the management of self-study seats.

(2) Improve the quality and efficiency of services

College libraries need to create a good atmosphere in the study space, strengthen the inspection and supervision of users' uncivilized behavior, and restrain uncivilized behavior with civilized norms. Through regular training to enhance the library staff's service awareness and service ability level, so that the staff can make a good response to users in a timely manner. To provide value-added services, rationalize the planning of study areas according to users' needs, increase study aids, and improve the quality of the space.

III. C. 3) Building a humanistic environment for self-study spaces

The study space in college libraries is the main place for users to carry out knowledge reading and learning, and as a kind of study space, it should be reconstructed according to users' needs. The re-construction of study space contains two major paths: one is the path of user demand satisfaction, which emphasizes in-depth understanding and effective satisfaction of the actual needs of users; the other is the path of user participation in the construction of the path, which advocates the participation of users in the planning and implementation of the space construction program to the process.

The study space should be a combination of physical space, virtual space and cultural space after reconstruction. By creating first-class space services to help users grow, learn and explore. Users in the study space, need to study and think in a peaceful and calm atmosphere full of books, need to communicate and exchange with like-minded friends through elegant space.

Re-creation of study space should focus on user experience and participation, and encourage active learning and creation. Provide different service products for different user groups and dynamically adjust the service model. The reengineered space should give full consideration to meeting the personalized and diversified needs of users for learning, communication and leisure, so that users can enjoy people-oriented humanistic care. By setting up study areas, communication areas, leisure areas, discussion areas and other areas combining motion and static, it is convenient for users to use. Re-creation of study space should also carry out a reasonable resource allocation supply, according to user demand, the resource supply mode from sloppy to accurate change. Self-study space reconstruction should also be combined with the real and the virtual, do a good job of physical space reconstruction, and at the same time build intelligent space, effectively expanding the spatial service area.

IV. Conclusion

In this study, the proposed optimization method for library space management effectiveness based on the Improved Gray Wolf Optimization (IGWO) algorithm and the Support Vector Regression (SVR) model has achieved remarkable results. Through experimental comparisons, the IGWO-SVR model excels in prediction accuracy with a root mean square error (RMSE) of 0.0008, a mean absolute error (MAE) of 0.0057, and a coefficient of determination (R^2) of 99.95%. This result shows that the improved SVR model can be better adapted to the nonlinear regression problem in library space management, and in the process of optimizing the parameters, the IGWO algorithm has a faster convergence speed and higher accuracy compared with the traditional GWO algorithm. In addition, the IGWO-SVR model also shows obvious advantages in terms of the maximum absolute error, which is 0.0057, much lower than the traditional BPNN model and the GWO-SVR model. The method not only provides a new perspective for the optimization of spatial management effectiveness in theory, but also has strong application value in practice, which can provide more scientific decision support for library managers.

References

[1] Rubin, R. E., & Rubin, R. G. (2020). Foundations of library and information science. American Library Association.

[2] Mandel, L. (2016). Visualizing the library as place. Performance measurement and metrics, 17(2), 165-174.

[3] Gu, B., & Tanoue, K. (2022). A research on library space layout and intelligent optimization oriented to readers’ needs. Mathematical Problems in Engineering, 2022(1), 4426091.

[4] Cha, S. H., & Kim, T. W. (2015). What matters for students' use of physical library space?. The Journal of Academic Librarianship, 41(3), 274-279.

[5] Xiao, J. (2022). Research on the Impact of Optimal Configuration of University Library Layout on Students’ Academic Literacy Development Based on 5G. Mathematical problems in engineering, 2022(1), 9865838.

[6] Fox, D. (2014). User perceptions of library buildings: Architectural and design element preferences in the public library. New Zealand Library & Information Management Journal, 54(4).

[7] Head, A. (2016). Planning and designing academic library learning spaces: Expert perspectives of architects, librarians, and library consultants. Librarians, and Library Consultants (December 6, 2016).

[8] Prizeman, O., Jones, C. B., Parisi, M., & Pezzica, C. (2018). How can century-old architectural hierarchies for the design of public libraries be re-interpreted and re-used?. Journal of Cultural Heritage Management and Sustainable Development, 8(4), 481-494.

[9] Lee, G. Y., & Oh, J. G. (2015). Passive Design Elements in the Architectural Planning of the Public Libraries: Focusing on the Comparison between Site and Building in the G-SEED Pre-certified and Non-certified library: Focusing on the Comparison between Site and Building in the G-SEED Pre-certified and Non-certified library. KIEAE journal, 15(6), 27-36.

[10] Panigrahi, S. K. (2020). Optimization of Space in Central Library: A case study of Jawaharlal Nehru University and Delhi University. Optimization, 10, 2.

[11] Zhou, Y. (2024, May). Optimization Strategy of University Library Knowledge Service Based on Data Management. In 2024 3rd International Joint Conference on Information and Communication Engineering (JCICE) (pp. 249-254). IEEE.

[12] Cui, X., & Ahn, C. W. (2025). Multi-Objective Optimization of Natural Lighting Design in Reading Areas of Higher Education Libraries. Buildings, 15(9), 1560.

[13] Fan, Y., Yuan, W., Kong, F., & Xue, J. (2022). A Study of Library Window Seat Consumption and Learning Efficiency Based on the ABC Attitude Model and the Proposal of a Library Service Optimization Strategy. Buildings, 12(10), 1547.

[14] Ibiso, B., & Enwin, A. D. (2021). Enhancing Spatial Organization and Relationship to Optimize Efficiency in Digital Library. GSJ, 9(5).

[15] Rossmann, D., & Young, S. W. (2015). Social media optimization: making library content shareable and engaging. Library Hi Tech, 33(4), 526-544.

[16] Wada, I. (2018). Cloud computing implementation in libraries: A synergy for library services optimization. International journal of library and Information Science, 10(2), 17-27.

[17] Allison Bayro & Heejin Jeong. (2025). Enhancing emotional response detection in virtual reality with quantum support vector machine learning. Computers & Graphics,128,104196-104196.

[18] Srishti Kumari,Shweta Jindal & Arun Sharma. (2025). Test case optimization using grey wolf algorithm. Software Quality Journal,33(2),20-20.

[19] Wangzhou Luo,Hailong Wu & Jiegang Peng. (2024). Improvement of Electric Fish Optimization Algorithm for Standstill Label Combined with Levy Flight Strategy. Biomimetics,9(11),677-677.