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Buffer Monitoring of Critical Chain Projects Based on Support Vector Machine Prediction

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ABSTRACT

Uncertainties have a negative impact on the duration of project activities. When an activity faces the higher uncertainty, it is likely to experience larger fluctuations in its duration. This increases the risk of delays. However, classical buffer monitoring methods usually adopt the setting mode of uniform and fixed monitoring time points for different activities, failing to account for differences in uncertainty levels between them, which reduces the effectiveness of project schedule control. Therefore, we propose a dynamic buffer monitoring method combining buffer monitoring and forecasting. Firstly, a duration prediction model based on support vector machine is established to predict the duration of the subsequent activity relying on the duration data of completed activities. Secondly, the buffer consumption rate is calculated according to the predicted activity duration and the corresponding monitoring frequency is obtained. Matlab is finally utilized to verify the method proposed in this paper. The results show that compared with classical buffer monitoring methods, the proposed method achieves the dual optimization of project duration and cost.

1. Introduction

The critical chain project management (CCPM) theory was proposed by Goldratt (1997), which combined the theory of constraints with project management. It is a major breakthrough in the field of project management after the network planning technology (Leach, 1999; Ghoddousi et al., 2017). Goldratt (1997) pointed out that the critical chain was determined based on the logical relationship of activities and resource constraints. It can also be extended to project scheduling and multi-project management (Ordoñez et al., 2019; Peng et al., 2023). Based on CCPM, the safe time of activities is extracted and concentrated at the end of the project so that risk sharing is realized in the form of buffer (Zhao et al., 2020). Then the overall control of the project progress is carried out through the monitoring of the buffer (Apaolaza and Lizarralde, 2020). A high-efficiency buffer monitoring method is the key to improve project performance. Therefore, buffer monitoring is a core issue in critical chain project management.

The buffer monitoring system controls the project progress by determining the monitoring time points, monitoring the project progress at the time points, and taking steps such as crashing to prevent the delay when there is a deviation (Hu et al., 2019; Liu et al., 2021). Monitoring frequency, also known as the number of monitoring time points per unit time, measures the density of monitoring. Reasonable monitoring frequency provides the benchmark of effective monitoring (Kose et al., 2022). On the basis of the CCPM presented by Goldratt (1997), scholars have conducted further research on buffer monitoring methods (Yuan et al., 2003; Ghaffari and Emsley, 2015). But most of these studies use fixed monitoring time points and a single monitoring form, which is not conducive to the flexible control of project development trends (Zhang and Liang, 2018). In addition, the existing research mainly optimizes the setting of monitoring trigger points and the selection of buffer allocation from the perspective of dynamic monitoring (Xiao et al., 2021). Buffer allocation is to distribute the project buffer by stages or activities, so the project is monitored on the ground of the allocated buffer amount. However, the usual research determines the fixed buffer allocation value in the planning stage (Zhang and Li, 2022), namely, the value does not change during the project execution, thus is difficult to adapt to the uncertain changes of the project.

Therefore, we explore the dynamic adjustment of monitoring

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frequency through an effective prediction technique and further ameliorate the buffer monitoring system. The innovations of this study are threefold.

1. The support vector machine is introduced into the field of project management, and the quantitative prediction of the activity duration is completed.
2. Different from the fixed buffer allocation type of the usual research, the adaptive buffer allocation is performed, which adapts to the actual situation of the project implementation and determines the buffer allocation according to the forecast of the duration.
3. The corresponding monitoring frequency is set in advance according to the forecasted activity buffer consumption amount, so as to dynamically adjust the monitoring time points in the project implementation and recognize and control deviations in time, which can realize the feedforward control of buffer monitoring and enhance the pertinence and flexibility of monitoring.

Table 1. Abbreviations and Symbols

	Notations	Explanations
Abbreviations	CCPM	Critical chain project management
	SVM	Support vector machine
	SBMM	The static buffer monitoring method
	RBMM	The relative buffer monitoring method
	IBMM	The integrated buffer monitoring method
Symbols	x_k	The duration sequence of the previous s activities
	y_k	The duration of the s+1th activity
	p	The amount of training samples
	ω	The weight variable
	C	The penalty coefficient
	ξ_k	The relaxation factor
	α_k	The Lagrange multiplier
	$K(x_k, x)$	The kernel function
	q	The total sample size of the original duration data
	∂_i	The initial buffer allocating weight
	n	The number of activities on the critical chain
	t_i	The planned duration of activity i
	σ_i	The standard deviation of the duration of activity i
	co_i	The buffer amendment factor of activity i
	t_{if}	The predicted duration value of activity i obtained by the SVM model
	pb_{i0}	The adjusted buffer allocation for each activity
	PB	The total buffer amount concentrated at the end of the critical chain
	Δpb_i	The cumulative buffer scrolling amount for activity i
	at_j	The actual duration of activity j
	PB_i	The final buffer amount allocated for activity i
	BC	The buffer consumption proportion of the activity
	MT	The monitoring frequency for the activity
	γ	The Gaussian kernel width coefficient
	MSE	The mean square error
	N	The number of samples in the test set
	y_j	The actual value of the duration
	$\hat{y}_j$	The forecasting value of the duration
	R^2	The evaluation indexes
	$\bar{y}_j$	The mean of y_j

The outline of this paper is as follows. Section 2 summarizes the existing research achievements on buffer monitoring approaches of the critical chain project. A new dynamic buffer monitoring model based on the support vector machine prediction method is investigated in Section 3. Section 4 verifies the effectiveness of the method in this paper. Section 5 is left to the summary of the paper and points out the research directions of the next step. The notations in this paper are listed in Table 1.

2. Literature Review

Goldratt (1997) developed the static trisection buffer monitoring method (SBMM), which divided the buffer into three equal areas. When the accumulated buffer consumption is located in the green, yellow and red areas, the corresponding monitoring behaviors are no action, planning to take action and taking action immediately, respectively. This method is prone to false early warnings ignoring the link between project progress and buffer consumption. In view of this shortcoming, Leach (2014) set the monitoring trigger line as two parallel rising straight lines; that is, the green-yellow and yellow-red monitoring trigger points rise with the increase of the link completion ratio. It is known as the relative buffer monitoring method (RBMM). This approach reduces the number of false warnings, but the preset monitoring thresholds are still difficult to adapt to the complex and changeable environment of the project. Given the dynamic environment of project execution, Bie and Cui (2010) proposed a dynamic buffer monitoring method. By dividing the remaining buffer into three equal parts, the two monitoring trigger points can be adjusted to reflect the information of the project execution better. The above monitoring methods are all top-down monitoring from the project level, losing sight of internal structural characteristics of a project, which is not conducive to the judgment of project progress deviation. Moreover, these techniques assume that the execution information of the project can be continuously obtained, however, continuous monitoring causes a lot of manpower and resource consumption and is not in line with the actual project situation.

Some scholars suggested that the project can be divided into stages considering the characteristics of the internal structure of the project, and then the buffer should be reasonably allocated and monitored according to the stages (Bevilacqua et al., 2009; Kuo et al., 2009; Gonzalez et al., 2013). Zhang and Cheng (2021) divided the project into monitoring stages in accordance with milestone events. In each stage, the risks were measured and monitoring cycles were determined. Zhang et al. (2018) allocated the buffer to each stage according to stage attributes such as the duration ratio and the network complexity as the benchmark for monitoring. Then buffer monitoring was carried out within each stage separately. This phasing approach depending on the project plan does not take into account the actual execution of the project sufficiently.

Zhang and Li (2022) divided the activities into cost-sensitive and duration-sensitive types on account of the activity heterogeneity, then the buffer was allocated according to the comprehensive perceived utility of the activity and differentially monitored in combination with the sensitivity. This method realizes the dynamic monitoring of projects from the activity level. Xiao et al. (2021) changed the buffer monitoring threshold according to the activity-dependent parameters in consideration of the correlation between activities. Vanhoucke (2011) proposed to build a sensitivity threshold as the monitoring trigger point. Activities with the sensitivity higher than the threshold are high-sensitive processes, which might have greater uncertainties and a major impact on project delays. Therefore high-sensitive activities require intensive monitoring. Hu et al. (2016) studied the calculation of activity sensitivity indicators and the setting of monitoring thresholds in dynamic environments. They introduced the activity sensitivity index CRI in the monitoring process of the yellow zone of the buffer, explored the effect of different CRI threshold setting methods on monitoring results and gave a more detailed monitoring strategy. But the cost performance of the project is not considered. Earned value management is based on the earned value and measures the progress and cost of a project through three basic cost indicators. It can provide a baseline for cost-progress measurement and reflect the status of the project. In view of the insufficiency of emphasizing time performance only in most research, Ghazvini et al. (2017) combined earned value management with CCPM and developed the concept of cost buffer to manage the schedule buffer and cost buffer of the project at the same time, so as to control the time and the cost risks related to the project. Hu et al. (2017) investigated a two-stage project schedule-cost control model based on resource availability to further improve the comprehensive control ability of the time, cost and resources of a project. In the execution phase of a critical chain project, buffer consumption can be monitored by constructing tolerance limits that generate warning signals through the data provided by earned value management (Martens and Vanhoucke, 2017). Song et al. (2020) addressed that the budgets were usually limited in project practice. On the basis of setting tolerance limits for buffers, they suggested to allocate the limited budgets at different stages of the project and take corrective measures. Then different patterns of budget allocation and corrective measures were compared to test the effects on the results.

The aforementioned studies only consider the current implementation situation and ignore the follow-up development trend, hence reducing the management efficiency of the project. In this regard, some scholars have introduced forecasting techniques to manage and control the project. Gong and Hu (2013) applied the Markov chain to predict the stage execution status of an IT project, but it could only qualitatively forecast the advance, delay or completion of a stage and could not judge the accurate execution information. Martens and Vanhoucke (2020) extended the exponential smoothing forecasting approach using earned value management and earned duration method to predict the final duration of a project. And corrective actions were incorporated into the forecasting process. However, these two methods are not combined with the monitoring of the buffer, and the control

Table 2. Relevant Literature List on Monitoring Methods

References	Monitoring unit			Prediction			Buffer allocation			Monitoring time points		Project performance	
	Pr	Ph	Ac	No	Qu	Qn	No	St	Dy	Fi	Dy	D	C
Goldratt (1997)	√	–	–	√	–	–	√	–	–	√	–	√	–
Leach (2014)	√	–	–	√	–	–	√	–	–	√	–	√	–
Bie and Cui (2010)	√	–	–	√	–	–	√	–	–	√	–	√	–
Gonzalez et al. (2013)	–	√	–	√	–	–	–	√	–	√	–	√	√
Zhang and Cheng (2021)	–	√	–	√	–	–	–	√	–	√	–	√	√
Zhang et al. (2018)	–	√	–	√	–	–	–	√	–	√	–	√	√
Zhang and Li (2022)	–	–	√	√	–	–	–	√	–	√	–	√	√
Xiao et al. (2021)	–	–	√	√	–	–	√	–	–	√	–	√	–
Hu et al. (2016)	–	–	√	√	–	–	√	–	–	√	–	√	–
Ghazvini et al. (2017)	–	√	–	√	–	–	√	–	–	√	–	√	√
Hu et al. (2017)	–	–	√	√	–	–	√	–	–	√	–	√	√
Song et al. (2020)	–	√	–	√	–	–	√	–	–	√	–	√	√
Zhang and Yang (2021)	–	√	–	–	√	–	–	√	–	√	–	√	√
Zhang and Wan (2019)	–	–	√	–	–	√	–	√	–	√	–	√	√
Current study	–	–	√	–	–	√	–	–	√	–	√	√	√

Note: Pr: Project; Ph: Phase; Ac: Activity; Qu: Qualitative; Qn: Quantitative; St: Static; Dy: Dynamic; Fi: Fixed; D: Duration; C: Cost.

intensity of the project progress is relatively weak. Zhang and Yang (2021) introduced the location information and rate information of activity buffer consumption to predict the follow-up trend of the project, so as to adjust the level of monitoring reference points, but this prediction approach is still qualitative. Taking advantage of the similarity of information and the complementarity of models for the grey model and neural network, Zhang and Wan (2019) employed the grey neural network to quantitatively forecast the active buffer consumption and formulate an integrated buffer monitoring method (IBMM).

The taxonomy of relevant literature is listed in Table 2. To sum up, the existing buffer monitoring approaches have two shortcomings. On the one hand, most of them are post-event control. More precisely, they only pay attention to the buffer consumption at the current monitoring point to decide whether to take measures for lack of active control of the project, hence increasing the resource waste and cost loss. On the other hand, despite the methodology of combining buffer monitoring and forecasting avoids the defect of a single buffer monitoring mode, this part of research is relatively fewer. In addition, the existing studies take the static buffer allocation mode and monitor a project at fixed monitoring time points. They often miss the best chance for correction and a lot of resources and costs have to be invested when the buffer is consumed too much, which may cause further continuation of the deviation trend due to untimely actions and hinder the progress of the project. Therefore, how to effectively predict the execution of activities, dynamically adjust the monitoring time points and enhance the efficiency of buffer management requires further research. Furthermore, as a new data mining method developed on the basis of statistical learning theory, the support vector machine (SVM) solves the over-adaptation phenomenon and local minima problems of classic machine learning techniques such as neural networks. It also handles the issue of dimensionality disaster by mapping the original problem to high-dimensional space. SVM has achieved rapid development in recent years owing to its tremendous performance and it has been widely applied to the classification and prediction in many fields such as aerospace, energy sources, wood identification, etc. (Juez et al., 2010; Zendehboudi et al., 2018; Yu et al., 2019). However, since the attributes of different fields are various, the specific application patterns of SVM are also discrepant. Consequently, how to apply SVM to the field of project management to produce superb forecasting effect and project performance is a problem worthy of in-depth study.

Against the background of fragmented insights, this paper takes care of the characteristics of activities and buffers in the project and incorporates the SVM forecasting approach into the critical chain project management to establish a new dynamic buffer monitoring system. From the perspective of the activity level, we predict the activity duration by SVM, determine the buffer monitoring frequency according to the activity completion time predicted in advance and monitor the project dynamically.

3. Critical Chain Project Buffer Monitoring

The project execution process is affected by a variety of uncertain factors, which directly influences the project duration. The critical chain project management absorbs and reflects the impact of risks and uncertainties by setting buffers (Ghaffari and Emsley, 2015). In this section, we construct a dynamic buffer monitoring model based on the support vector machine. In this model, by forecasting the duration of future activities depending on the duration performance of executed activities, the buffer allocation is updated in real time and the monitoring frequency is adapted according to the buffer consumption, which can realize the active control of unfinished activities and avoid getting into an irreversible situation.

3.1 Activity Duration Prediction

The activity duration of a project is subject to various risk factors such as the technical complexity, management efficiency, resource demand, environmental uncertainty, etc. It has strong randomness. Support vector machine is a machine learning algorithm developed from mathematical theory and has obvious intuitive geometric significance (Zendehboudi et al., 2018). Since its unique advantages when dealing with classification and regression problems with small samples and nonlinearities, it is introduced to achieve effective prediction of the follow-up activity duration.

The regression principle of the support vector machine is to map the input vector to a higher-dimensional feature space through nonlinear mapping for linear regression (Pande et al., 2023). Assuming that the activity duration data set is $T=\{(x_k, y_k), k=1,2,...,p, x_k \in R^s, y_k \in R\}$, x_k is the duration sequence for the previous s activities, y_k represents the duration of the $s+1$th activity, and p represents the amount of training samples, the decision function in a high-dimensional space is constructed as follows:

$$y(x)=\omega^T \varphi(x)+b\ . \tag{1}$$

Then the regression problem of finding the optimal decision function can be transformed into the following optimization problem:

$$\begin{aligned} &\min\{\frac{1}{2}\omega^T\omega + C\sum_{k=1}^{p}\xi_k\} \\ &s.t.\ \ y_k\left[\omega^T\varphi(x_k)+b\right]\geq 1-\xi_k, \\ &\qquad \xi_k \geq 0,\ k=1,2,...,p, \end{aligned} \tag{2}$$

where ω is the weight variable, C is the penalty coefficient, and ξ_k is the relaxation factor.

By solving the dual problem of the above model obtained by Lagrange transformation (Yu et al., 2019), the optimal solution of the original problem can be obtained.

$$f(x)=\sum_{k=1}^{p}\alpha_k K(x_k, x)+b\ , \tag{3}$$

where α_k is the Lagrange multiplier and $K(x_k, x)$ is the kernel function.

The essence of using support vector machine to predict activity duration is to ultilize the regression principle of SVM. In this paper, through the learning of sample data, the regression analysis of the duration of executed activities and unexecuted activities is realized, so as to obtain the prediction mode. The specific steps are as follows:

1. The total sample size of the original duration data is assumed to be q, p groups of data are randomly selected from it as the training set, and the remaining $q-p$ groups of data are the test set;
2. The parameters of the kernel function are optimized through the training set. Then the optimal parameters can be obtained and saved to construct the SVM duration prediction model. The model is verified through the test set;
3. The actual activity duration sequence $x_{i^*} = (x_1^*, x_2^*, ..., x_s^*)$ is input into the established model, and then the forecasts are output to obtain the predictive value of the subsequent activity duration.

3.2 Monitoring Frequency Determination

After predicting the duration of the succeeding activity, the allocated buffer amount is adaptively adjusted in accordance with the predicted duration of the activity. Then the buffer consumption rate is calculated, and based on it, the monitoring frequency during the activity execution process is determined. The corresponding monitoring is performed after the activity starts to detect and control adverse trends in a timely manner.

Buffer allocation aims to make a more accurate judgment on the buffer consumption and monitor the execution of the project more accurately by allocating the buffer concentrated in the tail to each activity. The normalized weight of the product of the mean and the standard deviation of the activity duration is taken as the initial buffer allocating weight:

$$\partial_i = \frac{t_i \times \sigma_i}{\sum_{i=1}^{n} t_i \times \sigma_i}, \tag{4}$$

where n is the number of activities on the critical chain, t_i is the planned duration of activity i, and σ_i is the standard deviation of the duration of activity i.

The allocated buffer is adaptively adjusted based on the forecasting duration of the activity. The buffer amendment factor of activity $i(i = 2, ..., n-1)$ is:

$$co_i = \frac{t_{if}}{t_i}, \tag{5}$$

where t_{if} is the predicted duration value of activity i obtained by the support vector machine model.

The adjusted buffer allocation for each activity is:

$$pb_{i0} = \begin{cases} PB \times \partial_i, & i = 1 \\ PB \times \partial_i \times co_i, & i = 2, \cdots n-1 \\ PB - PB \times \partial_1 - \sum_{l=2}^{i-1} PB \times \partial_l \times co_l, & i = n, \end{cases} \tag{6}$$

where PB is the total buffer amount concentrated at the end of the critical chain.

The difference between the actual duration and the allocated buffer of the completed activity is rolled up to the activity to be started, thus making a further adjustment to the buffer allocated for activities. The cumulative buffer scrolling amount for activity $i(i = 2, ..., n)$ is:

$$\Delta pb_i = \sum_{j=1}^{i-1} (at_j - pb_{j0}), \tag{7}$$

where at_j is the actual duration of activity j.

The final buffer amount allocated for activity i is:

$$PB_i = \begin{cases} pb_{i0}, & i = 1 \\ pb_{i0} + \Delta pb_i, & i = 2, \cdots, n \end{cases}$$
$$= \begin{cases} PB \times \partial_i, & i = 1 \\ PB \times \partial_i \times co_i + \sum_{j=1}^{i-1} (at_j - PB \times \partial_j \times co_j), & i = 2, \cdots, n-1 \\ PB - PB \times \partial_1 - \sum_{l=2}^{i-1} PB \times \partial_l \times co_l + \sum_{j=1}^{i-1} (at_j - PB \times \partial_j \times co_j), & i = n. \end{cases} \tag{8}$$

The buffer consumption proportion of the activity is calculated as:

$$BC = \frac{t_{if} - t_i}{PB_i}. \tag{9}$$

Then the formula of the monitoring frequency for the activity is given by:

$$MT = \begin{cases} 1, & BC < \frac{1}{3} \\ [2 + 6(BC - \frac{1}{3})], & \frac{1}{3} \le BC < \frac{2}{3} \\ [4 + 9(BC - \frac{2}{3})], & \frac{2}{3} \le BC < 1 \\ 7, & BC \ge 1, \end{cases} \tag{10}$$

where $[x]$ is the rounding function, representing the largest integer not to exceed x. When $0 \le BC < \frac{1}{3}$, the activities are predicted to have a lower rate of buffer consumption. It indicates that the uncertainty of the activity is small and the buffer is capable of playing a good protective role, so the monitoring can be performed once after the completion of the activity. If $\frac{1}{3} \le BC < \frac{2}{3}$, there is more buffer consumption at the end of the activity, therefore the monitoring intensity should be appropriately increased to deal with possible problems in a timely manner after the activity starts. In case of $\frac{2}{3} \le BC < 1$, a large amount of buffer will be consumed when the activity completes. It shows that the risk of activity execution is relatively higher, which may have an impact on the progress of the project. After the activity starts, the monitoring frequency should be increased, strict monitoring should be performed, and timely actions should be taken to prevent larger deviations. However, if $BC \geq 1$, the amount of the buffer required for the activity will exceed the allocated buffer, indicating that the buffer will not be able to cope with the delays and the project will likely be overdue. Accordingly, it is necessary to further strengthen the monitoring and take crashing measures to prevent the continuation of adverse trends so that the project can be completed on time.

In particular, when the buffer consumption proportion is located in areas $0 \sim \frac{1}{3}$, $\frac{1}{3} \sim \frac{2}{3}$ and $\frac{2}{3} \sim 1$, the corresponding changing rate of the monitoring frequency is $k_1 = 0$, $k_2 = 6$ and $k_3 = 9$, respectively, where $k_1 < k_2 < k_3$. This indicates that since an activity with a higher buffer consumption rate has a greater risk, the activity has a greater impact on the project progress so that the monitoring intensity should be increased faster, which is in line with the actual project execution. If the buffer consumption proportion is greater than 1, the monitoring frequency cannot be increased infinitely considering the cost factor, so it is controlled at a higher intensity.

3.3 Dynamic Monitoring Process Formation

During project execution, the monitoring frequency is dynamically adjusted in units of activities based on the forecasted duration. Specifically, before the activity starts, the support vector machine model is used to predict the activity duration, then the buffer allocation value of the activity and the estimated buffer consumption rate after the activity is completed are calculated to assess the uncertainty in advance. Subsequently, the appropriate monitoring frequency is determined. The monitoring can be implemented once the activity starts in order to detect the deviation in time, analyze the cause of its occurrence, and take corresponding actions to avoid the accumulation of deviation trends. Fig. 1 depicts the flow chart of applying the proposed dynamic buffer monitoring method based on the support vector machine prediction.

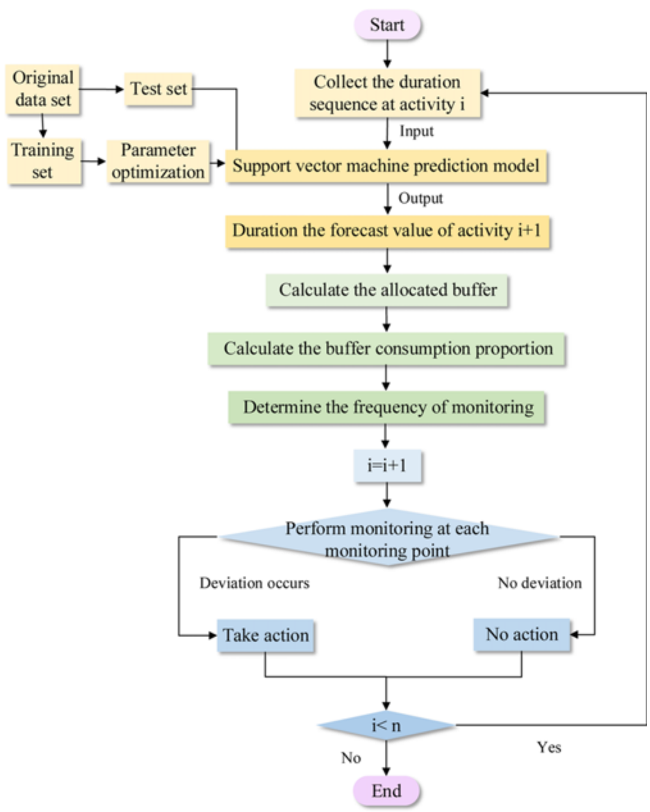

Fig. 1. Buffer Monitoring Model

4. The Empirical Study

This section carries out the empirical study to verify the model of this paper. Section 4.1 gives the information of a typical project and performs the basic calculation process using the proposed method. Section 4.2 simulates the execution of the project and compares with classic approaches to prove the optimization effect of our model.

4.1 Basic Information Calculation

A construction project (Lin and Zhou, 2011) is selected as the experimental case. The project consists of seven activities and the basic activity information is shown in Table 3. The network diagram of the critical chain project after scheduling is displayed in Fig. 2, where 1-2-4-5-6-7 is the critical chain. The project buffer (PB) and the feeding buffer (FB) are calculated by the cut-and-paste method (Goldratt, 1997).

The duration of the succeeding activity is predicted in turn after each critical activity is completed. More precisely, the duration sequence of the completed activities is input into the trained support vector machine prediction model to obtain the forecast data of the follow-up activity duration, and the corresponding monitoring frequency is set to realize the dynamic control of the monitoring intensity. Taking the monitoring strategy determination of activity 6 after activity 5 is completed as an example, the process is as follows:

Table 3. Basic Information of the Project

Activity	Ideal duration	Succeeding Activity	Type of the required resource
1	8	2	A
2	10	3,4	B
3	15	6	B
4	18	5	C
5	15	7	A
6	12	7	A
7	7	—	B

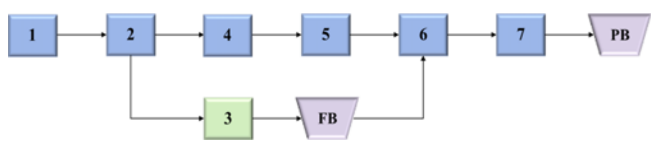

Fig. 2. Diagram of the Critical Chain Network

Activity duration follows the lognormal distribution with a right skew (Zhang et al., 2018). Depending on the information of activities 1, 2, 4, 5, and 6 in Table 3, the Lognrnd function in Matlab is adopted to generate the duration data of 100 groups including 5 activities in each group as the sample data. 80 groups are randomly selected as the training set, and 20 groups are used as the test set.

Different kernel functions generate different support vector machine models. Common kernel functions include linear kernel function, polynomial kernel function, radial basis kernel function, and Sigmoid kernel function. Among them, the radial basis kernel function has fast calculation speed, simple value and the best generalization performance, which is chosen to deal with nonlinear data (Ding et al., 2017). Therefore, the radial basis kernel function is selected as the kernel function of the prediction model, and its expression is shown in Eq. (11).

$$K(x_i, x) = \exp\left\{-\frac{\|x_k - x\|^2}{2\gamma^2}\right\}, \tag{11}$$

where γ is the Gaussian kernel width coefficient. The values of the penalty parameter C and the kernel parameter γ have a significant impact on the model performance. Hence, suitable parameters need to be determined to achieve the best prediction effect. Grid search method is a commonly used algorithm of SVM parameter optimization (Ding et al., 2017). It refers to obtaining value according to a certain data interval within the value range of C and γ and dividing them into grids. Then all parameter pairs in the grids are traversed when searching, where the combination with the highest prediction accuracy in the training set is the optimal parameter. We adopt the grid search method to find the optimal C and γ. C = 0.7071 and γ = 64 are obtained.

After the prediction model is produced based on the above optimal parameters, the test set is used to validate the effect of the model. The mean square error MSE and the determination coefficient R^2 are taken as the evaluation indexes (Song et al., 2022), whose calculation formulas are shown in Eqs. (12) and (13), respectively.

$$MSE = \frac{1}{N}\sum_{j=1}^{N}(y_j - \hat{y}_j)^2, \tag{12}$$

where N is the number of samples in the test set, y_j is the actual value of the duration, and $\hat{y}_j$ is the forecasting value of the duration. The smaller the value of MSE, the higher the accuracy of the prediction model.

$$R^2 = 1 - \frac{\sum_{j=1}^{N}(y_j - \hat{y}_j)^2}{\sum_{j=1}^{N}(y_j - \bar{y}_j)^2}, \tag{13}$$

where $\bar{y}_j$ is the mean of y_j. The larger the value of R^2, the better the fitting effect of the model.

For the obtained support vector machine model, the comparison diagrams of the prediction results are shown in Figs. 3 and 4. The mean square error and the determination coefficient of the model are listed in Table 4. It can be seen that the model has a good prediction effect.

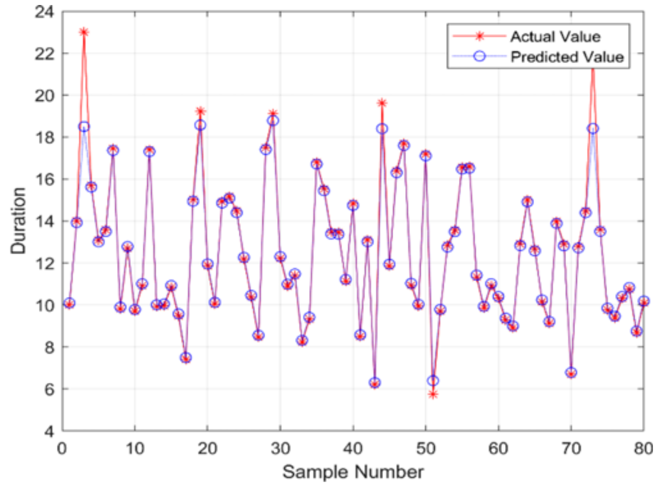

Fig. 3. Prediction Results Comparison of the Training Set

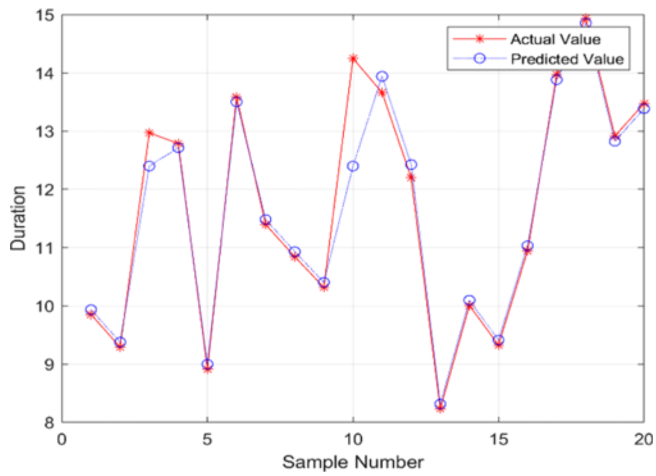

Fig. 4. Prediction Results Comparison of the Test Set

Table 4. Evaluation Parameters of the Prediction Effect

	Mean square error MSE	Determination coefficient R^2
Training set	0.0027	0.9739
Test set	0.0058	0.9527

Table 5. Actual Duration Sequence of Activities

Activity	1	2	4	5
Duration	9.2	15.7	34.6	10.0

Assuming that after activity 5 finishes, the actual duration sequence of the completed activities on the critical chain is shown in Table 5. The sequence is input to the above trained prediction model, then we can get that the predicted duration of activity 6 is 21.6 days. The buffer consumption proportion is

Table 6. Frequency of the Buffer Consumption Located in Each Area

Buffer monitoring method	Buffer consumption area	Activity					
		1	2	4	5	6	7
SBMM	Green	996	987	933	872	784	715
	Yellow	4	13	67	127	213	280
	Red	0	0	0	1	3	5
RBMM	Green	998	989	947	899	815	761
	Yellow	2	11	53	101	183	235
	Red	0	0	0	0	2	4
IBMM	Green	720	684	693	786	845	950
	Yellow	183	190	184	181	139	48
	Red	97	126	123	33	16	2
The proposed method	Green	1000	937	959	993	999	1000
	Yellow	0	58	41	7	1	0
	Red	0	5	0	0	0	0

calculated to be 38.4% by Eqs. (4) – (9) and the monitoring frequency is 2 from Eq. (10), so the monitoring for activity 6 is performed twice after it starts.

4.2 Project Execution Simulation

By Matlab software, 1000 groups of random duration data are generated for each activity, and 1000 iterations of experimental simulations are performed on the project. The proposed method is compared with the static buffer monitoring method (SBMM) (Goldratt, 1997), the relative buffer monitoring method (RBMM) (Leach, 2014) and the integrated buffer monitoring method (IBMM) (Zhang and Wan, 2019) to verify the overall effect of the proposed dynamic monitoring model. Table 6 depicts the frequency statistics of the buffer consumption in each zone of different methods.

It can be seen from Table 6 that, the frequency of the yellow and red areas shows an increasing trend in SBMM, indicating that the method results in the continuous accumulation of problems regardless of the actual implementation of the project; The RBMM has a certain improvement. The number of times buffer consumption falls in red and yellow zones is relatively reduced, however, it still appears an increasing trend with the project proceeds; Whereas, there is a trend of decline for which of the IBMM and the proposed method; Furthermore, as opposed to the other three approaches, the frequency in the green area of the proposed method has increased significantly, and the number in yellow and red areas has been substantially decreased, especially in the later stage of the project. This illustrates that the proposed method can predict and control the project implementation in a timely manner, avoid the accumulation of deviations effectively, and improve the monitoring effect.

Comparing the duration and cost performance of the four methods, the statistical results of the project duration are displayed in Figs. 5 and 6, and the cost results are exhibited in Figs. 7 and 8.

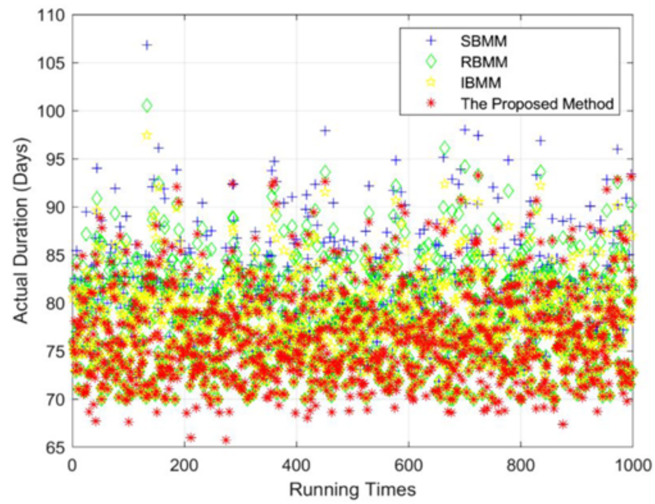

Fig. 5. Comparison of the Duration of Different Methods

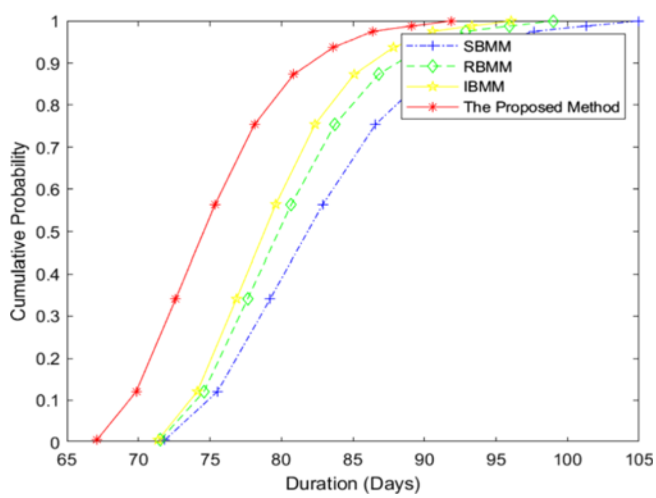

Fig. 6. Distribution of the Duration Cumulative Probability

Figures 5 and 6 demonstrate that the actual duration of the proposed method is lower than the other three methods, and the duration distribution is more concentrated. The reasons are as follows. First, the SBMM divides the monitoring area by fixed monitoring thresholds, so it is difficult to accurately judge the deviation in the project execution. Second, the RBMM adopts the incremental monitoring threshold setting mode, which can reduce the waste of buffer and shorten the project duration. However, in the later phases of the project, it is easy to cause irreversible situations due to excessive buffer consumption at the monitoring point, leading to the accumulation of the bad trend. Third, the IBMM monitors a project in the unit of activity, hence avoiding the accumulation of deviations to a certain extent. But the use of fixed monitoring time points is not conducive to flexible control of the project duration. Finally, the proposed method judges the future execution of the project through prediction and determines the corresponding monitoring frequency according to the buffer consumption situation. This enables the deviations to be timely detected, thus avoiding the continuation of deviation trends and further shortening the project completion time.

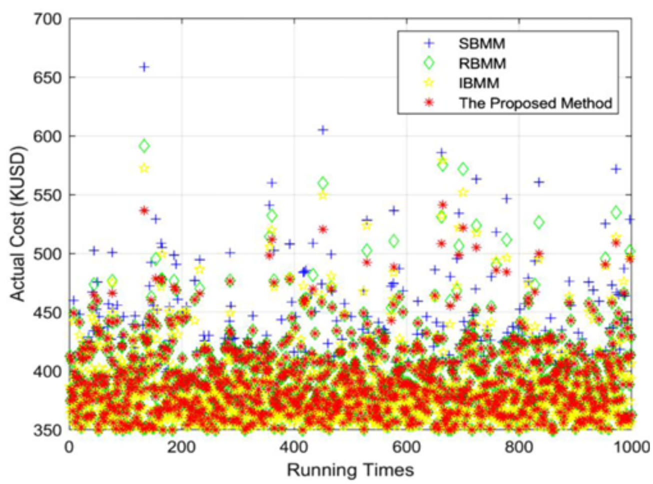

Fig. 7. Comparison of the Cost of Different Methods

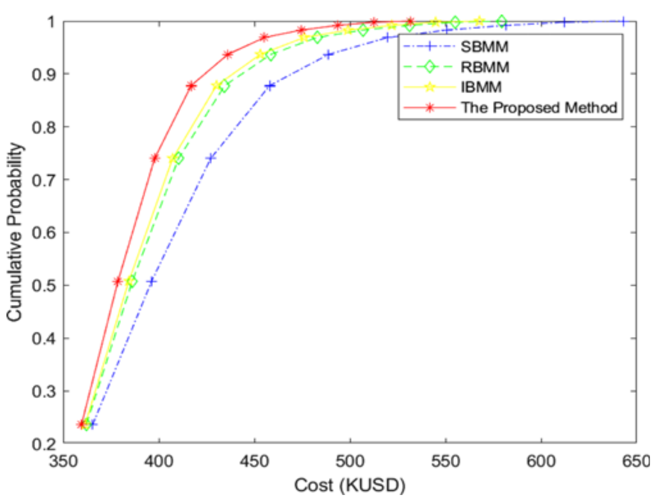

Fig. 8. Distribution of the Cost Cumulative Probability

Figures 7 and 8 illustrate that the cost performance of the proposed method is the best among four methods. The reasons are revealed as follows. First, the SBMM sets a high monitoring threshold in the early stage of the project, which results in unnecessary crashing actions and increases the monitoring cost. Second, taking into account the relationship between the project progress and buffer consumption, the RBMM divides the monitoring areas more reasonably, hence reducing the cost of the project. But the monitoring time point setting of this approach does not consider the difference in the characteristics among the activities. This increases the possibility of false warnings and makes the cost relatively high. Third, the IBMM is concerned with the subsequent buffer consumption of activities, which further saves the cost, however, it does not adjust the buffer allocation amount according to the actual situation, so that the monitoring reference points are not accurate enough and false warnings may occur. Finally, the method in this paper combines forecasting and monitoring organically, judges the implementation of activities in advance and adapts the buffer allocation and monitoring frequency dynamically for different activities. Therefore, in this method, more reasonable monitoring time points can be determined through the pre-judgment of the buffer consumption, which enables the monitoring measures more effective, decreases resource waste and further reduces the project execution cost.

5. Conclusions

In this paper, we introduce the support vector machine into the field of project management and construct a dynamic buffer monitoring model based on SVM prediction. Taking care of the difference in uncertainties of activity duration, we evaluate the uncertainty in the execution of activities in advance depending on the prediction algorithm and set different monitoring frequencies to perform feed-forward control on the project. Firstly, considering the influence of the dynamic changes of uncertain factors on the duration in the project execution, the support vector machine is used to predict the activity duration. Subsequently, the execution of the activities is forecasted based on the predicted duration and the corresponding monitoring frequency is set. The monitoring frequency of each activity is dynamically adjusted during the project, so that the monitoring actions can be taken more accurately and efficiently. The pre-differential setting of the monitoring frequency not only avoids the loss of a lot of manpower and material resources caused by continuous monitoring, but also makes up for the shortcoming that the fixed monitoring time point easily leads to the accumulation of bad trends, which can achieve a better monitoring effect by limited times of monitoring. Finally, a case simulation is carried out using Matlab. The results show that compared with the classical buffer monitoring methods, the method in this paper effectively shortens the project duration and saves the project execution cost.

In CCPM, the critical chain is the restriction factor of the project, and its length determines the shortest duration of the project (Goldratt, 1997). The project schedule is controlled by the buffer monitoring of the critical chain to shorten the duration. While in a multi-project system, the shortest duration is determined by the system critical chain, and buffer monitoring is implemented based on the system critical chain (Apaolaza and Lizarralde, 2020). In this study, the duration sequence of completed activities in the critical chain is input into the SVM model for a single project, and then the duration of the follow-up activity is predicted. Relying on this, buffer monitoring is performed. When the method is applied to a multi-project system, the activities in the system critical chain need to be predicted and monitored. Where, for an activity on the system critical chain to be started, the duration sequence is constructed by taking the single project as the unit, then the duration of the activity can be predicted. According to the above steps, the buffer monitoring method in this paper can be extended to the buffer monitoring of the multi-project system.

This research not only enriches the theoretical system of critical chain project management, but also has important significance in guiding the practice of project management teams. Constant dynamic changes may occur during the project execution process due to the increasingly complex enterprise environment changes, which increases the difficulty of project management. The feasibility and generalizability of the proposed approach have been verified by the project case. In the actual project management, when the project uncertainty is large, the project management team can apply the proposed dynamic buffer monitoring method to predict the project execution and control the project schedule flexibly, which will help strengthen the pertinence and adaptability of project management practice, improve the management efficiency of the project and enhance the competitiveness of the company.

A limitation of the study is that the parameter selection of the support vector machine model adopts the commonly-used grid search method. Appropriate parameter selection can enhance the generalization ability of SVM to some extent. Generalization is the ability of a machine learning algorithm to adapt to fresh samples. Traditional machine learning techniques emphasize the minimization of the experience risk, which usually leads to the over-learning problem and reduces the generalization ability (Pande et al., 2023). Since SVM is based on the structural risk minimization criterion, it can realize the minimization of the empirical risk and confidence range at the same time. It can obtain good statistical rules under the condition of a small statistical sample size, thus has stronger generalization ability. In the next step, we can consider to combine intelligent algorithms such as particle swarm optimization (Ipek, 2022) and tabu search algorithm (Gmira et al., 2021) with the SVM duration prediction model to further improve the generalization ability of the model.

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References

Apaolaza U, Lizarralde A (2020) Managing multiple projects in uncertain contexts: A case study on the application of a new approach based on the critical chain method. *Sustainability* 12(15):5999, DOI: 10.3390/su12155999

Bevilacqua M, Ciarapica FE, Giacchetta G (2009) Critical chain and risk analysis applied to high-risk industry maintenance: A case study. *International Journal of Project Management* 27(4):419-432, DOI: 10.1016/j.ijproman.2008.06.006

Bie L, Cui NF (2010) Research on dynamic buffer monitoring method of critical chain. *Journal of Chinese Management Science* 18(6):97-103, DOI: 10.16381/j.cnki.issn1003-207x.2010.06.003 (in Chinese)

Ding SF, An YX, Zhang XK, Wu FL, Xue Y (2017) Wavelet twin support vector machines based on glowworm swarm optimization. *Neurocomputing* 225:157-163, DOI: 10.1016/j.neucom.2016.11.026

Ghaffari M, Emsley MW (2015) Current status and future potential of the research on critical chain project management. *Surveys in Operations Research and Management Science* 20(2):43-54, DOI: 10.1016/j.sorms.2015.10.001

Ghazvini MS, Ghezavati V, Raissi S, Makui A (2017) An integrated efficiency-risk approach in sustainable project control. *Sustainability* 9(9):1575, DOI: 10.3390/su9091575

Ghoddousi P, Ansari R, Makui A (2017) A risk-oriented buffer allocation model based on critical chain project management. *KSCE Journal of Civil Engineering* 21(5):1536-1548, DOI: 10.1007/s12205-016-0039-y

Gmira M, Gendreau M, Lodi A, Potvin JY (2021) Tabu search for the time-dependent vehicle routing problem with time windows on a road network. *European Journal of Operational Research* 288(1):129-140, DOI: 10.1016/j.ejor.2020.05.041

Goldratt EM (1997) Critical chain. Great Barrington: The North River Press

Gong W, Hu JF (2013) Control management in IT project progress based on Markov chain. *Journal of Electronic Testing* (24):208-209 (in Chinese)

Gonzalez V, Alarcon LF, Yiu TW (2013) Integrated methodology to design and manage work-in-process buffers in repetitive building projects. *Journal of the Operational Research Society* 64(8):1182-1193, DOI: 10.1057/jors.2012.163

Hu XJ, Cui NF, Demeulemeester E, Bie L (2016) Incorporation of activity sensitivity measures into buffer management to manage project schedule risk. *European Journal of Operational Research* 249(2):717-727, DOI: 10.1016/j.ejor.2015.08.066

Hu XJ, Demeulemeester E, Cui NF, Wang JJ, Tian WD (2017) Improved critical chain buffer management framework considering resource costs and schedule stability. *Flexible Services and Manufacturing Journal* 29(2):159-183, DOI: 10.1007/s10696-016-9241-y

Hu XJ, Wang JJ, Leng KJ (2019) The interaction between critical chain sequencing, buffer sizing, and reactive actions in a CC/BM framework. *Asia-Pacific Journal of Operational Research* 36(3):1950010, DOI: 10.1142/S0217595919500106

Ipek AB (2022) Stock price prediction using improved extreme learning machine methods during the Covid-19 pandemic and selection of appropriate prediction method. *Kybernetes*, DOI: 10.1108/K-12-2021-1252

Juez FJD, Nieto PJ, Torres JM, Castro JT (2010) Analysis of lead times of metallic components in the aerospace industry through a supported vector machine model. *Mathematical and Computer Modelling* 52(7):1177-1184, DOI: 10.1016/j.mcm.2010.03.017

Kose T, Bakici T, Hazir Ö (2022) Completing projects on time and budget: A study on the analysis of project monitoring practices using real data. *IEEE Transactions on Engineering Management*, ahead-of-print, DOI: 10.1109/TEM.2022.3227428

Kuo TC, Chang SH, Huang SN (2009) Due-date performance improvement using TOC's aggregated time buffer method at a wafer fabrication factory. *Expert Systems with Applications* 36(21):1783-1792, DOI: 10.1016/j.eswa.2007.12.038

Leach LP (1999) Critical chain project management improves project performance. *Project Management Journal* 30(02):39-51, DOI: 10.1177/875697289903000207

Leach LP (2014) Critical chain project management. London: Artech House

Lin JJ, Zhou GH (2011) Research on critical chain buffer setting method based on process uncertainty. *Journal of Technology Management Research* 31(2):227-230 (in Chinese)

Liu X, Shen L, Zhang K (2021) Estimating the probability distribution of construction project completion times based on drum-buffer-rope theory. *Applied Sciences* 11(15):7150, DOI: 10.3390/app11157150

Martens A, Vanhoucke M (2017) The integration of constrained resources into top-down project control. *Computers & Industrial Engineering* 110:277-288, DOI: 10.1016/j.cie.2017.05.020

Martens A, Vanhoucke M (2020) Integrating corrective actions in project time forecasting using exponential smoothing. *Journal of Management in Engineering* 36(5):04020044, DOI: 10.1061/(ASCE)ME.1943-5479.0000806

Ordoñez REC, Vanhoucke M, Coelho J, Anholon R, Novaski O (2019) A study of the critical chain project management method applied to a multiproject system. *Project Management Journal* 50(3):322-334, DOI: 10.1177/8756972819832203

Pande CB, Kushwaha NL, Orimoloye, IR, Kumar R, Abdo HG, Tolche AD, Elbeltagi A (2023) Comparative assessment of improved SVM method under different kernel functions for predicting multi-scale drought index. *Water Resources Management* 37(3):1367-1399, DOI: 10.1007/s11269-023-03440-0

Peng WL, Lin XJ, Li HT (2023) Critical chain based proactive-reactive scheduling for resource-constrained project scheduling under uncertainty. *Expert Systems with Applications* 214:119188, DOI: 10.1016/j.eswa.2022.119188

Song J, Martens A, Vanhoucke M (2020) The impact of a limited budget on the corrective action taking process. *European Journal of Operational Research* 286(3):1070-1086, DOI: 10.1016/j.ejor.2020.03.069

Song JL, Tang CY, Yu SY, Yang XY, Yang L (2022) Prediction of product yields using fusion model from co-pyrolysis of biomass and coal. *Bioresource Technology* 353:127132, DOI: 10.1016/j.biortech.2022.127132

Vanhoucke M (2011) On the dynamic use of project performance and schedule risk information during project tracking. *Omega-International Journal of Management Science* 39(4):416-426, DOI: 10.1016/j.omega.2010.09.006

Xiao L, Bie L, Bai X (2021) Controlling the schedule risk in green building projects: Buffer management framework with activity dependence. *Journal of Cleaner Production* 278:123852, DOI: 10.1016/j.jclepro.2020.123852

Yu Y, Dackermann U, Li JC, Niederleithinger E (2019) Wavelet packet energy-based damage identification of wood utility poles using support vector machine multi-classifier and evidence theory. *Structural Health Monitoring-An International Journal* 18(1):123-142, DOI: 10.1177/1475921718798622

Yuan KJ, Chang SH, Li RK (2003) Enhancement of theory of constraints replenishment using a novel generic buffer management procedure. *International Journal of Production Research* 41(4):725-740, DOI: 10.1080/0020754031000065502

Zendehboudi A, Baseer MA, Saidur R (2018) Application of support vector machine models for forecasting solar and wind energy resources: A review. *Journal of Cleaner Production* 199:272-285, DOI: 10.1016/j.jclepro.2018.07.164

Zhang JG, Cheng N (2021) Risk-driven critical chain project monitoring cycle setting. *Journal of Industrial Engineering and Management* 26(5):10-17, DOI: 10.19495/j.cnki.1007-5429.2021.05.002 (in Chinese)

Zhang JG, Jia SK, Diaz E (2018) Dynamic monitoring and control of a critical chain project based on phase buffer allocation. *Journal of the Operational Research Society* 69(12):1966-1977, DOI: 10.1080/01605682.2017.1415641

Zhang JG, Li J (2022) Critical chain project buffer monitoring based on process heterogeneity. *Journal of Chinese Management Science* 30(6):106-115, DOI: 10.16381/j.cnki.issn1003-207x.2019.1548

Zhang S, Liang C (2018) Research on construction schedule control based on critical chain method and BIM. *Journal of Applied Science and Engineering Innovation* 5(2):47-50

Zhang JG, Wan D (2019) Integrated buffer monitoring and control based on grey neural network. *Journal of the Operational Research Society* 70(3):516-529, DOI: 10.1080/01605682.2018.1447251

Zhang JG, Yang PZ (2021) A critical chain adaptive buffer monitoring strategy based on trend prediction. *Forecasting* 40(1):84-89 (in Chinese)

Zhao Y, Cui NF, Tian WD (2020) A two-stage approach for the critical chain project rescheduling. *Annals of Operations Research* 285:67-95, DOI: 10.1007/s10479-019-03347-3