Exploration of Maximizing the Benefits of Secondary Model Optimization in Empowering Ancient Book Restoration

Guangyu Wu [1], Yuanlin Zheng [2(*)] and Jinju Chen [3]

[1] Fujian Provincial Library, Fuzhou Fujian Province, China
[2] College of Computer and Cyberspace Security, Fujian Normal University, Fuzhou Fujian Province, China
[3] College of Sociology and History, Fujian Normal University, Fuzhou Fujian Province, China
*wuguangyu_fjlib@sina.com

Abstract. To address the difficulty of priority decision-making in ancient book restoration under resource constraints, this study proposes a scientific and efficient dynamic decision-making method. A restoration priority model based on monotone submodular optimization, namely MOSM, is constructed to incorporate multiple indicators, including documentary value, restoration cost, diversity, and urgency, into a unified quantitative framework. The restoration prioritization problem is further formulated as a monotone submodular function maximization problem subject to budget constraints, thereby effectively characterizing the diminishing marginal utility of restoration benefits and improving resource allocation efficiency. Experimental results indicate that, under both dynamic and fixed budget scenarios, the MOSM model significantly outperforms the traditional greedy algorithm and random selection strategy in terms of restoration benefit and cost-effectiveness. The proposed method provides a feasible and effective solution for restoration priority decision-making and offers both theoretical and practical support for the conservation, restoration, and sustainable management of ancient books. These findings further demonstrate its potential value in real-world cultural heritage preservation practice.

Keywords: Submodular Optimization, Ancient Book Restoration Benefits, Priority Decision-Making, Intelligent Protection of Ancient Books

1 Introduction

Ancient books represent crystallizations of the wisdom of the Chinese nation and constitute invaluable treasures of historical and cultural heritage. They possess irreplaceable documentary, historical, and artistic significance[1]. Nevertheless, over centuries of transmission, a large number of precious ancient books have suffered various forms of deterioration caused by environmental erosion, human damage, and improper storage. Some are even on the verge of irreversible loss, making their emergency conservation and restoration an urgent task[3].

N. Malik et al. (eds.), *Proceedings of the 6th International Conference on Public Management and Intelligent Society (PMIS 2026)*, Advances in Engineering Research 301,
https://doi.org/10.2991/978-94-6239-721-7_32

Genealogical documents, such as Fujian–Taiwan genealogical collections, form a distinctive category of regional and cross-strait cultural heritage. Owing to their scarcity and high research value, as well as the generally poor preservation conditions under which they are kept, these materials often require priority in rescue-oriented conservation efforts. Importantly, ancient book restoration is not merely a technical procedure. It involves complex value judgments, delicate craftsmanship, and rational allocation of limited restoration resources. How to achieve the greatest restoration benefit under resource constraints has therefore become a key practical challenge in the field of ancient book conservation.

In recent years, substantial progress has been made in research on ancient book protection. Regarding value assessment, scholars have increasingly focused on developing multidimensional and quantitative evaluation frameworks to better capture the intrinsic worth of ancient books and to support restoration decision-making. From perspectives such as philology, history, and art studies, various grading standards and value systems have been proposed. Genealogical documents, in particular, play an important role in family history research, local historical documentation, and cross-strait cultural studies, and thus deserve special consideration in value evaluation and priority determination.

With respect to restoration techniques and management, the establishment of standards and guidelines has contributed to improving restoration quality and efficiency[4]. However, practical challenges remain, including shortages of skilled conservators, inconsistencies in restoration criteria, and the risk of excessive intervention. These issues further underscore the necessity of scientific and data-driven decision-making for optimal allocation of restoration resources[5]. Meanwhile, the rapid development of information technologies has promoted digital preservation as an essential component of ancient book conservation, providing new data sources and methodological support for value assessment and restoration planning[6]. Despite these advances, existing studies still lack a unified framework that can simultaneously quantify multiple value dimensions, restoration cost, diversity requirements, and urgency, and further perform dynamic multi-objective optimization under resource constraints.

To address this gap, this study introduces submodular optimization theory to establish a dynamic prioritization model for ancient book restoration. Submodular functions, characterized by the property of diminishing marginal returns, have shown strong effectiveness in resource-constrained optimization problems and have been widely applied in domains such as sensor placement and feature selection. In this work, the restoration prioritization task is formulated as a set selection problem: selecting an optimal subset of ancient books from a large candidate pool to maximize overall benefit subject to budget constraints in manpower, funding, and time. The diminishing-return property of submodular functions naturally accords with the practical characteristics of restoration activities, enabling preferential selection of high-value and high-urgency documents and improving overall resource utilization efficiency.

The main contributions of this study are threefold:

1. A multidimensional comprehensive benefit function is constructed by integrating documentary value (rarity, scholarly value, and artistic value), restoration cost, document diversity, and restoration urgency, thereby enabling holistic quantification of

factors affecting restoration prioritization.

2. The prioritization problem is formulated as a monotone submodular maximization problem under budget constraints, providing theoretical support and efficient approximation strategies for dynamic decision-making.
3. A high-fidelity simulation dataset consistent with real-world conservation scenarios is developed, and extensive experiments under both fixed-budget and dynamic-budget settings demonstrate the effectiveness and robustness of the proposed approach compared with baseline methods.

The remainder of this paper is organized as follows. Section 1 reviews related work on ancient book value assessment, restoration resource management, and submodular optimization. Section 2 presents the proposed model and analyzes its theoretical properties. Section 3 describes the experimental design and discusses the results. Section 4 concludes the paper and outlines future research directions.

2 Related Works

2.1 Quantitative Evaluation of the Multidimensional Value of Ancient Books

The value of ancient books is one of the core determinants of their restoration priority. The evaluation of ancient book value is not based on a single dimension, but rather on a comprehensive consideration of multiple attributes. China's Standards for Grading Ancient Books classify the value of ancient books according to the "three-principle" framework, namely historical and cultural significance, scholarly and documentary significance, and artistic representativeness[7]. Building upon this foundation, Li Mingjie[8] further proposed the establishment of a hierarchical protection system for Chinese ancient books, advocating graded protection of physical carriers, textual content, and their associated intangible cultural heritage. These studies have laid a solid theoretical basis for ancient book value assessment; however, how to transform these qualitative principles into operational and quantifiable indicators that can support intelligent decision-making remains a key research focus.

In recent years, researchers have begun to incorporate multiple dimensions—such as the degree of deterioration, carrier value, utilization rate, and restoration risk—into the selection of restoration targets[9]. In addition, ancient book restoration archives, which provide detailed records of the restoration process, have attracted increasing attention for their scientific research value, standardized management value, and bibliographic organization value, offering important data support for dynamic value assessment and optimization of restoration schemes[10]. Among various categories, Fujian–Taiwan genealogical collections constitute a representative case for multidimensional quantification, owing to their unique significance in cross-strait kinship studies and local historical documentation. These collections possess irreplaceable academic value in research on family migration, folk social history, and cross-sea cultural exchange; therefore, their value assessment must simultaneously account for documentary rarity, cultural continuity, and regional identity. Although existing studies have made progress in theoretical modeling and partial indicator design, substantial challenges remain in achieving fine-grained, computable quantification of the multidimensional and complex value of ancient books to effectively support intelligent decision-making.

2.2 Optimized Management of Ancient Book Restoration Resources

Ancient book restoration is a labor-intensive and time-consuming process that imposes stringent requirements on resources such as technology, materials, and skilled personnel. Under limited resource constraints, achieving the coordinated improvement of restoration efficiency and restoration benefits constitutes the central objective of optimized resource management. To standardize restoration practice, Du Weisheng[12] systematically elaborated the core contents of technical specifications and quality requirements for ancient book restoration, aiming to unify restoration standards and ensure restoration quality. Building on this foundation, Zhang Meifang et al.[13] further pointed out that current restoration techniques are difficult to standardize and that quality control remains challenging, and they proposed a conceptual framework for establishing a national technical standards system for ancient book restoration. The development of such standards provides fundamental guidelines for the scientific allocation of restoration resources.

Nevertheless, inappropriate restoration operations may result in "restoration-induced damage"[14], highlighting the necessity of strict adherence to restoration principles and the importance of emphasizing reversible techniques[15]. Wu Fangjuan[16] reported that ancient book restoration and conservation in libraries are still confronted with multiple bottlenecks, including outdated technologies, shortages of professional personnel, lack of unified standards, over-restoration, and insufficient digital processing. To address these issues, scholars have called for the introduction of advanced technologies, strengthened professional training, the establishment of standardized regulations, enhanced supervision of restoration practices, and the active promotion of digital preservation[17]. For Fujian–Taiwan genealogical collections, whose primary forms of deterioration include paper embrittlement and ink fading, their geographically dispersed condition further poses special challenges for restoration resource allocation and inter-institutional collaboration. This reality underscores the necessity of constructing quantifiable models for resource optimization. Although the above studies provide valuable guidance on technical standardization and management optimization, how to quantitatively relate the degree of deterioration, the resources required for restoration, and the expected restoration benefits, and thereby achieve optimal resource allocation, remains a critical issue requiring further in-depth investigation.

2.3 Applications and Implications of Submodular Optimization in Decision-Making Problems

In multi-objective decision-making and optimization problems under limited resources, submodular functions have attracted extensive attention due to their distinctive property of diminishing marginal returns, and have been proven capable of yielding high-quality approximate solutions via greedy algorithms in many practical applications. The core principle of submodular optimization lies in the fact that the marginal gain obtained by adding an element to a set decreases as the size of the existing set increases. Guestrin et al.[18] first exploited submodularity in the sensor placement problem and demonstrated that near-optimal sensor configurations can be obtained in polynomial time by leveraging this property. Subsequently, submodular optimization theory has undergone substantial development. Badanidiyuru et al.[19] achieved significant breakthroughs in fast algorithms, enabling efficient maximization of monotone submodular functions under various constraints. Liu et al.[20] provided a comprehensive survey of submodular optimization problems and greedy strategies, emphasizing the approximation performance bounds of greedy approaches for multi-action decision optimization. These studies have established a solid theoretical and algorithmic foundation for applying submodular optimization to real-world problems.

Submodular optimization has been widely applied in areas such as data summarization, network coverage, feature selection, and healthcare resource scheduling. In the field of cultural heritage conservation, although some studies have attempted to introduce optimization methods for allocating digital resources, there has been little exploration of applying submodular optimization theory to the dynamic decision-making of restoration priority for physical ancient books. Given the limited availability of restoration resources, the diminishing marginal benefits of restoration, and the diversity of decision objectives, submodular optimization provides a powerful framework for addressing such problems. Motivated by this gap, this study models the ancient book restoration priority decision problem as a submodular function maximization task, aiming to provide a more scientific and efficient dynamic decision-making model for ancient book restoration.

3 Research Methodology

3.1 Problem Formulation

In the practice of ancient book conservation, the central challenge of restoration-priority decision-making lies in achieving coordinated multi-objective optimization of cultural value preservation, restoration cost control, and document diversity protection under limited resources (i.e., manpower, funding, and time). This problem can be abstracted as a set-function optimization task, in which a subset of ancient books is selected from a candidate collection so as to maximize overall benefit. Owing to the property of diminishing marginal returns, submodular functions are naturally suited to priority decision problems in resource-constrained scenarios. Specifically, the marginal benefit of additional resource investment decreases as the amount of resources already allocated increases, which is highly consistent with the restoration principle of "prioritizing high-value documents and gradually extending coverage to secondary targets." Based on the above problem formulation, we construct the ancient book restoration priority optimization model as follows:

3.2 Mathematical Model Construction

Let the candidate set of ancient books be denoted as $V = \{v_1, v_2, \ldots, v_n\}$. A subset $S \subseteq V$ is selected as the set of ancient books to be restored. Under a given budget constraint B, the objective is to maximize the overall benefit function $f(S)$:

$$f(S) = \alpha \cdot Value(S) - \beta \cdot Cost(S) + \gamma \cdot Div(S) + \delta \cdot Urg(S),$$

Where $\alpha, \beta, \gamma, \delta \geq 0$ are weighting parameters determined using the Analytic Hierarchy Process (AHP) in combination with expert scoring. $\mathrm{Value}(S)$ denotes the documentary value of the selected subset, $\mathrm{Cost}(S)$ represents the restoration cost, $\mathrm{Div}(S)$ indicates document diversity, and $\mathrm{Urg}(S)$ corresponds to restoration urgency.

Definition 1 (Submodular Function): Let Ω be a finite ground set. For any $A \subseteq B \subseteq V$ and any $v \in V \setminus B$, a set function $f: 2^V \to R$ is said to be submodular if:

$$f(A \cup \{v\}) - f(A) \geq f(B \cup \{v\}) - f(B),$$

Documentary Value Function.

According to the “three-principle” framework (i.e., historical and cultural significance, scholarly and documentary significance, and artistic representativeness) proposed in [7], the documentary value function is defined as:

$$\mathrm{Value}(S) = \sum_{v \in S} \left(w_1 \cdot \mathrm{Scarcity}(v) + w_2 \cdot \mathrm{Academic}(v) + w_3 \cdot \mathrm{Artistic}(v)\right).$$

(1) Rarity $\mathrm{Scarcity}(v)$:

$$\mathrm{Scarcity}(v) = \begin{cases} 2 \text{ Unique Copy (sole surviving edition in China or overseas)} \\ 1 \text{ Common Document (more than one extant copy)} \end{cases}$$

(2) Scholarly Value $\mathrm{Academic}(v)$:

$$Academic(v) = log(1 + N_{citation}(v)) + TF\_IDF(v, K) + \lambda \cdot Special(v),$$

Where $N_{\mathrm{citation}}(v)$ denotes the number of historical academic citations of document v; $\mathrm{TF\_IDF}(v, K)$ represents the matching degree between the content of document v and the research-hotspot keyword set K; and the special historical significance score $\mathrm{Special}(v)$ is defined according to the “priority-by-grade principle” in [7] as:

$$\mathrm{Special}(v) = \begin{cases} 2 \text{ Documents with annotations or colophons by renowned scholars} \\ 1 \quad \text{Other} \end{cases}$$

(3) Artistic Value $\mathrm{Artistic}(v)$:

$$\mathrm{Artistic}(v) = \begin{cases} 3 \text{ special printing techniques (e.g., Ming editions)} \\ 2 \text{ special movable}-\text{type editions (e.g., Qing editions)} \\ 1 \quad \text{Standard Edition} \end{cases}$$

According to the qualitative descriptions of printing techniques and binding artistry in [7] and the practical classification schemes of binding and engraving complexity reported in professional conservation practice[21], a discrete scoring strategy of 3/2/1 is adopted to categorize common artistic techniques.

Restoration Cost Function.

The restoration cost function is formulated in a linear additive form:

$$Cost(S) = \sum_{v \in S} c(v),$$

$$c(v) = \left[c_{material}(v) + c_{time}(v) \cdot t_{expert}\right] \cdot \left(1 + \theta \cdot \mathbb{I}_{Unique}(v)\right),$$

Where $c_{material}$ denotes the estimated cost of restoration materials (CNY/page) according to the type of deterioration (e.g., insect damage, mildew, etc.); $c_{time} = \frac{Damaged\ Area(v)}{Restoration\ Efficiency}$ represents the unit time cost (hours/page); t_{expert} denotes the estimated labor cost based on the hourly wage of restoration experts (CNY/hour); $\mathbb{I}_{Unique}(v)$ is an indicator function that equals 1 if v is a unique copy and 0 otherwise. To capture the distinctive characteristics of unique copies in terms of restoration process complexity, preservation requirements, and conservation risk, a restoration difficulty coefficient, denoted by θ, is introduced. According to the restoration time statistics for unique copies published by the Ancient Books Protection Center of Fujian Provincial Library, the average restoration cost of unique copies in actual conservation practice is approximately 20% higher than that of ordinary documents. Therefore, θ is set to 0.2.

Diversity Function.

Diversity is measured using information entropy to avoid excessive concentration on a single document category and to encourage coverage of multiple categories:

$$Div(S) = -\sum_{k=1}^{K} p_k \log p_k,$$

Where $p_k = \frac{|S \cap V_k|}{|S|}$ denotes the proportion of documents in subset S that belong to the k-th category, and V_k represents the subset of documents belonging to the k-th category according to the Chinese Library Classification (CLC) system[24] (e.g., category K for History and category I for Literature).

Urgency Function.

The urgency function reflects the time-critical requirement of document restoration:

$$Urg(S) = \sum_{v \in S} (d(v)/(1 + 1/age(v))),$$

Here, $d(v) \in \{1,2,3,4,5\}$ denotes the damage level, where Level 1 indicates minor damage and Level 5 indicates a critically endangered condition. $age(v)$ represents the preservation age of the ancient book; the older the book is, the larger the value of $age(v)$. As $age(v)$ increases, the term $1 + 1/age(v)$ becomes smaller and gradually approaches 1. Since this term appears in the denominator, the urgency function $Urg(S)$

correspondingly increases. In other words, a longer preservation age implies a higher restoration urgency.

3.3 Properties of the Submodular Function

Theorem 1. The objective function $f(S)$ is a non-negative submodular function under the budget constraint.

Proof. The objective function is given by

$$f(S) = \alpha \cdot Value(S) - \beta \cdot Cost(S) + \gamma \cdot Div(S) + \delta \cdot Urg(S),$$

where the properties of the component functions are summarized as follows:

(1) Non-negativity: For any $\forall A \in V, f(A) \geq 0$ holds.

For the documentary value term, since $Scarcity(v) \geq 1$、$Academic(v) \geq 0$ and $Artistic(v) \geq 1$, and the weights $\alpha, w_1, w_2, w_3 \geq 0$, it follows that $Value(S) \geq 0$.

Cost constraint: Since the restoration cost function $Cost(S) \geq 0$, it is necessary to ensure that the term $-\beta \cdot Cost(S)$ does not make the overall objective function negative. That is,

$$\alpha \cdot Value(S) + \gamma \cdot Div(S) + \delta \cdot Urg(S) \geq \beta \cdot Cost(S),$$

For the diversity term, since $p_k \in [0,1]$, the entropy-based measure satisfies $Div(S) \geq 0$.

For the urgency term, because the damage level $d(v) \geq 1$, and preservation age $age(v) \geq 0$, we have $Urg(S)Div(S) \geq 0$.

Therefore, under reasonable parameter settings, $f(S) \geq 0$ holds.

(2) Submodularity. For any $A \subseteq$和$v \in V \setminus B$, $f(A \cup \{v\}) - f(A) \geq f(B \cup \{v\}) - f(B)$ the objective function satisfies. For the documentary value term $Value(S)$, which is linear, the marginal gain is a constant:

$$\Delta Value(v) = w_1 \cdot Scarcity(v) + w_2 \cdot Academic(v) + w_3 \cdot Artistic(v),$$

Which is independent of A or B; hence, $Value(S)$ is submodular.

For the restoration cost term $Cost(S)$, which is also linear, the marginal gain is a constant $\Delta Cost(v) = c(v)$. After multiplication by the negative coefficient, the function remains submodular.

For the diversity term $Div(S)$, the marginal gain of information entropy decreases as the set S expands. Let $A \subseteq B$. The diversity gain of adding document v to A is

$$\Delta Div_A(v) = Div(A \cup \{v\}) - Div(A).$$

and similarly $\Delta Div_B(v)$ for set B. Since B contains more documents and exhibits a more balanced category distribution, the increase in entropy caused by adding v is smaller, i.e.,

$$\Delta Div_A(v) \geq \Delta Div_B(v).$$

Therefore, $Div(S)$ is submodular.

For the urgency term $\mathrm{Urg}(S)$, which is linear, the marginal gain is constant $\frac{d(v)}{1+1/age(v)}$, and thus it is submodular.

Consequently, the submodularity of $\mathrm{f}(S)$ is guaranteed by the submodularity of each component function and the property that a non-negative linear combination of submodular functions remains submodular.

In summary, the objective function $\mathrm{f}(S)$ satisfies non-negativity and submodularity. Under the budget constraint, a greedy algorithm can achieve an approximate solution with a performance guarantee of $1-\frac{1}{e}$.

4 Experimental Design

4.1 Dataset.

To validate the effectiveness of the ancient book restoration priority decision-making model, this study constructed a dataset aligned with real-world conservation practice based on the core principles of the *Standards for Grading Ancient Books* [7]. The dataset was derived from the ancient book database of Fujian Provincial Library and includes 500 cataloged ancient books selected from its collection. It covers five major categories: history (K), literature (I), philosophy (B), culture (G), and economics (F). The preservation age ranges from 50 to 300 years, and the damage levels follow the actual distribution observed in preservation surveys, spanning Grades 1 to 5.

Regarding value attributes, unique copies account for 10% of the dataset, artistic value is graded according to printing and binding techniques, and scholarly value is generated using a Poisson distribution with λ=15 to simulate citation counts. Restoration costs are dynamically generated based on damage levels, with an additional 20% cost coefficient applied to unique copies. Accession times are simulated as random dates within the past year, enabling temporal analysis. Table 1 presents several representative samples from the dataset.

Table 1. Examples of the Ancient Book Dataset

Document ID	Category	Damage Level	Preservation Age (years)	Unique Copy	Artistic Value Score	Scholarly Value Score	Restoration Cost (CNY)	Accession Time
001	K(History)	4	276	False	3(Douban Printing)	1.08	8495	2025-03-22
002	I(Literature)	2	117	False	1(Standard Edition)	1.73	4247	2024-07-31
003	B(Philosophy)	1	202	False	2(Ceramic Movable Type)	1.15	1750	2024-07-21
004	G(Culture)	1	180	True	1(Standard Edition)	1.23	2401	2025-04-05
…	…	…	…	…	…	…	…	…

4.2 Comparative Experiments

Focusing on the optimization problem of ancient book restoration priority decision-making, a series of comparative experiments are systematically designed to verify the effectiveness and superiority of the proposed Multi-Objective Submodular Method (MOSM). Using the simulated dataset, MOSM is evaluated against three baseline methods under a strictly controlled parameter setting: Damage-Priority Approach (DPA), First-In–First-Out (FIFO), and Random Selection (RAND).

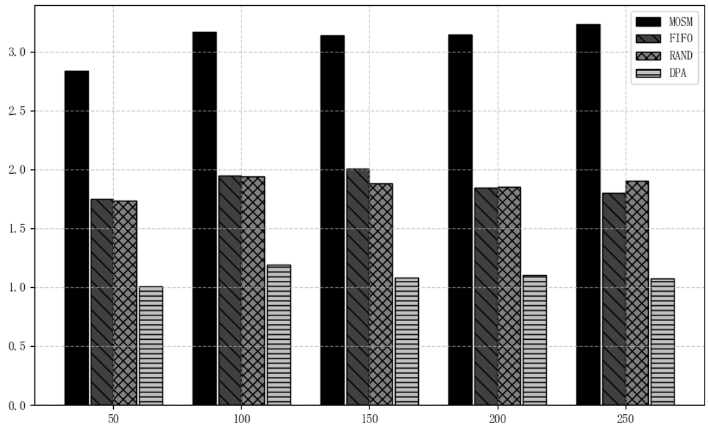
Two experimental scenarios are considered: dynamic-budget and fixed-budget settings. The core evaluation metrics include the cost–benefit ratio (i.e., the comprehensive value obtained per unit cost) and the restoration throughput per unit budget (i.e., the number of documents restored per 10,000 CNY of budget). In the dynamic-budget scenario, the budget is adjusted proportionally with the number of candidate documents, simulating real-world situations where resources are allocated on demand. In the fixed-budget scenario, a uniform budget upper bound is imposed, reflecting the decision-making challenges under rigid resource constraints.

The experimental dataset covers document scales ranging from 50 to 250 items. Variable control was implemented through random sampling to ensure the comparability of results. Model parameters were determined using the Analytic Hierarchy Process (AHP). Given its extensive application in archaeological evaluation and multi-criteria decision-making, and its validated use in the field of document restoration and conservation, the adoption of AHP to determine the weights of the four subfunctions is methodologically justified in this study [25]. Specifically, the pairwise comparison matrix was provided by experts in ancient book conservation, and the final weights were obtained after passing the consistency test. These parameters were kept unchanged throughout all experiments to ensure the comparability and reproducibility of the results. To reduce the influence of randomness, the RAND method was repeated 30 times and the average value was reported to ensure statistical significance.

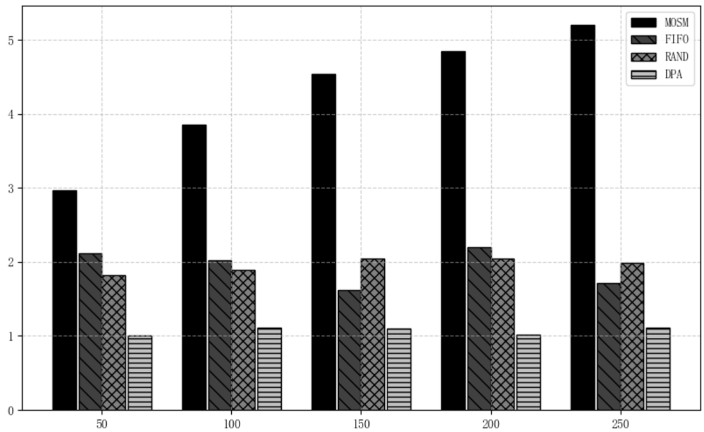
The weight parameters obtained through AHP are as follows: the cultural value weight is $\alpha = 0.6$, the restoration cost penalty factor is $\beta = 0.2$, the diversity gain weight is $\gamma = 0.1$, and the urgency response weight is $\delta = 0.1$. It should be noted that, in the model construction described in Section 2.2, the diversity function is based on information entropy derived from the categories of the Chinese Library Classification. As a result, when documents are evenly distributed across different categories, entropy may be maximized, which could lead to the selection of low-value documents from underrepresented categories merely to improve diversity. To address this issue, experts generally agreed in the AHP analysis that, compared with the other three subfunctions, document value more directly reflects the importance of restoration, that is, priority should be given to ancient books with higher cultural value and stronger academic significance. Therefore, the AHP results show that the cultural value weight, $\alpha = 0.6$, is significantly higher than the other three weight parameters.

4.3 Results Analysis

The experimental results demonstrate that MOSM exhibits significant decision-making advantages under both budget scenarios. As shown in Fig. 1(a), in the dynamic-budget setting, when the number of candidate ancient books increases from 50 to 250, the restoration throughput per unit budget achieved by MOSM remains stable in the range of 2.838–3.232 documents per 10,000 CNY, with an average of 3.103 documents per 10,000 CNY, which is substantially higher than that of the baseline methods. Specifically, when the number of documents reaches 250, the throughput of MOSM (3.232 documents/10,000 CNY) is 79.5%, 69.6%, and 200.7% higher than those of FIFO (1.801 documents/10,000 CNY), RAND (1.906 documents/10,000 CNY), and DPA (1.075 documents/10,000 CNY), respectively.



(a) Dynamic-Budget Scenario



(b) Fixed-Budget Scenario

Fig. 1. Comparison of Restoration Throughput per Unit Budget under Different Budget Strategies

This superior performance can be attributed to MOSM's dynamic trade-off mechanism among multidimensional value attributes. Under on-demand resource allocation, MOSM prioritizes documents with high rarity (e.g., unique copies) to preserve long-term cultural value, while simultaneously maintaining restoration efficiency for ordinary documents, thereby avoiding resource dilution. In contrast, DPA relies excessively on the single indicator of damage level, leading to a rapid decline in restoration efficiency when the dataset size exceeds 100 documents, decreasing from 1.189 to 1.075 documents per 10,000 CNY. FIFO and RAND lack value-oriented prioritization, resulting in dispersed resource allocation and unstable performance, with throughput ranges of 1.751–2.115 and 1.734–2.048 documents per 10,000 CNY, respectively.

As illustrated in Fig. 1(b), in the fixed-budget scenario, MOSM exhibits a counter-trend gradual increase in restoration throughput, rising from 2.965 documents per 10,000 CNY at 50 documents to 5.206 documents per 10,000 CNY at 250 documents, representing an improvement of 75.6%. This phenomenon indicates that MOSM optimizes the restoration sequence through its nonlinear value-fusion mechanism as the scale increases. The mechanism dynamically emphasizes attributes such as artistic value (e.g., douban or overprinting techniques) and scholarly value (e.g., documents containing annotations or colophons), enabling the model to identify higher-value restoration targets under rigid budget constraints. In contrast, the baseline methods are unable to adaptively adjust priorities, and their restoration efficiency stagnates or declines with increasing scale: FIFO decreases from 2.115 to 1.716 documents per 10,000 CNY (a reduction of 18.9%), RAND fluctuates between 1.824 and 2.048 documents per 10,000 CNY, and DPA remains at a consistently low level of 1.005–1.117 documents per 10,000 CNY. These results further highlight the flexibility and effectiveness of MOSM in multi-objective collaborative optimization.

Further incorporating the cost–benefit ratio analysis in Fig. 2, MOSM exhibits a continuous improvement in cost–benefit ratio under the fixed-budget scenario as the number of candidate ancient books increases, rising from 0.171 at 50 documents to 0.216 at 250 documents, representing an increase of 26.3%. This trend indicates that MOSM achieves cumulative gains in value density under limited resources. Meanwhile, it also suggests that MOSM's ranking mechanism tends to prioritize documents with higher unit efficiency at earlier stages, that is, those with prominent marginal restoration efficiency, thereby avoiding uniform budget allocation to low-value documents.

For example, even as the budget and dataset size increase, MOSM continues to preferentially select documents with high rarity and high value density (e.g., unique copies and special editions). In contrast, the cost–benefit ratio of DPA increases only from 0.056 to 0.067 (19.6%), and its overall level remains significantly lower than that of MOSM. The RAND method, due to the absence of prioritization, exhibits random fluctuations in restoration outcomes, with cost–benefit ratios ranging from 0.106 to 0.121. FIFO shows a noticeable decline at 150 documents (0.077), further indicating instability in its resource allocation strategy.

Taken together, these three sets of experiments demonstrate that, through dynamic priority-gradient design, MOSM is capable of balancing conservation efficiency and cultural heritage preservation under the dual challenges of resource constraints and value heterogeneity.

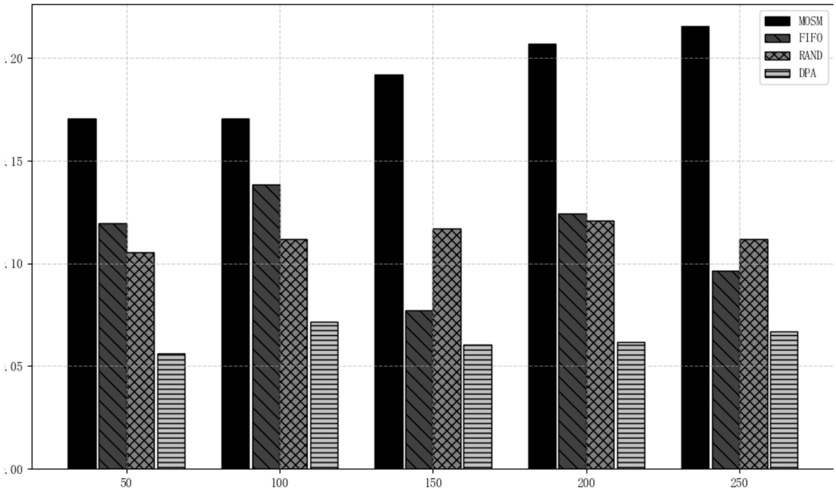


Fig. 2. Cost–Benefit Ratio under Fixed Budget

5 Conclusion

This study addresses the challenging problem of restoration priority decision making for ancient books under limited resources and proposes a novel dynamic decision model for ancient book restoration priority based on submodular optimization, referred to as the Multi Objective Submodular Method (MOSM). By constructing a comprehensive benefit function, multiple factors including documentary value, restoration cost, diversity, and urgency are quantitatively integrated. By exploiting the diminishing marginal returns property of submodular functions, the complex priority decision problem is transformed into a submodular function maximization problem under budget constraints.

Experimental results demonstrate that, in both dynamic budget and fixed budget scenarios, the MOSM model effectively improves restoration benefits and achieves optimal resource allocation, significantly outperforming traditional greedy strategies and random selection methods. These findings confirm the strong potential of submodular optimization theory in the field of cultural heritage conservation and provide a new perspective and practical tool for the scientific restoration and sustainable preservation of ancient books.

Acknowledgements

This work was supported by the Science and Technology Project of the National Archives Administration of China (Grant No. 2023-X-072), the Fujian Province Innovation Strategy Research Project (Grant No. 2023R0090), and the Fujian Province Social Science Foundation Project (Grant No. FJ2025A026).

References

1. Wang, Y.X.: Practices and Reflections on the Conservation of Ancient Books in Inheriting and Carrying Forward Excellent Traditional Chinese Culture. Library Work and Study (8), 89–91+100 (2016). DOI:10.16384/j.cnki.lwas.2016.08.018.
2. Wang, X.J.: Conservation and Utilization of Ancient Books in Libraries. Journal of Modern Information 31(8), 151–153 (2011).
3. General Office of the State Council: Opinions of the General Office of the State Council on Further Strengthening the Conservation of Ancient Books. (2007). https://www.gov.cn/gongbao/content/2007/content_549033.htm. Accessed 26 Apr 2026.
4. Luo, H.Q., Wang, X.E., Lin, Y., et al.: Practice and Reflection on the Construction of a Specialized Paper Warehouse for Ancient Books Restoration in Sichuan. Digital & Micrographic Imaging (1), 17–21 (2025).
5. Lin, F.: Study on the Cultivation Path of Ancient Books Restoration Talents in Fujian Province. Educational Review (4), 53–55 (2016).
6. Feng, T., Tan, Y.: Research on the Activation Path of Ancient Literature Value under the Cultural Digitalization Strategy. Shanxi Archives (3), 130–133 (2024).
7. Ministry of Culture of the People's Republic of China: The Standard for Distinction of the Chinese Ancient Books: WH/T 20–2006. Ministry of Culture of the People's Republic of China, Beijing (2006).
8. Li, M.J.: A Conception of Constructing a Hierarchical Protection System for Chinese Ancient Books: Innovating the Conservation Approach from the Perspective of Ancient Books Value Attributes. Library Journal 28(3), 14–19 (2009). DOI:10.13663/j.cnki.lj.2009.03.009.
9. Yan, L.: Selection Strategies for Ancient Books Restoration Objects. Library Tribune 36(7), 97–101 (2016).
10. Lin, H.Z.: Value Attributes and Application of Ancient Books Restoration Archives. Journal of Academic Library and Information Science 31(6), 45–48 (2013).
11. Huo, Y.F., Xue, Y.C., Yang, L.M.: Learning from the Past to Enlighten the Future: The Current Situation of the Management and Utilization of Ancient Books Restoration Archives. Research on the Conservation of Ancient Books (3), 127–142 (2024).
12. Du, W.S.: An Interpretation of the "Technical Specifications and Quality Requirements for the Restoration of Ancient Books". Journal of the National Library of China (3), 19–25 (2006).
13. Zhang, M.F., Chen, M.: A Study on the Construction of a Technical Standard System for the Restoration of Ancient Books and Archives in China. Library Tribune 34(12), 111–115 (2014).
14. Wang, G.Q., Shi, Q.G.: Analysis of the Causes and Preventive Measures for Restoration-Induced Damage to Ancient Books. Library Tribune 38(11), 164–171 (2018).
15. Wang, G.Q.: The Principle of Reversibility, Technical Application Strategies, and Realization Approaches in Ancient Books Restoration. Journal of Academic Libraries 41(1), 106–112+128 (2023). DOI:10.16603/j.issn1002-1027.2023.01.015.
16. Wu, F.J.: Analysis of the Restoration and Conservation of Ancient Books in Libraries. Paper Technology & Application 53(2), 28–30 (2025).
17. Chen, Y.: Exploration of the Restoration of Ancient Books in Public Libraries. The Library Journal of Henan 44(4), 27–29 (2024).
18. Guestrin, C., Krause, A., Singh, A.P.: Near-optimal Sensor Placements in Gaussian Processes. In: Proceedings of the 22nd International Conference on Machine Learning, pp. 265–272. ACM, New York (2005).

19. Badanidiyuru, A., Vondrák, J.: Fast Algorithms for Maximizing Submodular Functions. In: Proceedings of the Twenty-Fifth Annual ACM-SIAM Symposium on Discrete Algorithms, pp. 1497–1514. Society for Industrial and Applied Mathematics, Philadelphia (2014).
20. Liu, Y., Chong, E.K.P., Pezeshki, A., et al.: Submodular Optimization Problems and Greedy Strategies: A Survey. Discrete Event Dynamic Systems 30(3), 381–412 (2020).
21. Deng, Z.H., Huang, X., Lu, Y.J., et al.: On the Construction of an Ontology Base for Chinese Ancient Book Editions. Documentation, Information & Knowledge (4), 80–87+93 (2014). DOI:10.13366/j.dik.2014.04.080.
22. Chen, L.: Analysis of the Inheritance and Development Path of the Binding Art of Chinese Ancient Books. View on Publishing (4), 65–67 (2019). DOI:10.16491/j.cnki.cn45-1216/g2.2019.04.017.
23. Li, A.H.: Tracing the Origin and Appreciating the Artistic Beauty of Chinese Ancient Books Binding. Identification and Appreciation to Cultural Relics (17), 85–91 (2022). DOI:10.20005/j.cnki.issn.1674-8697.2022.17.021.
24. Editorial Committee of the Chinese Library Classification, National Library of China: Chinese Library Classification. 5th edn. National Library of China Publishing House, Beijing (2010).
25. Zhang, B.J.: Analytic Hierarchy Process and Its Application Cases. Publishing House of Electronics Industry, Beijing (2009).
26. Hu, Y.: Research on the Evaluation of Urgency of Cultural Relics Restoration Based on Stochastic Analytic Hierarchy Process. Master's thesis, Harbin Institute of Technology, Harbin (2013).
27. Huang, X.X.: Construction of a Professional Competence Evaluation System for Archives and Ancient Books Restorers Based on Fuzzy Analytic Hierarchy Process. Beijing Archives (2), 12–16 (2020).