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Service Provider Portfolio Selection across the Project Life Cycle Considering Synergy Effect

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Abstract: During the project life cycle, selecting the appropriate service provider portfolio (SPP) is essential to guaranteeing the successful implementation of manufacturing tasks. However, the existence of the synergy effect among service providers poses a challenge for decision makers in selecting the most suitable SPP. To effectively address this challenge, this study constructs a novel service provider portfolio selection (SPPS) model across the project life cycle, considering the synergy effect. The model is based on the integration of a radial basis function neural network (RBFNN), the technique for order preference by similarity to ideal solution (TOPSIS), and the entropy method (EM). First, the evaluation criteria for service provider selection are defined, followed by the identification of alternative service providers and feasible SPPs based on project life cycle division. Subsequently, a quantitative analysis of the synergy effect among service providers within the same stage, as well as between different stages, throughout the project life cycle, is carried out. This analysis helps to determine the input variables and expected output variables that will be utilized in the model. Additionally, the feasibility and applicability of the proposed model are illustrated through an example. Finally, a comparison between the proposed hybrid model and the BPNN is conducted to validate the model's accuracy and efficiency. This study contributes to making sound decisions in the SPPS process from a project life cycle perspective.

Keywords: project management; service provider portfolio selection; project life cycle; synergy effect; radial basis function neural network

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1. Introduction

The success of project construction can be simply described as providing efficient services that enable the timely completion of project components, while staying within the budget and ensuring the desired quality level [1]. The process of implementing project construction involves many tasks, facing a large number of service requirements. These service requirements need to be delivered by service providers, each of which has different features in terms of quality level, service capability, service cost, etc. [2]. The characteristic performances exhibited by different service providers will have a significant impact on the overall completion of the project [3]. The careful selection of suitable service providers can greatly mitigate quality deficiencies, schedule delays, cost overruns, and other challenges, thereby fostering the successful implementation of the project [4].

Nowadays, it has been widely recognized that apposite service provider selection serves as an antecedent to a project's success [5]. More and more studies focus on the service provider selection problem in project management, including project contractor selection [6], project part service provider selection [7], project material service provider selection [8,9], etc. However, these studies often limit their selection of service providers to a specific stage of project construction, resulting in providing service support only for the completion of tasks at that particular stage. But the project construction process spans a life cycle, from the conceptual stage to the completion stage, each stage of which has its specific service requirements. The smooth completion of the entire project construction

relies on the collaborative efforts of service providers across various stages. Therefore, it is necessary to explore the service provider portfolio selection (SPPS) from the project life cycle perspective.

The SPPS is influenced by various factors throughout the life cycle of project construction. There is an inevitable synergistic effect that emerges among service providers operating within the same stage, as well as between different stages. For example, the diversity of operational mechanisms and decision-making systems may incur a negative synergy effect among the service providers. This will affect the result of the SPPS. Hence, this study is dedicated to solving a critical research question: "how to select the optimal service provider portfolio (SPP) across the project life cycle considering the synergy effect". Compared with SPPS studies that do not consider the synergy effect among service providers [10,11], the problem addressed in this study is confronted with more complexities and uncertainties. Until now, the issue of service provider selection considering the synergy effect has been discussed [12–14]. Nevertheless, these authors primarily focus on the synergy effect among the served subjects, rather than among the service providers themselves, which cannot provide a comprehensive decision-making reference for the current research.

Service provider evaluation and selection is a complicated multiple-criteria decision-making process [15,16]. It is confronted with a lot of complexities and uncertainties, such as construction plan rationality, design variety, and team cohesion [17]. Artificial neural networks (ANNs) are recognized among the effective systems for addressing complex and uncertain problems [18–20]. Therefore, they have been extensively applied to solve service provider selection decision problems [21,22]. The radial basis function neural network (RBFNN) is an effective ANN [23], which has the benefits of strong simulation, strong classification, and fast learning speed [24]. In addition, its training procedure is fast and simple, and can achieve a global optimum [25]. These advantages have contributed to its widespread utilization across various fields and industries, including service provider selection [26,27]. Thus, to effectively tackle the uncertainty in SPPS, this study is based on the RBFNN method.

This study aims to propose an SPPS model across the project life cycle considering the synergy effect. First, the SPPS evaluation criteria are determined. Second, a comprehensive SPPS model is developed, taking into account the synergy effect across the project life cycle. The model is based on the integration of the RBFNN, the technique for order preference by similarity to ideal solution (TOPSIS), and the entropy method (EM). Third, taking the SPPS of a construction project as an example, the feasibility and applicability of the proposed model are demonstrated. Finally, the proposed hybrid model is compared with the back propagation neural network (BPNN) model to illustrate its effectiveness. The major contributions of this study can be highlighted as follows:

(1) This research focuses on the SPPS from the perspective of project life cycle. Based on this perspective, the SPPS can ensure the efficient completion of construction tasks through all stages. This, in turn, contributes to the overall success of project implementation.
(2) A pioneering SPPS hybrid model that considers the synergy effect across the project life cycle is presented. The model integrates the RBFNN with the TOPSIS and the EM to address service provider selection challenges comprehensively. This innovative approach offers a fresh perspective and valuable insights for tackling the SPPS problem, potentially providing a novel and effective solution.
(3) This study conducts a quantitative analysis of the synergy effect among service providers within the same stage, as well as between different stages across the project life cycle. By considering the quantitative assessment of the synergy effect, decision makers can enhance their decision-making process and select the optimal SPP for the project.

The rest of the paper is organized as follows. Section 2 reviews the related work. Section 3 outlines the step-by-step procedures for constructing the proposed SPPS model. In Section 4, the feasibility and applicability of the proposed model are demonstrated by utilizing the SPPS for a construction project as a case study example. Section 5 presents

the comparison results between the RBFNN and the BPNN, highlighting the effectiveness of the proposed model. Section 6 discusses the theoretical and managerial implications derived from this research. Section 7 concludes this study.

2. Literature Review

2.1. Service Provider Selection Considering Synergy Effect

During the SPPS process of the project life cycle, there is a synergistic phenomenon that affects service efficiency, due to the complex competition and cooperation relationships among service providers. This study defines this phenomenon as the synergy effect of SPPs, which will affect the result of SPPS. For example, kitchen equipment suppliers and carpenters installing kitchen surfaces are two types of service providers that need to cooperate with each other very well. Otherwise, the kitchen installation project might suffer from delays or overrunning, bringing down project performance and customer satisfaction. Consequently, it is necessary to explore the SPPS considering the synergy effect. Through examination of the literature, it can be observed that previous studies mainly focus on the selection of a single service provider considering the synergy effect. Very little research attempts to explore SPPS, and the existing studies do not consider the synergy effect among service providers [10,11]. Yu and Wong [13] presented an agent-based negotiation model to automate the service provider selection process involving a bundle of products with synergy. Considering the synergy between products, Yu and Wong [12,28] constructed a product bundle determination model and multi-agent system architecture, respectively, to provide decision support for multi-product service provider selection.

To sum up, the above-reviewed studies mainly considered the synergy effect among the served subjects, rather than among the service providers. This is inadequate to provide an effective reference for the SPPS considering the synergy effect among service providers. Being aware of the importance of the synergy effect among service providers for SPPS results in project management, the authors of this study take it into account and propose an SPPS model across the project life cycle.

2.2. Artificial Neural Network Application in Service Provider Selection

Service provider selection is a complex decision-making problem in an uncertain environment [29]. As previously stated, ANN is a kind of artificial intelligence that is similar to architectural structure and functions like brain cells or the human nervous system. It can learn from experience and provide reliable answers to complex problems [30,31]. As an efficient methodology, ANN has been extensively applied in the field of service provider selection. Kar [32] presented a group decision support method based on fuzzy set theory, the analytic hierarchy process, and neural networks (NNs) for the service provider selection problem. Tavana et al. [33] proposed a hybrid adaptive neuro fuzzy inference system and ANN model to assist managers in evaluating and selecting service providers. Gegovska et al. [34] used the committee fuzzy multiple-criteria decision-making (MCDM) and ANN to select the best green service provider.

The aforementioned literature indicates that ANN is an efficient service provider selection model. The RBFNN is one of the most popular ANN methods, due to its convenient and fast training with accurate performance [35]. It has also been successfully applied to the problem of service provider selection. Zhou et al. [27] exploited a hybrid ANP-RBFNN model to select the optimal green service provider. Kong et al. [26] established a fuzzy RBFNN model to select the best logistics service provider. This shows that, as a traditional ANN model, the RBFNN not only has the advantages of ANN, but also has certain advantages in solving complex uncertain decision-making problems compared with other neural network forms. Given its successful applications in the field of service provider selection, this study constructs an SPPS model across the project life cycle, considering the synergy effect, based on the RBFNN.

2.3. Service Provider Selection in the Field of Project Management

Service provider selection is a context-specific strategic decision that contributes to creating a sustainable competitive advantage. Previously, it was successfully applied in various fields [36–38]. In the field of project management, service provider selection is increasingly recognized as a crucial component of project management. Many relevant studies have been conducted, most of which concentrate on project contractor selection and building material service provider selection.

In terms of project contractor selection, Elbarkouky et al. [39] proposed a fuzzy logic-based project contractor selection framework to help evaluate and select the most appropriate contractor. Abbasianjahromi et al. [40] proposed a comprehensive decision-making process for subcontractor selection, based on the Kano and fuzzy TOPSIS models, which overcomes some of the uncertainty and complexity that occurs during the selection process. Vardin et al. [41] proposed a new contractor selection model based on the best–worst method and well-known fuzzy-VIKOR techniques to overcome the deficiencies of the traditional "lowest bid price" rule. The applicability of the model is verified with an engineering example. Bao and Wang [42] established a contractor selection evaluation model based on the entropy-VIKOR algorithm. The rationality and feasibility of this model are verified with an example that intends to provide a reference for selecting a high-quality engineering procurement construction project contractor. Hasnain et al. [43] constructed a decision support system based on the analytic network process to select the most valuable contractor for a construction project.

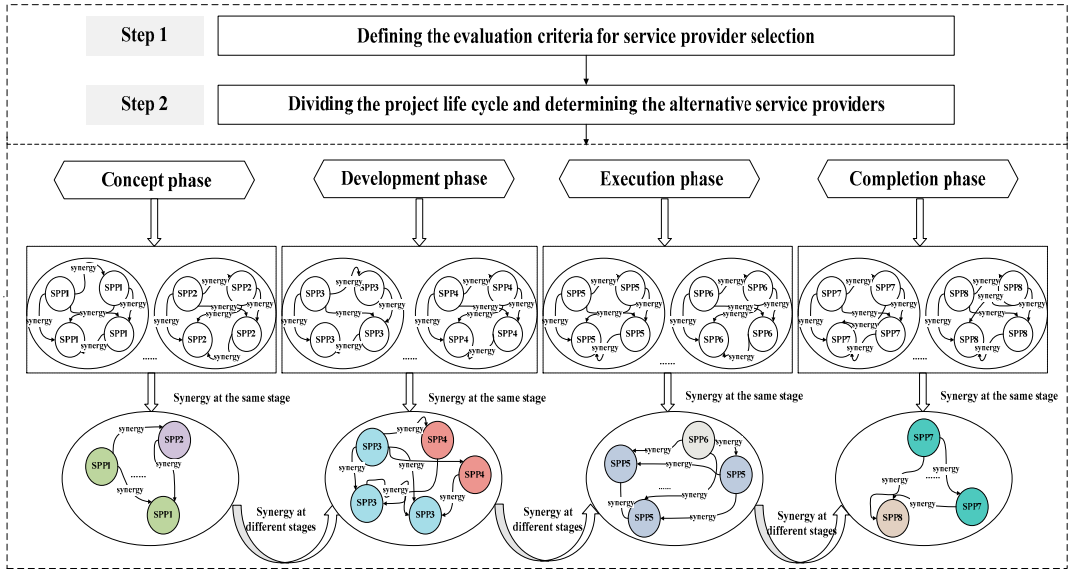
In terms of building material service provider selection, Cengiz et al. [8] proposed a novel multi-criteria decision model with which to choose the optimal building materials for the project, such as wall, cladding, and roofing construction materials. Su [44] investigated how to select the optimal building material service provider for projects under the background of economic globalization based on the intuitionistic fuzzy analytic hierarchy process. Borissova and Atanassova [45] proposed a multi-criteria decision methodology with which to determine the most reliable material service provider for a green building project. Wang et al. [9] developed a MCDM model with which to evaluate and select the optimal material service provider for an oil production project.

The above research shows that the selection of a project contractor and a building material service provider has become a research hotspot in the field of project management. Indeed, as the subject of project implementation, the contractor plays a decisive role in the process of project construction. The reason lies in that, except for the in-role behaviors specified in the contract, the contractor's extra-role behavior beyond the formal expectations of the contract also affects project performance [46]. Selecting a contractor to meet the needs of project development is the key to ensuring the successful implementation of the project. In addition, in the process of project construction, material-related activities constitute more than half of the total cost and have huge effects on the project schedule [8]. Therefore, it is of great significance to study the selection of the project contractor and the building material service provider for the continued advancement of the project. However, the project construction is a life cycle process comprising four stages: the concept stage, the development or definition stage, the execution stage, and the completion stage. The completion of the entire project can only be ensured by meeting the task requirements of all four stages. The current research mainly focuses on contractor selection in the project concept stage and material service provider selection in the project execution stage. They cannot provide service support for the whole life cycle of the project. Therefore, to ensure the success of the entire project, the authors of this paper study the SPPS for the project from the perspective of the project life cycle.

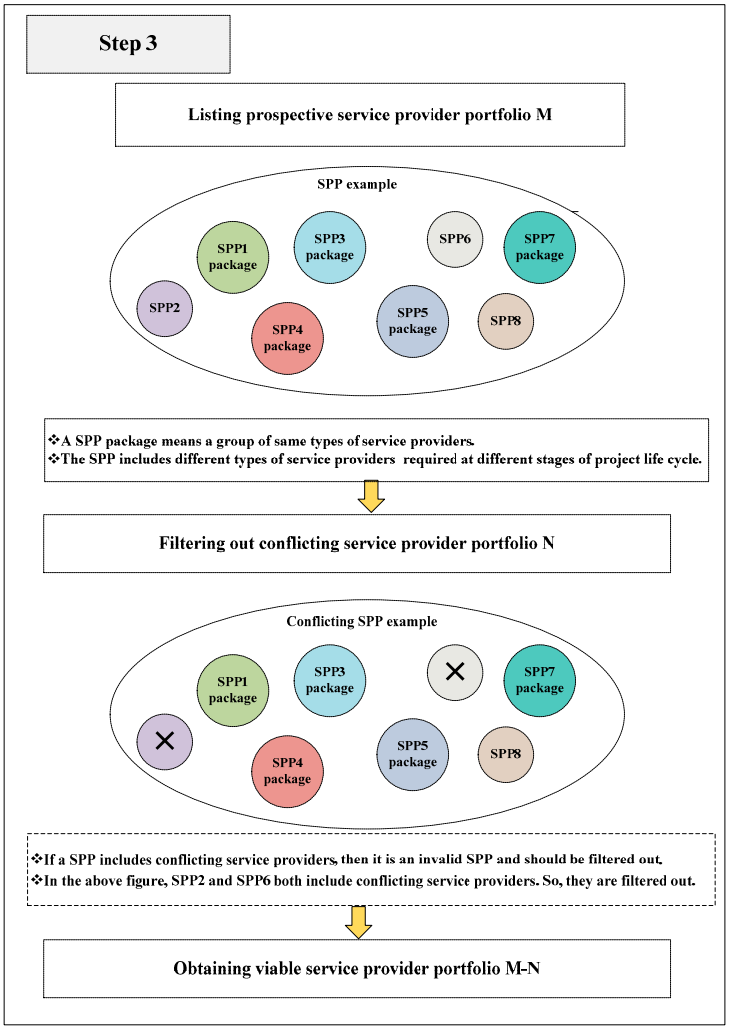
3. Modeling

In this study, a novel model for SPPS is proposed by integrating the RBFNN with the TOPSIS-EM. The aim is to select the optimal SPP across the project life cycle. The

step-by-step procedures for constructing the proposed SPPS model are outlined as follows and are sketched in Figure 1.

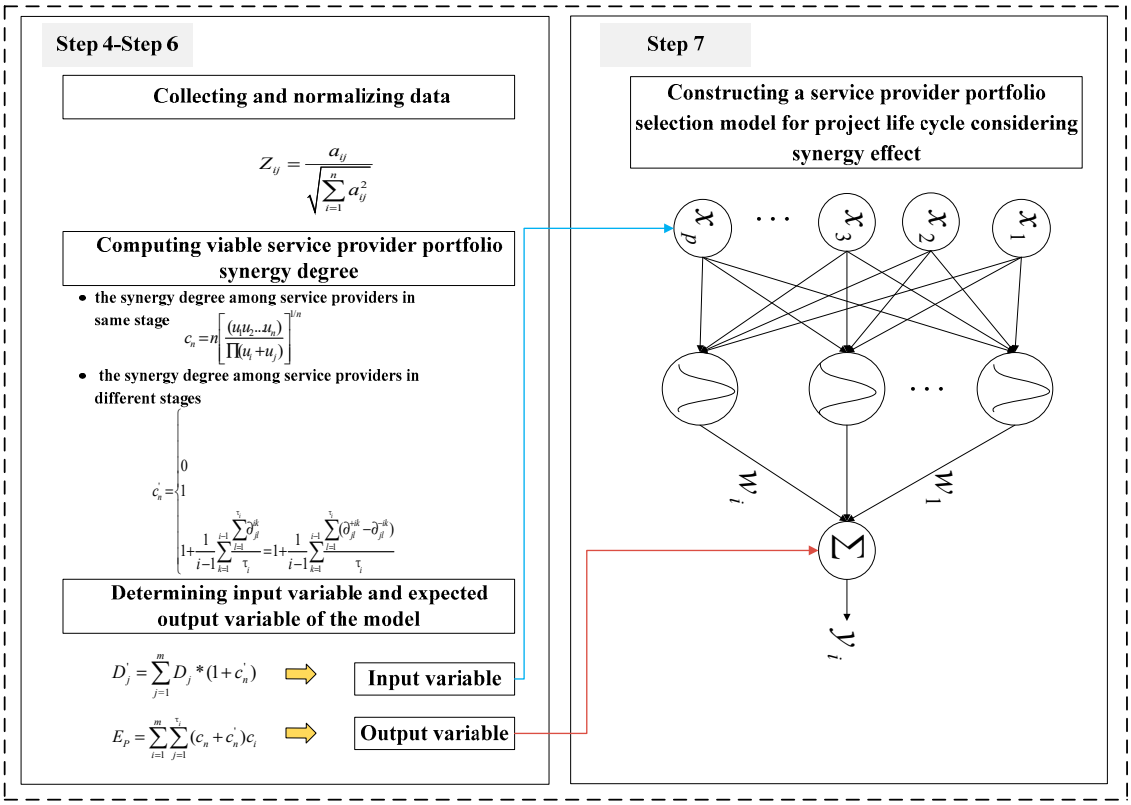


(**a**) Steps 1–2



(**b**) Step 3

Figure 1. *Cont.*



(**c**) Steps 4–7

Figure 1. Basic steps of building the proposed SPPS model across the project life cycle.

(1) Defining a set of evaluation criteria for service provider selection;
(2) Determining the number of stages for SPPS by dividing the life cycle of the project, as well as determining the types and quantity of alternative service providers at each stage according to the task requirements of each stage;
(3) Listing prospective SPPs and filtering out conflicting SPPs to obtain a feasible SPP;
(4) Collecting and processing the evaluation criteria data of the service provider;
(5) Computing synergy degrees of feasible SPPs among service providers within the same stage and between different stages across the project life cycle;
(6) Determining the input variables and expected output variables of the model;
(7) Constructing the proposed SPPS model considering the synergy effect.

In the rest of this section, we will describe the steps in detail.

Before proceeding, we explain several important notations used throughout this study, as shown in Table 1.

Table 1. Description of important symbols.

Symbol	Description
q	The number of project life cycle stages.
g^q	The set of alternative service providers at stage q.
C^q	The synergy degree among service providers at stage q.
$C^{q\sim(q-1)}$	The synergy degree among service providers between stage q and stage $q-1$.
D^q	The index values of the SPP at stage q.
$D^{q\sim(q-1)}$	The index values of the SPP between stage q and stage $q-1$, which serve as the input variables of the model.
C_i	The relative closeness of values for the $i-th$ service provider.
E	The excepted output variables of the model.

3.1. Defining Evaluation Criteria

The purpose of SPP evaluation is to choose the best scheme for a project. A set of evaluation criteria has to be defined prior to evaluating and selecting an SPP. Herein, the evaluation criteria are defined from the following two aspects: Firstly, the profitability and debt-paying capabilities of the service providers are considered, as they can reflect the service providers' service quality level, service cost level, user satisfaction standard, risk resistance strength, etc. Secondly, the operation and contribution capabilities of the service providers are also taken into account, as they can reflect the strong advantages of the service providers, including fine reputation, flexible fund operation and turnover, and superior growth potential. Based on four dimensions, ten evaluation criteria of the SPPS are defined as shown in Table 2.

Table 2. Detailed information of evaluation criteria.

Dimension	Criterion	Description
Profitability	The reward rate of the total capital C_1	The ratio between the investment remuneration of the service provider and the total investment, which is an indicator of the service providers' profitability based on sales income investment remuneration.
	The rate of sales profit C_2	The ratio between the service providers' profits and sales, which is an indicator of the service providers' profitability based on sales income.
	The return on assets C_3	The ratio between the net profit and total assets, which is used to measure the net profit per unit of assets for the service provider.
Debt-paying ability	The multiplier capital of preservation C_4	Reflects the operational efficiency and safety of service providers, which is defined as the ratio between the current proprietor's rights and interests and the previous proprietor's rights and interests.
	The asset–liability ratio C_5	The ratio between total debts and total assets; it reflects the proportion of capital provided by creditors to total capital.
	The current ratio C_6	The ratio of current assets to current debts; it measures the ability of the service provider's current assets to become cash for repaying short-term debts before they expire.
Operation ability	The accounts receivable turnover C_7	The ratio between the net sales of the service provider and the average balance of accounts receivable during a certain period. This ratio measures the management efficiency of a service provider.
	The inventory turnover rate C_8	An effective indicator for measuring and evaluating the management statuses of the service providers' purchasing, inventory, production, and sales recovery.
Contribution ability	The rate of social contribution C_9	Refers to the ratio of the total contribution of a service provider to the society and average total assets. This ratio measures the value that a service provider creates for society.
	The social accumulation rate C_{10}	Represents the financial revenue and social contribution of the service provider, which directly or indirectly reflects the social responsibility of the service provider.

3.2. Dividing the Project Life Cycle and Determining Alternative Service Providers

The life cycle of all projects, large or small, can be divided into several stages. The simplest form is mainly composed of four main stages: the concept stage, the development or definition stage, the execution (implementation or development) stage, and the completion or commissioning stage. The number of stages depends on the complexity of the project

and the industry, and each stage can be further broken down into smaller sub-stages. For different types of projects, the standards for dividing their life cycles are different, according to a project's specific characteristics. Additionally, the manufacturing tasks at different stages of the project life cycle are different, and so is the workload of the manufacturing tasks. Therefore, it is indispensable to determine the types and number of service providers at each stage as a standard for the selection of alternative service providers.

Assume that the project life cycle is composed of q ($q > 0$) stages, and the types and number of primary service providers at stage q are s_i^q and x_i^q, respectively. The alternative service providers at stage q can be represented as $g^q = \left\{ s_1^q \left\{ g_1^q, g_2^q, g_3^q \cdots g_n^q \right\}, s_2^q \left\{ g_{n+1}^q, g_{n+2}^q, g_{n+3}^q, \cdots g_m^q \right\}, \cdots s_i^q \left\{ g_{m+1}^q, g_{m+2}^q, g_{m+3}^q, \cdots g_{x_i^q}^q \right\} \right\}$ ($i \geq 1$). For example, the types and number of primary service providers in the first stage are s_i^1 and x_i^1, respectively. The alternative service providers in the first stage can be represented as $g^1 = \left\{ s_1^1 \{ g_1^1, g_2^1, g_3^1 \cdots g_n^1 \}, s_2^1 \{ g_{n+1}^1, g_{n+2}^1, g_{n+3}^1, \cdots g_m^1 \}, \cdots s_i^1 \left\{ g_{m+1}^1, g_{m+2}^1, g_{m+3}^1, \cdots g_{x_i^1}^1 \right\} \right\}$ ($i \geq 1$).

3.3. Determining the Feasible Service Provider Portfolio

Based on Section 3.2, in order to meet the manufacturing tasks at each stage of the project life cycle, a certain number x_i of service providers needs to be selected from the alternative sets at each stage to form an SPP, denoted as $SPP = \left\{ g^{1'}, g^{2'}, \ldots g^{q'} \right\} = \left\{ g_1^{1'}, g_2^{1'}, \ldots, g_n^{1'}, g_1^{2'}, g_2^{2'}, \ldots, g_m^{2'}, \ldots, g_1^{q'}, g_2^{q'}, \ldots, g_{x_i}^{q'} \right\}$ ($g_{x_i}^{q'} \in g_{x_i}^q$). This SPP is labeled as a prospective SPP that includes conflicting SPPs and feasible SPPs. Affected by the different operating mechanisms and service methods of service providers, there are inabilities to cooperate among service providers, which is defined in this study as a conflict phenomenon. Under the influence of a conflict phenomenon, an SPP cannot complete the corresponding project construction tasks. Such an SPP is called a conflict SPP, which needs to be screened out in order to obtain feasible SPPs.

3.4. Collecting and Processing the Evaluation Criteria Data of Service Providers

After determining the feasible SPPs, evaluation criteria data of the service providers need to be collected and processed. As the dimensions of each criterion are different, it is necessary to normalize the criteria data by transforming them into the numbers between [0, 1]. Also, the order of magnitude difference among the data is eliminated to avoid large prediction errors. To this end, we use a standardization method that was widely used in the previously discussed literature, namely the vector normalization method [47]. The formula is as follows:

$$Z_{ij} = \frac{a_{ij}}{\sqrt{\sum_{i=1}^{m} a_{ij}^2}} \quad j = 1, \ldots, n \tag{1}$$

where m is the total number of samples and n is the total number of evaluation criteria. a_{ij} represents the values of the $i-th$ evaluation object on the $j-th$ criterion.

3.5. Computing the Synergy Degree of Feasible Service Provider Portfolios

In the multi-stage SPPS process across the project life cycle, there exists a synergistic effect among service providers within the same stage, as well as between different stages. That is, the performance of the service providers will be influenced by those of the others in the same stage and that in the previous stage. The synergy effect of SPPs considered in this study includes both positive and negative synergistic effects, i.e., those that improve and those that reduce service efficiency. Their specific definitions are as follows:

Positive synergy effect: Service providers have similar service methods, management systems, or technical requirement guidelines, so that service providers can provide support for each other in the process of cooperation.

Negative synergy effect: The diversity of operational mechanisms and decision-making systems of service providers hinders necessary cooperation among service providers.

The synergy degree is defined to measure the synergy effect among service providers within the same stage and between different stages, which can be calculated as follows:

Step 1: Calculating the synergy degree among service providers within the same stage (including the same type and different types of service providers):

(1) Using the EM to calculate the weight of service provider criteria at each stage.

The EM is an objective weighting method that avoids the bias caused by human factors. In information theory, entropy is the measure of system disorder; information entropy can be used to calculate the weight of each indicator based on its variation degree.

(1) Based on Formula (1), calculating the weight of the j-th index value of the i-th service provider as follows:

$$P_{ij} = \frac{a_{ij}}{\sum_{i=1}^{m} a_{ij}} \quad j = 1, \ldots, n \tag{2}$$

(2) Calculating the index information entropy of the j-th indicator:

$$e_j = -k \sum_{i=1}^{m} p_{ij} \ln p_{ij} \quad j = 1, \ldots, n \tag{3}$$

where k is a constant that is related to the sample m, i.e., $k = 1/\ln m$, $0 \leq e_j \leq 1$.

(3) Calculating the utility values of each index:

$$d_j = 1 - e_j \quad j = 1, \ldots, n \tag{4}$$

The larger the value d_j is, the more valuable the index a_j is, and its weight is accordingly greater.

(4) Calculating the index weight of a_j:

$$w_j = d_j / \sum_{j=1}^{n} d_j \tag{5}$$

(2) Calculating the order degree of each subsystem.

$$U_i(a_i) = \sum_{j=1}^{n} w_j a_{ij} \quad i = 1, \ldots, m \tag{6}$$

The greater the value of the order degree $U_i(a_i)$ of the subsystem (in this study, the subsystem refers to the service provider), the greater the contribution of a_{ij} to the order degree of the system, and the higher the degree of the system order—and vice versa.

(3) Calculating the synergy degree among service providers within the same stage.

$$C^q = m \left[\frac{(u_1 u_2 \ldots u_m)}{\prod (u_i + u_j)} \right]^{1/m} \quad i = 1, \ldots, m; \ j = 1, \ldots, n \tag{7}$$

where the numerator is the arithmetic product of each service provider's overall contribution, and the denominator is the arithmetic product of the sum of every two service providers' overall contributions. Then, the quotient extracts "m" roots, where m represents the number of service providers. Through Formulae (1) to (7), the service providers' mutual relationships are combined, which reveals the synergy degree among service providers within the same stage.

Step 2: Calculating the synergy degree among service providers between different stages:

$$C^{q\sim(q-1)} = \begin{cases} 0 \\ 1 \\ 1+\frac{1}{q-1}\sum_{k=1}^{q-1}\frac{\sum_{l=1}^{\tau_k} g_{ol}^{pk}}{\tau_k} = 1+\frac{1}{q-1}\sum_{k=1}^{q-1}\frac{\sum_{l=1}^{\tau_k}(g_{ol}^{+pk}-\partial_{ol}^{-pk})}{\tau_k} \end{cases} \tag{8}$$

where $C^{q\sim(q-1)}$ represents the synergy degree among the service providers at stage q and its previous stage $q-1$. g_{ol}^{pk} ($g_{ol}^{pk} \geq 0$) represents the influence factor of service provider g_o^p at stage p on service provider g_l^k at stage k. g_{ol}^{+pk} and $g_{ol}^{-\mathrm{p}k}$ denote the positive and negative impact factors of g_o^p to g_l^k, respectively.

3.6. Determining the Input Variables and Expected Output Variables of the Model

Before training the model, the input variables and expected output variables of the model should be determined.

Step 1: Determining the input variables of the model:

(1) Calculating the index values of the SPP within the same stage.

The synergy degree C^q of the SPP within the same stage can be obtained according to Formulae (1)–(7). Then, the index values of the SPP within the same stage can be received using the following formula:

$$D^q = \sum_{i=1}^{m} a_{ij} * (1 + C^q) \quad j = 1, \ldots, n \tag{9}$$

(2) Calculating the index values of the SPP between different stages.

$$D^{q\sim(q-1)} = \sum_{q=1}^{q} D^q * (1 + C^{q\sim(q-1)}) \tag{10}$$

where $C^{q\sim(q-1)}$ represents the synergy degree of SPP between different stages, and the values of $D^{q\sim(q-1)}$ will be regarded as the input variables of the model.

Step 2: Determining the expected output variables of the model

(1) Using the TOPSIS to determine the nearness degree of plans at each stage.

The TOPSIS method is an evaluation method based on the distance between the evaluation object and the ideal target. It has the advantages of simple calculation, reasonable results, and low information distortion [48]. Let $M = \{M_1, M_2, \ldots, M_m\}(m \geq 2)$ be a finite set of M service providers, and $N = \{N_1, N_2, \ldots, N_n\}(n \geq 2)$ be a finite set of N criteria attributes. Suppose that the service providers are evaluated with respect to each criteria attribute, and that the value constitutes a decision matrix $A = (a_{ij})_{m\times n}$. The steps of the TOPSIS are presented as follows:

(1) Constituting decision matrix $Z = (z_{ij})_{m\times n}$ by normalizing the decision matrix $A = (a_{ij})_{m\times n}$ using Formula (1);

(2) Constituting weighted normalized decision matrix $V = (v_{ij})_{m\times n}$;

The weight of each indicator w_j can be obtained using Formula (5), and the element v_{ij} of the weighted normalized decision matrix is calculated as:

$$v_{ij} = w_j \times z_{ij} \quad i = 1, \ldots, m \; j = 1, \ldots, n \tag{11}$$

(3) Determining the positive ideal solution (PIS) $V^+ = (v_1^+, v_2^+, \ldots, v_t^+)$ and the negative ideal solution (NIS) $V- = (v_{\bar{1}}^-, v_{\bar{2}}^-, \ldots, v_{\bar{t}}^-)$;

$$v_j^+ = v_j^+ = \begin{cases} \max\limits_{1\leq i\leq m} v_{ij}, j \in J^+ \\ \min\limits_{1\leq i\leq m} v_{ij}, j \in J^- \end{cases} \quad j = 1, \ldots, n \tag{12}$$

$$v_j^+ = v_j^- = \begin{cases} \min\limits_{1\le i\le m} v_{ij}, j \in J^+ \\ \max\limits_{1\le i\le m} v_{ij}, j \in J^- \end{cases} \quad j = 1, \ldots, n \tag{13}$$

where J^+ is the index set of the benefit attributes (higher values are desirable) and J^- is the index set of the cost attributes (lower values are desirable).

(4) Calculating the Euclidean distances from the service provider to the PIS and NIS, respectively;

$$D_i^+ = \sqrt{\sum_{j=1}^{n} \left(v_j^+ - v_{ij}\right)^2} \quad i = 1, \ldots, m \tag{14}$$

$$D_i^- = \sqrt{\sum_{j=1}^{n} \left(v_j^- - v_{ij}\right)^2} \quad i = 1, \ldots, m \tag{15}$$

(5) Calculating the relative closeness values of the service providers to the ideal solution. The relative closeness values of the $i-$th service provider are defined as follows:

$$C_i = \frac{D_i^-}{\left(D_i^+ + D_i^-\right)} \quad i = 1, \ldots, m \tag{16}$$

The relative closeness values are used to order the service providers. The greater the value of C_i is, the higher priority the *i*-th service provider has.

(2) Determining the model expected output variables.

The expected output variables of the model can be obtained according to the synergy degree among service providers between different stages, as obtained using Formula (8), and the relative closeness of service providers, obtained using Formula (16), which is expressed as follows:

$$E = \sum_{i=1}^{m} \sum_{q=2}^{q} (D^{q\sim(q-1)}) C_i \tag{17}$$

3.7. Model Construction Based on Radial Basis Function Neural Network

The RBFNN was first proposed by Moody and Darken [49]. It is a type of forward neural network and can approximate any continuous function with arbitrary precision. The structure of the RBFNN is similar to a multi-layer forward network comprising a single hidden layer, an input layer, and an output layer [30,50]. The input layer is composed of signal source nodes, and only plays a role in transmitting data and information; it does not make any changes to the input information. The number of hidden nodes in the hidden layer depends on the specific needs of the studied problem. The transformation function of the hidden nodes is a radially symmetric and attenuated non-negative nonlinear function with respect to the center point. The kernel function (action function) of neurons in the hidden layer is used to learn and train the data. In this way, the original linearly inseparable problem is made linearly separable so that it can be solved using a linear system of equations, which largely speeds up the learning efficiency and avoids local minima in the process [51]. The output layer can respond to the effects of the input modes. The transformation from the input space to the hidden layer space is non-linear, and the output layer space transformation from the hidden layer space is linear. The architecture of the RBFNN is shown in Figure 2.

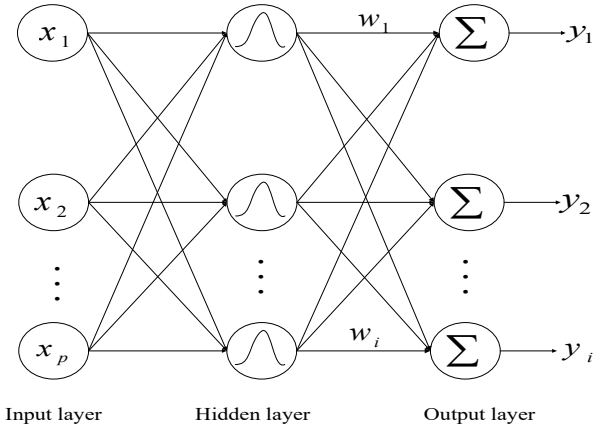


Figure 2. Structure of a typical RBFNN model.

Gaussian function is a commonly used radial basis function in RBFNNs, and its activation function can be expressed as:

$$R(x_i - c_p) = \exp\left(-\frac{1}{2{\sigma_p}^2 x_i}^{\|x_i - c_p\|^2}\right) \; i = 1, \ldots, m \;\; p = 1, \ldots, h \tag{18}$$

where m is the total number of samples, and h the number of hidden layer nodes. x_i,$i = 1, \ldots, m$, represents the input vector of the RBFNN, σ_p,$p = 1, \ldots, h$ is the variance of the Gaussian function, c_p represents the center of the Gaussian function, and $\|.\|$ denotes the vector norm (usually Euclidean).

According to the RBFNN structure, the output of it would be as follows:

$$y_p = \sum_{p=1}^{h} w_p \exp\left(-\frac{1}{2\sigma_p^2}\|x_i - c_p\|^2\right) \; i = 1, \ldots, m \;\; p = 1, \ldots, h \tag{19}$$

where w_p represents the connection weights between hidden layer nodes and output layer nodes, y_p represents the output vector of the RBFNNs.

To solve output vector y_p, the parameters c_p, σ_p, and w_p in Equation (19) should be confirmed. If they are not selected properly, the processing capacity of the RBFNN will be greatly affected.

The center c_p of the RBFNN can be determined by using the K-means algorithm. It is considered that the appropriate center can simplify the network. Thus, the data that are selected as the RBFNN center should immensely reduce the number of elements in the hidden layer.

A suitable σ_p leads to several orders of magnitude difference in interpolation accuracy. The relation presented below can be used to simplify the design.

$$\sigma_p = \frac{c_{\max}}{\sqrt{2h}} \;\; p = 1, \ldots, h \tag{20}$$

where $c_{\max}$ is the maximum distance between the selected centers.

Then, we adjust the weight of w_p between the hidden layer and output layer using Equations (21) and (22).

$$Y = W * \Phi = T \tag{21}$$

$$W = T\Phi^T(\Phi^T\Phi)^{-1} \tag{22}$$

In this study, the RBFNN is mainly used to predict the comprehensive economic benefit of SPPs, which provides a reference for decision makers to select the optimal SPP across the project life cycle.

4. Model Application

In this study, an SPPS model across the project life cycle, considering the synergy effect, is constructed to select the optimal SPP across the project life cycle. In this section, the SPPS of a construction project is taken as an example through which to demonstrate the feasibility and applicability of the model.

4.1. The Project Life Cycle and Alternative Service Providers

The building project life cycle includes material and component production, planning and design, construction and transportation, operation and maintenance, and demolition and disposal. It is divided into four stages, namely, the planning stage, the design stage, the construction stage, and the operation stage. Different types of service providers are needed at each stage to assist in completing the corresponding manufacturing tasks. In general, service requirements in the planning and design stages of a project can be regarded as integrated services. Therefore, the types of service providers can be classified as planning and design service providers, construction service providers, and operation service providers. Among them, construction service providers include service providers of concrete building materials, glass building materials, pipeline building materials, etc. In the studied project, there are seven alternative service providers in the planning and design stage, denoted as $g^1 = s_1^1\{g_1^1, g_2^1, g_3^1, g_4^1, g_5^1, g_6^1, g_7^1\}$. There are 15 alternative service providers of 5 types of services in the construction stage, including 3 sand and stone building material service providers, 3 concrete building material service providers, 3 steel structure building material service providers, 3 prefabricated building material service providers, and 3 green building material service providers, denoted as $g^2 = \{s_1^2\{g_1^2, g_2^2, g_3^2\}, s_2^2\{g_4^2, g_5^2, g_6^2\}, s_3^2\{g_7^2, g_8^2, g_9^2\}, s_4^2\{g_{10}^2, g_{11}^2, g_{12}^2\}, s_5^2\{g_{13}^2, g_{14}^2, g_{15}^2\}\}$. There are 10 alternative service providers in the operation stage, indicated as $g^3 = s_1^3\{g_1^3, g_2^3, g_3^3, g_4^3, g_5^3, g_6^3, g_7^3, g_8^3, g_9^3, g_{10}^3\}$. Note that, to facilitate calculation, this research sets the number of service providers of the same type selected at each stage to one, which is regarded as the principle of service provider selection in this study.

4.2. The Feasible Service Provider Portfolio

First, we calculated the number of prospective SPPs. There are 15 alternative service providers of 5 types in the construction stage. According to the service provider selection principle in this study, the number of SPPs in the construction stage would be $P = 3^5 = 243$. To make the calculation simple while ensuring optimal SPPS, the top 10 groups with the highest degree of synergy are selected as alternative service providers for the construction stage. The numbers of alternative service providers at each stage are 7, 10 and 10, respectively. In accordance with the description in Section 3.3, the number of prospective SPPs is $N = 7 \times 10 \times 10 = 700$. Then, the business experts provide the conflict service providers, which are $g_2^1 \otimes g_3^2$, $g_6^1 \otimes g_5^2$, $g_3^1 \otimes g_7^2$, $g_5^1 \otimes g_7^2$, $g_3^1 \otimes g_5^3$, $g_7^1 \otimes g_2^3$, $g_4^1 \otimes g_{10}^3$, $g_1^1 \otimes g_7^3$, $g_5^2 \otimes g_7^3$, $g_3^2 \otimes g_3^3$, and $g_2^2 \otimes g_{10}^3$. After removing the SPPs that include any of the above 11 pairs of service providers, the number of feasible SPPs is 594.

4.3. The Evaluation Criteria Data of Service Providers

According to the evaluation criteria of service providers, data on service providers' comprehensive economic benefit are collected. These data are obtained from the listed firm annual reports of construction project service providers in 2019 at www.cninfo.com.cn, accessed on 6 May 2022. After collecting the data, Formula (1) is used to normalize them, and the processed data are shown in Table 3.

Table 3. Evaluation criteria data of the service providers at each stage after normalization.

Stage	Type		C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}
The planning and design stage		g_1^1	0.37	0.42	0.37	0.38	0.42	0.32	0.12	0.98	0.35	0.35
		g_2^1	0.19	0.15	0.21	0.38	0.47	0.24	0.48	0.03	0.54	0.25
		g_3^1	0.39	0.36	0.41	0.36	0.31	0.31	0.32	0.06	0.42	0.25
		g_4^1	0.46	0.48	0.50	0.38	0.27	0.38	0.24	0.10	0.39	0.27
		g_5^1	0.35	0.34	0.36	0.38	0.28	0.57	0.14	0.12	0.41	0.36
		g_6^1	0.18	0.13	0.18	0.36	0.45	0.30	0.75	0.04	0.15	0.46
		g_7^1	0.56	0.56	0.49	0.40	0.38	0.42	0.14	0.07	0.26	0.58
The construction stage	Type 1	g_1^2	0.09	0.14	0.05	0.49	0.67	0.16	0.15	0.22	0.20	0.61
		g_2^2	0.83	0.82	0.78	0.70	0.69	0.27	0.30	0.18	0.76	0.57
		g_3^2	0.55	0.55	0.62	0.53	0.27	0.95	0.94	0.96	0.61	0.55
	Type 2	g_4^2	0.72	0.75	0.66	0.59	0.46	0.42	0.86	0.85	0.60	0.63
		g_5^2	0.64	0.61	0.67	0.61	0.37	0.77	0.45	0.28	0.60	0.51
		g_6^2	0.28	0.26	0.35	0.52	0.81	0.48	0.24	0.44	0.53	0.59
	Type 3	g_7^2	0.20	0.29	0.19	0.57	0.83	0.38	0.13	0.21	0.30	0.60
		g_8^2	0.87	0.73	0.86	0.56	0.37	0.82	0.86	0.32	0.82	0.49
		g_9^2	0.44	0.62	0.47	0.60	0.42	0.43	0.49	0.92	0.49	0.64
	Type 4	g_{10}^2	0.82	0.94	0.73	0.52	0.54	0.62	0.12	0.43	0.58	0.59
		g_{11}^2	0.10	0.06	0.10	0.53	0.77	0.59	0.11	0.14	0.43	0.56
		g_{12}^2	0.56	0.34	0.68	0.67	0.32	0.52	0.99	0.89	0.69	0.59
	Type 5	g_{13}^2	0.76	0.56	0.75	0.61	0.60	0.55	0.76	0.75	0.47	0.75
		g_{14}^2	0.45	0.69	0.48	0.56	0.58	0.54	0.43	0.20	0.80	0.23
		g_{15}^2	0.48	0.46	0.46	0.57	0.56	0.64	0.49	0.63	0.37	0.62
The operation stage		g_1^3	0.19	0.29	0.26	0.30	0.28	0.14	0.05	0.24	0.21	0.24
		g_2^3	0.16	0.17	0.13	0.32	0.30	0.18	0.18	0.32	0.32	0.32
		g_3^3	0.11	0.41	0.13	0.29	0.26	0.29	0.03	0.06	0.17	0.24
		g_4^3	0.70	0.49	0.68	0.28	0.06	0.81	0.19	0.71	0.49	0.27
		g_5^3	0.45	0.50	0.38	0.31	0.26	0.13	0.11	0.39	0.43	0.39
		g_6^3	0.22	0.22	0.22	0.30	0.34	0.19	0.41	0.20	0.24	0.29
		g_7^3	0.16	0.15	0.12	0.33	0.38	0.21	0.39	0.20	0.19	0.31
		g_8^3	0.40	0.35	0.46	0.30	0.31	0.21	0.62	0.24	0.50	0.33
		g_9^3	0.02	0.18	0.09	0.25	0.41	0.21	0.07	0.10	0.21	0.36
		g_{10}^3	0.06	0.06	0.06	0.45	0.41	0.14	0.46	0.18	0.14	0.37

4.4. The Synergy Degree of Feasible Service Provider Portfolio

Step 1: Calculating the synergy degrees among service providers in the construction stage:

(1) Using the EM to calculate the weight of service provider criteria at each stage.

The results are shown in Table 4.

Table 4. Criteria weights of service providers in the construction stage.

Criteria	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}
Weights	0.07	0.09	0.07	0.05	0.06	0.10	0.30	0.15	0.06	0.05

(2) Calculating the order degree of each service provider.

The results are shown in Table 5.

Table 5. Order degree of service providers in construction stage.

Service Provider	Order Degree
g_1^2	0.23
g_2^2	0.48
g_3^2	0.76
g_4^2	0.72
g_5^2	0.51
g_6^2	0.39
g_7^2	0.29
g_8^2	0.70
g_9^2	0.56
g_{10}^2	0.48
g_{11}^2	0.26
g_{12}^2	0.72
g_{13}^2	0.68
g_{14}^2	0.46
g_{15}^2	0.53

(3) Calculating the synergy degrees among service providers in the construction stage.

In the construction stage, one service provider of each type is selected. There are five types of service providers in total. If choosing one of each type, the resulting SPP is composed of five service providers. Therefore, $m = 5$ in Equation (7), and through the calculation, the synergy degrees for the 243 SPPs in the project construction stage are obtained. The top 10 groups with the highest synergy degrees are selected as alternative service providers in the construction stage, which is shown in Table 6.

Table 6. Top 10 groups with the highest synergy degrees of SPP in construction stage.

SPP	Synergy Degree
$g_1^2 g_5^2 g_8^2 g_{11}^2 g_{14}^2 \left(g_1^{2'}\right)$	3.53
$g_1^2 g_5^2 g_8^2 g_{11}^2 g_{15}^2 \left(g_2^{2'}\right)$	3.40
$g_1^2 g_6^2 g_8^2 g_{10}^2 g_{14}^2 \left(g_3^{2'}\right)$	3.35
$g_1^2 g_6^2 g_8^2 g_{10}^2 g_{15}^2 \left(g_4^{2'}\right)$	3.23
$g_1^2 g_6^2 g_8^2 g_{11}^2 g_{13}^2 \left(g_5^{2'}\right)$	3.35
$g_1^2 g_6^2 g_8^2 g_{11}^2 g_{14}^2 \left(g_6^{2'}\right)$	3.81
$g_1^2 g_6^2 g_8^2 g_{11}^2 g_{15}^2 \left(g_7^{2'}\right)$	3.66
$g_1^2 g_6^2 g_9^2 g_{11}^2 g_{14}^2 \left(g_8^{2'}\right)$	3.24
$g_2^2 g_6^2 g_8^2 g_{11}^2 g_{14}^2 \left(g_9^{2'}\right)$	3.29
$g_2^2 g_6^2 g_8^2 g_{11}^2 g_{15}^2 \left(g_{10}^{2'}\right)$	3.18

Step 2: Calculating the synergy degree among service providers between different stages:

Based on the historical data and the synergy effect of service providers, experts give the service provider's impact factors of the planning and design stage to the construction stage, the planning and design stage to the operation stage, and the construction stage to the operation stage, which are shown in Tables 7–9, respectively. Then, Formula (8) is used to calculate the service provider's synergy degree between the construction stage and the planning and design stage. And the synergy degrees among service providers in the operation stage under different combinations are also calculated using Formula (8). The results are shown in Appendix A.

Table 7. Service provider's impact factors of the planning and design stage to the construction stage.

	$g_1^{2'}$	$g_2^{2'}$	$g_3^{2'}$	$g_4^{2'}$	$g_5^{2'}$	$g_6^{2'}$	$g_7^{2'}$	$g_8^{2'}$	$g_9^{2'}$	$g_{10}^{2'}$
g_1^1	0.1	0.1	0.2	0.2	0.1	0.1	0	0.2	0	0.1
g_2^1	0.2	0.2	⊗	0.1	1	0.2	0.2	0	0	0.1
g_3^1	0.2	0.1	0.2	0.2	0.1	0.1	⊗	0.2	0.1	−0.2
g_4^1	0.1	0	0.1	0.1	0.1	0.2	0.2	0.2	0.1	0
g_5^1	0	0.1	0.2	0.1	0.1	0.2	⊗	0.1	0	0.2
g_6^1	0.1	0.2	0	0.1	⊗	0.1	0	0.2	0.2	0
g_7^1	0	0.1	0.2	0	0.2	0.1	0.1	0.1	0.2	−0.1

Table 8. Service provider's impact factors of the planning and design stage to the operation stage.

	g_1^3	g_2^3	g_3^3	g_4^3	g_5^3	g_6^3	g_7^3	g_8^3	g_9^3	g_{10}^3
g_1^1	−0.1	0.1	−0.1	0.2	0.2	0.2	⊗	0.1	−0.1	−0.1
g_2^1	0.2	−0.1	⊗	0.2	0.1	0.1	0.1	0	−0.2	0.1
g_3^1	0.1	−0.2	0.2	−0.1	⊗	−0.2	−0.1	0.2	0.1	0
g_4^1	0.2	0.1	−0.1	0.1	0.2	0.1	0.2	0.1	0	⊗
g_5^1	−0.2	0.2	0	0	0.1	0.2	−0.1	0	−0.2	0
g_6^1	0.1	0	−0.2	0.2	0	−0.2	0.1	−0.2	0	−0.1
g_7^1	−0.2	⊗	0.1	0	0.1	0	−0.2	−0.1	−0.2	0.1

Table 9. Service provider's impact factors of the construction stage to the operation stage.

	g_1^3	g_2^3	g_3^3	g_4^3	g_5^3	g_6^3	g_7^3	g_8^3	g_9^3	g_{10}^3
$g_1^{2'}$	0.1	−0.2	−0.1	−0.2	−0.1	0.2	−0.1	0.2	0.1	−0.2
$g_2^{2'}$	−0.1	0.1	0.1	−0.1	−0.2	0.1	−0.2	−0.2	0.2	⊗
$g_3^{2'}$	0.2	−0.2	⊗	−0.1	0.2	0.2	0.1	−0.1	0.1	0.1
$g_4^{2'}$	0	0.2	0	0.1	−0.1	0.1	−0.1	0	0.2	0.2
$g_5^{2'}$	0.1	−0.1	0.1	0.2	−0.1	−0.1	⊗	0.2	−0.1	0
$g_6^{2'}$	−0.2	0.1	−0.1	0.2	0.1	0	0	0	0.1	0.1
$g_7^{2'}$	0.2	0	0.2	−0.2	0.1	0.1	−0.1	0.2	−0.2	−0.1
$g_8^{2'}$	0	−0.1	0.1	0	−0.2	0	−0.2	−0.2	−0.1	−0.2
$g_9^{2'}$	−0.1	0	−0.1	0.1	−0.1	0.2	0	−0.1	0	0.2
$g_{10}^{2'}$	0	−0.2	0	0.2	0.1	−0.1	0.2	−0.2	0.2	0

4.5. The Input Variables and Expected Output Variables of the Model

Step 1: Determining the input variables of the model:

(1) Calculating the index values of the SPP in construction stage.

The index values of the SPP in the construction stage can be obtained according to Formula (9), as shown in Table 10.

Table 10. Index values of the SPP in the construction stage.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}
$g_1^{2'}$	6.70	8.08	6.75	12.50	14.62	11.09	5.72	4.77	10.57	11.34
$g_2^{2'}$	6.65	6.84	6.46	12.18	14.11	11.19	5.83	6.51	8.36	12.72
$g_3^{2'}$	8.00	10.06	7.84	11.58	14.91	9.48	4.62	6.56	10.50	11.37
$g_4^{2'}$	7.93	8.83	7.55	11.30	14.42	9.63	4.76	8.19	8.38	12.71
$g_5^{2'}$	6.22	5.70	6.27	11.81	16.00	9.40	6.04	7.70	8.42	13.50
$g_6^{2'}$	5.38	6.90	5.66	12.83	17.61	10.35	5.08	5.86	10.91	12.44
$g_7^{2'}$	5.37	5.62	5.39	12.47	16.98	10.48	5.21	7.67	8.55	13.87
$g_8^{2'}$	5.74	7.48	6.19	11.43	13.80	9.33	5.99	8.19	10.41	11.14
$g_9^{2'}$	7.94	9.08	8.16	12.35	15.77	9.68	5.18	5.04	12.15	10.91
$g_{10}^{2'}$	7.87	7.88	7.86	12.06	15.27	9.82	5.30	6.69	10.02	12.24

(2) Calculating the index values of the SPP between different stages.

The index values of the SPP between different stages can be obtained according to Formula (10). The values will be used as the input variables of the model.

Step 2: Determining the excepted output variables of the model:

(1) Using the TOPSIS to determine the nearness degree of plans at each stage.

(1) Constituting decision matrix $Z = (z_{ij})_{m\times n}$ by normalizing the decision matrix $A = (a_{ij})_{m\times n}$ using Formula (1). The results are shown in Appendix B.

(2) Constituting weighted normalized decision matrix $V = (v_{ij})_{m\times n}$.

The weights of criteria at each stage can be obtained using Formula (5), as shown in Table 11. The weighted decision matrix of each stage is shown in Appendix C.

(3) Determining the PIS $V^+ = (v_1^+, v_2^+, \ldots, v_t^+)$ and NIS $V^- = (v_{\bar{1}}^-, v_{\bar{2}}^-, \ldots, v_{\bar{t}}^-)$. The results are shown in Table 12.

(4) calculating the Euclidean distances from the service provider to the PIS and NIS in each stage. The results are shown in Tables 13–15.

(5) Calculating the relative closeness values of the service providers to the ideal solution. The nearness degrees of each service provider to the ideal solution in each stage are shown in the Tables 16–18.

(2) Determining the expected output variables of the model.

Table 11. Criteria weights of the service providers at each stage.

	The Planning and Design Stage	**The Construction Stage**	**The Operation Stage**
Criteria	**Weights**	**Weights**	**Weights**
C_1	0.05	0.10	0.12
C_2	0.05	0.10	0.06
C_3	0.05	0.10	0.11
C_4	0.04	0.10	0.05
C_5	0.04	0.10	0.05
C_6	0.05	0.10	0.28
C_7	0.06	0.10	0.08
C_8	0.58	0.10	0.13
C_9	0.05	0.10	0.06
C_{10}	0.05	0.10	0.05

Table 12. PIS and NIS at each stage (Unit: 1×10^{-2}).

The Planning and Design Stage		The Construction Stage		The Operation Stage	
PIS	**NIS**	**PIS**	**NIS**	**PIS**	**NIS**
2.58	0.84	3.69	2.48	8.64	0.23
2.59	0.58	4.11	2.29	3.11	0.40
2.26	0.83	3.75	2.48	7.61	0.68
1.77	1.58	3.36	2.96	2.28	1.25
1.22	2.10	2.83	3.61	0.31	2.04
1.10	2.64	2.93	3.51	3.71	22.52
4.13	0.68	3.54	2.71	5.08	0.23
57.04	1.45	3.81	2.22	9.26	0.75
2.48	0.68	3.88	2.67	3.14	0.85
2.66	1.14	3.57	2.81	1.92	1.17

Table 13. Euclidean distances from the service provider to the PIS and NIS in the planning and design stage (Unit: 1×10^{-2}).

	Euclidean Distances to PIS	**Euclidean Distances to NIS**
g_1^1	3.99	55.64
g_2^1	55.71	3.08
g_3^1	53.93	3.29
g_4^1	51.53	5.18
g_5^1	50.48	5.71
g_6^1	55.11	3.85
g_7^1	53.04	4.41

Table 14. Euclidean distances from the service provider to the PIS and NIS in the construction stage (Unit: 1×10^{-2}).

	Euclidean Distances to PIS	**Euclidean Distances to NIS**
$g_1^{2'}$	2.24	1.78
$g_2^{2'}$	2.30	1.67
$g_3^{2'}$	1.46	2.79
$g_4^{2'}$	1.62	2.74
$g_5^{2'}$	2.52	1.94
$g_6^{2'}$	2.64	1.29
$g_7^{2'}$	2.93	1.64
$g_8^{2'}$	1.99	2.30
$g_9^{2'}$	1.83	2.66
$g_{10}^{2'}$	1.51	2.30

Table 15. Euclidean distances from the service provider to the PIS and NIS in the operation stage (Unit: 1×10^{-2}).

	Euclidean Distances to PIS	**Euclidean Distances to NIS**
g_1^3	11.20	19.11
g_2^3	11.43	18.11
g_3^3	14.56	14.74
g_4^3	19.17	14.42
g_5^3	7.60	20.64
g_6^3	10.97	17.83
g_7^3	12.16	17.10
g_8^3	8.08	18.83
g_9^3	14.68	16.63
g_{10}^3	13.24	19.16

Table 16. Nearness degree of each service provider to the ideal solution in the planning and design stage (Unit: 1×10^{-2}).

Service Provider	g_1^1	g_2^1	g_3^1	g_4^1	g_5^1	g_6^1	g_7^1
Nearness degree	93.31	5.23	5.75	9.13	10.16	6.54	7.68

Table 17. Nearness degree of each service provider to the ideal solution in the construction stage (Unit: 1×10^{-2}).

Service Provider	$g_1^{2'}$	$g_2^{2'}$	$g_3^{2'}$	$g_4^{2'}$	$g_5^{2'}$	$g_6^{2'}$	$g_7^{2'}$	$g_8^{2'}$	$g_9^{2'}$	$g_{10}^{2'}$
Nearness degree	44.29	42.06	65.64	62.85	43.43	32.83	35.88	53.65	59.21	60.32

Table 18. Nearness degree of each service provider to the ideal solution in the operation stage (Unit: 1×10^{-2}).

Service Provider	g_1^3	g_2^3	g_3^3	g_4^3	g_5^3	g_6^3	g_7^3	g_8^3	g_9^3	g_{10}^3
Nearness degree	62.86	61.32	50.31	42.92	73.07	61.91	58.44	69.97	53.12	59.13

Excepted output variables of the model can be obtained according to Formula (17).

4.6. Model Structure and Results

This study proposes an RBFNN to predict the comprehensive economic benefit of the SPP considering the synergy effect. Thus, the 10 economic benefit criteria of SPPs are regarded as input variables. The purpose of this study is to select an SPP with the best comprehensive economic benefit for the project; thus, the characteristic values of the measured comprehensive economic capacity of the SPPs are taken as the output variables through which to construct the RBFNN.

The network needs to be trained and tested before applying the RBFNN to the comprehensive economic benefit prediction of SPPs. The essence of training is to converge free parameters of the network to a desired level. The essence of testing is to examine the effectiveness of the model after training. This study employs python3.7 for code programming to realize the proposed algorithm. As mentioned above, 594 sample data sets are obtained through processing. Of these sample data, 80% served as training data, and 20% of them served as testing data. The training data are utilized for training the neural network model, while the testing data are used for assessing the model's prediction performance. The comparison between the predicted values of the RBFNN and the actual values is shown in Figure 3.

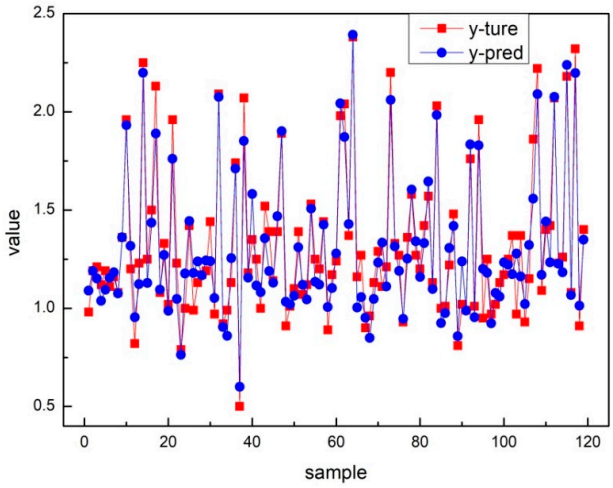


Figure 3. Comparison between the predicted values of the RBFNN and the actual values.

To intuitively judge the prediction of the model, this study chooses two commonly used error evaluation indicators to measure the performance of the model, namely, the root mean square error (RMSE) and the determination coefficient (R^2). The RMSE is an inverse index that measures the deviation between the observed values and the actual values (smaller is better). R^2 represents the degree of dispersion, and its value is considered to be the determinant with which to assess the accuracy of the model [52]. The greater the value of R^2 is, the more reliable the model is in terms of stableness in predicting values [53]. The expressions of these two indices are provided as Equation (23) and Equation (24), respectively [54]. Based on our analysis, the values of RMSE and R^2 for the RBFNN model are 11.28% and 0.928, respectively. The variation trends of RMSE and R^2 for the RBFNN are shown in Figures 4 and 5, respectively.

$$RMSE = \sqrt{\frac{1}{m}\sum_{i=1}^{m}(y_i - \hat{y})^2} \tag{23}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{m}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{m}(y_i - \overline{y}_i)^2} \tag{24}$$

where m represents the number of samples, y_i indicates the actual values, $\hat{y}$ denotes the predicted values, and $\overline{y}_i$ represents the mean of the actual values.

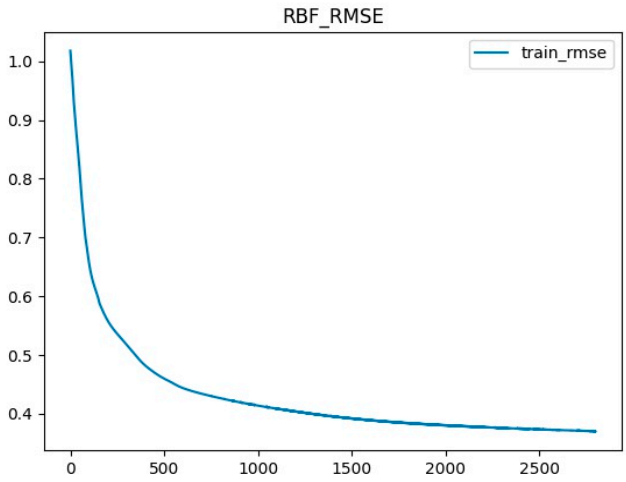


Figure 4. Variation trend of RMSE for the RBFNN model.

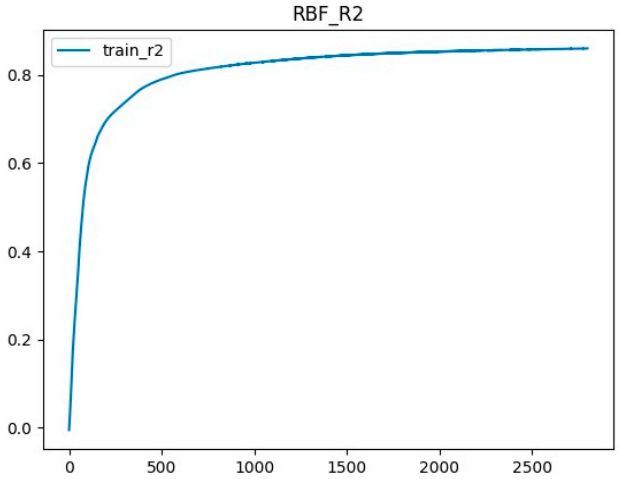


Figure 5. Variation trend of R^2 for the RBFNN model.

5. Model Comparison

In order to verify the accuracy and efficiency of the proposed model, the proposed RBFNN is compared with the BPNN in this section. The topological structure of the BPNN includes the input layer, hidden layer, and output layer. The neural network structure's main characteristics are the numbers of neurons in these layers. The number of input layer nodes is equal to the feature dimension of the input variables. This study considers 10 criteria for the input variables. The number of output layer nodes is equal to the comprehensive economic benefit of an SPP. According to the literature, the number of hidden layer nodes is often determined with experiments. One common method through which to determine the optimal number of hidden layer nodes is trial and error. The number of hidden layer nodes is limited to a range, as shown in Formula (25). Each hidden layer node within the range is brought into the neutral network for training, and the prediction performance of the neutral network under each node is compared. The number of nodes with the best performance is selected as the final number of hidden layer nodes.

$$H = \sqrt{I + O} + a \tag{25}$$

where I, O, and H represent the number of neurons in the input, output, and hidden layers, respectively, and a is a constant, taking values in the interval [1, 10].

It can be seen from the above formula that the range of the number of hidden layer nodes is [4, 14]. By comparing the performance of the neural networks under different hidden layer nodes, the optimal number of hidden layer nodes is found to be 12. Hence, the topology of the BPNN in this study is 10-12-1.

In total, 594 sample data sets are obtained through processing. Of these sample data, 80% served as training data, and 20% of them served as test data. The comparison between the predicted values of the BPNN and the actual values is shown in Figure 6. After analysis, the values of RMSE and R^2 of the BPNN model are 11.96% and 0.902, respectively. The variation trends of RMSE and R^2 for the BPNN are shown in Figures 7 and 8.

In summary, 118 test sample data sets will be applicable to test the effectiveness of the neural network, and the prediction results of the RBFNN would be compared with those of the BPNN. The relative error values of the prediction results of the RBFNN and the BPNN are shown in Appendix D. They indicate that the relative error of prediction results using the RBFNN is smaller than that of the BPNN. In addition, the values of RMSE and R^2 for the two neural networks are shown in Table 19. They demonstrate that the proposed RBFNN has more reliable predictive stability than does the BPNN. Therefore, the RBFNN has a better predictive effect for predicting the comprehensive economic benefit of an SPP across the project life cycle considering the synergy effect.

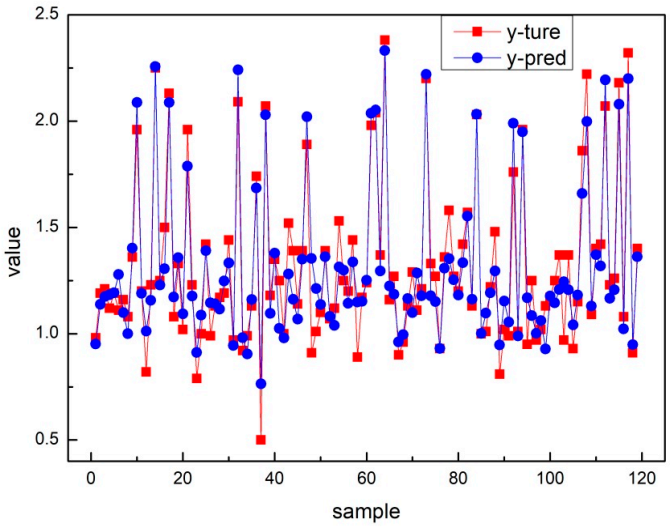


Figure 6. Comparison between the predicted values of the BPNN and the actual values.

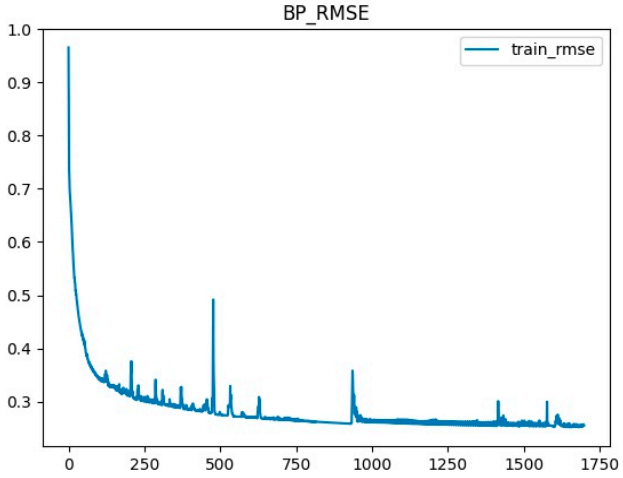


Figure 7. Variation trend of RMSE for the BPNN model.

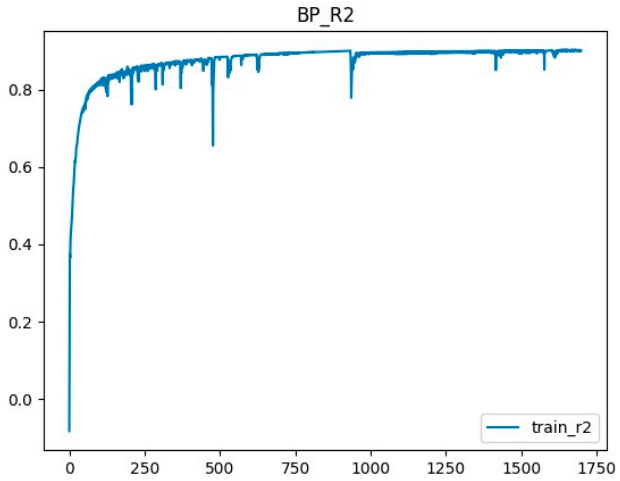


Figure 8. Variation trend of R^2 for the BPNN model.

Table 19. The values of RMSE and R^2 for the two neural networks.

	RMSE	R^2
RBFNN	11.28%	0.928
BPNN	11.96%	0.902

6. Discussion

This study proposes a novel SPPS model across the project life cycle considering the synergy effect. The model is based on the integration of the RBFNN with the TOPSIS-EM. Also, the SPPS of a construction project has been taken as an example through which to demonstrate the feasibility and applicability of the proposed model. Simultaneously, the accuracy and efficiency of the proposed model has been verified by comparing it with the BPNN. In this section, the theoretical and managerial implications of this study are discussed.

6.1. Theoretical Implications

(1) In this study, a service provider selection method was conducted throughout all stages across the project life cycle, and a new SPPS perspective was proposed. This research perspective is different from the service provider selections that only focus on the construction stage of a project [2,7,45]. It considers not only the comprehensive capabilities of single-stage service providers, but also the comprehensive capabilities of multi-stage SPPs. Based on this, choosing the best SPP can guarantee the efficient

completion of tasks at all stages of the project, so as to ensure the smooth completion of the whole project construction mission.

(2) This study considers the effect of synergy among service providers across the project life cycle, which makes up for the lack of direct consideration of the synergy effect among service providers in previous research. Affected by various factors in the process of project implementation, there are inevitable synergistic effects among service providers within the same stage and between different stages. These will affect the result of SPPS. In previous work, although the issue of service provider selection considering the synergy effect has been discussed [12,14,28], the authors considered the synergy effect only among the served subjects, instead of among the service providers, which cannot provide a decision-making reference for this study. Being aware of the importance of the synergy effect among service providers for SPPS results in project management, the authors of this study take this into account and propose an SPPS model for use across the project life cycle.

(3) The authors of this study propose an innovative model with which to answer the problem: "how to select the optimal SPP across the project life cycle considering the synergy effect". Currently, despite the existence of a few SPPS models [10,11], the research field in this area appears to be relatively nascent and underdeveloped. The proposed hybrid model based on the RBFNN, that is integrated with the TOPSIS and the EM in this study, provides a systemic analytical model for SPPS. Furthermore, the model is flexible and extensible. The framework of the model can be generalized to other application fields.

6.2. Managerial Implications

(1) The selection of a multi-stage SPP throughout the project life cycle is influenced by the presence of synergistic effects among service providers, both within the same stage and across different stages. These synergistic effects have direct impacts on the result of the SPPS. Therefore, for the project managers, when selecting the optimal SPP, the influence of the synergy effect among service providers on the SPPS result should be considered. This study provides the synergy effect calculation formula for SPPs. It can thus provide an effective reference with which managers can clarify the synergy effect among service providers in the SPPs.

(2) Considering the synergy effect among service providers, the present study constructs the research framework of an SPPS model for use across the project life cycle. According to the entire framework process, practitioners can calculate the synergy degrees among service providers within the same stage and between different stages, define conflicts between service providers, obtain the final evaluation result of the SPPS, etc. This study offers practitioners a comprehensive and effective selection process for choosing the optimal SPP throughout the project life cycle. The proposed method equips project managers with practical tools and strategies with which to make informed decisions when it comes to selecting the most suitable SPP.

(3) This study discusses the SPPS problem across the project life cycle considering the synergy effect. The research provides a new insight for scholars in the area of project management in understanding the relationships among service providers. Moreover, the authors of this study proposed an innovative SPPS model that provides a new research perspective to researchers in the field of project management and service provider management. Researchers can refer to this study to explore the SPPS problem of project management from a more in-depth level.

7. Conclusions

Throughout the project life cycle, the SPPS is subject to the influence of various factors, giving rise to complex synergistic effects among service providers. These synergies can significantly impact the result of the SPPS. In order to help decision makers choose the optimal SPP from the perspective of the project life cycle, a novel model for SPPS across

the project life cycle considering the synergy effect is proposed herein by integrating the RBFNN with the TOPSIS-EM. The model can quantitatively analyze the synergy effect among service providers within the same stage and between different stages across the project life cycle. Then, the model is applied to the SPPS of a real construction project to demonstrate its feasibility. Finally, the proposed hybrid model is compared with the BPNN to further illustrate its effectiveness and superiority. The results show that the model proposed in this research has better stability than the BPNN in predicting the comprehensive economic benefit of an SPP across the project life cycle considering the synergy effect, providing a practical tool through which managers can make informed decisions when selecting the most suitable SPP.

Nevertheless, this study also suffers limitations in twofold, indicating future research directions. On one hand, the generalization of the proposed model needs further demonstrating, since it is only verified using the SPPS of a construction project in the present study. Future work could extend the application fields of the hybrid model to many other areas in order to facilitate its wider application. On the other hand, although this study considers synergistic effects among service providers between different stages from a life cycle perspective, it solely takes into account the impact of service providers at one stage on those at the following one. In fact, interactive influences exist among different service providers at different stages. For example, the service providers at the planning and design stage could also affect the work efficiencies service providers at the operation stage. Therefore, it is recommended to study the SPPS while considering dynamic interactive relationships among service providers.

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Data Availability Statement: The data presented in this study are available on request from the corresponding author.

Conflicts of Interest: The authors declare no conflict of interest regarding the publication of this paper.

Appendix A

Table A1. Service provider degrees of synergy between the construction stage and the planning and design stage.

	$g_1^{2'}$	$g_2^{2'}$	$g_3^{2'}$	$g_4^{2'}$	$g_5^{2'}$	$g_6^{2'}$	$g_7^{2'}$	$g_8^{2'}$	$g_9^{2'}$	$g_{10}^{2'}$
g_1^1	0.9	1.1	1.2	0.8	1.1	0.9	1	0.8	1	0.9
g_2^1	0.8	1.2	⊗	0.9	0	1.2	1.2	1	1	0.9
g_3^1	0.8	0.9	0.8	1.2	1.1	0.9	⊗	1.2	0.9	1.2
g_4^1	1.1	1	1.1	0.9	0.9	0.8	1.2	0.8	1.1	1
g_5^1	1	0.9	0.8	1.1	1.1	1.2	⊗	0.9	1	0.8
g_6^1	0.9	0.8	1	0.9	⊗	0.9	1	1.2	0.8	1
g_7^1	1	1.1	0.8	1	0.8	1.1	0.9	0.9	1.2	1.1

Table A2. The degrees of synergy among service providers in the operation stage under different combinations.

	g_1^3	g_2^3	g_3^3	g_4^3	g_5^3	g_6^3	g_7^3	g_8^3	g_9^3	g_{10}^3
$g_1^1 g_1^{2'}$	1	0.95	0.9	1	1.05	1.2	⊗	1.15	1	0.85
$g_1^1 g_2^{2'}$	0.9	1.1	1	1.05	1	1.15	⊗	0.95	1.05	⊗
$g_1^1 g_3^{2'}$	1.05	0.95	⊗	1.05	1.2	1.2	⊗	1	1	1
$g_1^1 g_4^{2'}$	0.95	1.15	0.95	1.15	1.05	1.15	⊗	1.05	1.05	1.05
$g_1^1 g_5^{2'}$	1	1	1	1.2	1.05	1.05	⊗	1.15	0.9	0.95
$g_1^1 g_6^{2'}$	0.85	1.1	0.9	1.2	1.15	1.1	⊗	1.05	1	1
$g_1^1 g_7^{2'}$	1.05	1.05	1.05	1	1.15	1.15	⊗	1.15	0.85	0.9
$g_1^1 g_8^{2'}$	0.95	1	1	1.1	1	1.1	⊗	0.95	0.9	0.85
$g_1^1 g_9^{2'}$	0.9	1.05	0.9	1.15	1.05	1.2	⊗	1	0.95	1.05
$g_1^1 g_{10}^{2'}$	0.95	0.95	0.95	1.2	1.15	1.05	⊗	0.95	1.05	0.95
$g_2^1 g_1^{2'}$	1.15	0.85	⊗	1	1	1.15	1	1.1	0.95	0.95
$g_2^1 g_2^{2'}$	1.05	1	⊗	1.05	0.95	1.1	0.95	0.9	1	⊗
$g_2^1 g_3^{2'}$	1.2	0.85	⊗	1.05	1.15	1.15	1.1	0.95	0.95	1.1
$g_2^1 g_4^{2'}$	1.1	1.05	⊗	1.15	1	1.1	1	1	1	1.15
$g_2^1 g_5^{2'}$	1.15	0.9	⊗	1.2	1	1	⊗	1.1	0.85	1.05
$g_2^1 g_6^{2'}$	1	1A	⊗	1.2	1.1	1.05	1.05	1	0.95	1.1
$g_2^1 g_7^{2'}$	1.2	0.95	⊗	1	1.1	1.1	1	1.1	0.8	1
$g_2^1 g_8^{2'}$	1.1	0.9	⊗	1.1	0.95	1.05	0.95	0.9	0.85	0.95
$g_2^1 g_9^{2'}$	1.05	0.95	⊗	1.15	1	1.15	1.05	0.95	0.9	1.15
$g_2^1 g_{10}^{2'}$	1.1	0.85	⊗	1.2	1.1	1	1.15	0.9	1	1.05
$g_3^1 g_1^{2'}$	1.1	0.8	1.05	0.85	⊗	1	0.9	1.2	1.1	0.9
$g_3^1 g_2^{2'}$	1	0.95	1.15	0.9	⊗	0.95	0.85	1	1.15	⊗
$g_3^1 g_3^{2'}$	1.15	0.8	⊗	0.9	⊗	1	1	1.05	1.1	1.05
$g_3^1 g_4^{2'}$	1.05	1	1.1	1	⊗	0.95	0.9	1.1	1.15	1.1
$g_3^1 g_5^{2'}$	1.1	0.85	1.15	1.05	⊗	0.85	⊗	1.2	1	1
$g_3^1 g_6^{2'}$	0.95	0.95	1.05	1.05	⊗	0.9	0.95	1.1	1.1	1.05
$g_3^1 g_7^{2'}$	1.15	0.9	1.2	0.85	⊗	0.95	0.9	1.2	0.95	0.95
$g_3^1 g_8^{2'}$	1.05	0.85	1.15	0.95	⊗	0.9	0.85	1	1	0.9
$g_3^1 g_9^{2'}$	1	0.9	1.05	1	⊗	1	0.95	1.05	1.05	1.1
$g_3^1 g_{10}^{2'}$	1.05	0.8	1.1	1.05	⊗	0.85	1.05	1	1.15	1
$g_4^1 g_1^{2'}$	1.15	0.95	0.9	0.95	1.05	1.15	1.05	1.15	1.05	⊗
$g_4^1 g_2^{2'}$	1.05	1.1	1	1	1	1.1	1	0.95	1.1	⊗
$g_4^1 g_3^{2'}$	1.2	0.95	⊗	1	1.2	1.15	1.15	1	1.05	⊗
$g_4^1 g_4^{2'}$	1.1	1.15	0.95	1.1	1.05	1.1	1.05	1.05	1.1	⊗
$g_4^1 g_5^{2'}$	1.15	1	1	1.15	1.05	1	⊗	1.15	0.95	⊗
$g_4^1 g_6^{2'}$	1	1.1	0.9	1.15	1.15	1.05	1.1	1.05	1.05	⊗
$g_4^1 g_7^{2'}$	1.2	1.05	1.05	0.95	1.15	1.1	1.05	1.15	0.9	⊗
$g_4^1 g_8^{2'}$	1.1	1	1	1.05	1	1.05	1	0.95	0.95	⊗
$g_4^1 g_9^{2'}$	1.05	1.05	0.9	1.1	1.05	1.15	1.1	1	1	⊗
$g_4^1 g_{10}^{2'}$	1.1	0.95	0.95	1.15	1.15	1	1.2	0.95	1.1	⊗
$g_5^1 g_1^{2'}$	0.95	1	0.95	0.9	1	1.2	0.9	1.1	0.95	0.9
$g_5^1 g_2^{2'}$	0.85	1.15	1.05	0.95	0.95	1.15	0.85	0.9	1	⊗
$g_5^1 g_3^{2'}$	1	1	⊗	0.95	1.15	1.2	1	0.95	0.95	1.05
$g_5^1 g_4^{2'}$	0.9	1.2	1	1.05	1	1.15	0.9	1	1	1.1
$g_5^1 g_5^{2'}$	0.95	1.05	1.05	1.1	1	1.05	⊗	1.1	0.85	1
$g_5^1 g_6^{2'}$	0.8	1.15	0.95	1.1	1.1	1.1	0.95	1	0.95	1.05
$g_5^1 g_7^{2'}$	1	1.1	1.1	0.9	1.1	1.15	0.9	1.1	0.8	0.95
$g_5^1 g_8^{2'}$	0.9	1.05	1.05	1	0.95	1.1	0.85	0.9	0.85	0.9
$g_5^1 g_9^{2'}$	0.85	1.1	0.95	1.05	1	1.2	0.95	0.95	0.9	1.1
$g_5^1 g_{10}^{2'}$	0.9	1	1	1.1	1.1	1.05	1.05	0.9	1	1
$g_6^1 g_1^{2'}$	1.1	0.9	0.85	1	0.95	1	1	1	1.05	0.85
$g_6^1 g_2^{2'}$	1	1.05	0.95	1.05	0.9	0.95	0.95	0.8	1.1	⊗

Table A2. *Cont.*

	g_1^3	g_2^3	g_3^3	g_4^3	g_5^3	g_6^3	g_7^3	g_8^3	g_9^3	g_{10}^3
$g_6^1 g_3^{2'}$	1.15	0.9	⊗	1.05	1.1	1	1.1	0.85	1.05	1
$g_6^1 g_4^{2'}$	1.05	1.1	0.9	1.15	0.95	0.95	1	0.9	1.1	1.05
$g_6^1 g_5^{2'}$	1.1	0.95	0.95	1.2	0.95	0.85	⊗	1	0.95	0.95
$g_6^1 g_6^{2'}$	0.95	1.05	0.85	1.2	1.05	0.9	1.05	0.9	1.05	1
$g_6^1 g_7^{2'}$	1.15	1	1	1	1.05	0.95	1	1	0.9	0.9
$g_6^1 g_8^{2'}$	1.05	0.95	0.95	1.1	0.9	0.9	0.95	0.8	0.95	0.85
$g_6^1 g_9^{2'}$	1	1	0.85	1.15	0.95	1	1.05	0.85	1	1.05
$g_6^1 g_{10}^{2'}$	1.05	0.9	0.9	1.2	1.05	0.85	1.15	0.8	1.1	0.95
$g_7^1 g_1^{2'}$	0.95	⊗	1	0.9	1	1.1	0.85	1.05	0.95	0.95
$g_7^1 g_2^{2'}$	0.85	⊗	1.1	0.95	0.95	1.05	0.8	0.85	1	⊗
$g_7^1 g_3^{2'}$	1	⊗	⊗	0.95	1.15	1.1	0.95	0.9	0.95	1.1
$g_7^1 g_4^{2'}$	0.9	⊗	1.05	1.05	1	1.05	0.85	0.95	1	1.15
$g_7^1 g_5^{2'}$	0.95	⊗	1.1	1.1	1	0.95	⊗	1.05	0.85	1.05
$g_7^1 g_6^{2'}$	0.8	⊗	1	1.1	1.1	1	0.9	0.95	0.95	1.1
$g_7^1 g_7^{2'}$	1	⊗	1.15	0.9	1.1	1.05	0.85	1.05	0.8	1
$g_7^1 g_8^{2'}$	0.9	⊗	1.1	1	0.95	1	0.8	0.85	0.85	0.95
$g_7^1 g_9^{2'}$	0.85	⊗	1	1.05	1	1.1	0.9	0.9	0.9	1.15
$g_7^1 g_{10}^{2'}$	0.9	⊗	1.05	1.1	1.1	0.95	1	0.85	1	1.05

Appendix B

Table A3. Standardized decision matrix in the planning and design stage.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}
g_1^1	0.37	0.42	0.37	0.38	0.42	0.32	0.12	0.98	0.35	0.35
g_2^1	0.19	0.15	0.21	0.38	0.47	0.24	0.48	0.03	0.54	0.25
g_3^1	0.39	0.36	0.41	0.36	0.31	0.31	0.32	0.06	0.42	0.25
g_4^1	0.46	0.48	0.50	0.38	0.27	0.38	0.24	0.10	0.39	0.27
g_5^1	0.35	0.34	0.36	0.38	0.28	0.57	0.14	0.12	0.41	0.36
g_6^1	0.18	0.13	0.18	0.36	0.45	0.30	0.75	0.04	0.15	0.46
g_7^1	0.56	0.56	0.49	0.40	0.38	0.42	0.14	0.07	0.26	0.58

Table A4. Standardized decision matrix in the construction stage.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}
$g_1^{2'}$	0.31	0.33	0.31	0.33	0.30	0.35	0.34	0.22	0.34	0.29
$g_2^{2'}$	0.31	0.28	0.30	0.32	0.29	0.35	0.34	0.30	0.27	0.33
$g_3^{2'}$	0.37	0.41	0.36	0.30	0.31	0.30	0.27	0.30	0.34	0.29
$g_4^{2'}$	0.37	0.36	0.35	0.30	0.30	0.30	0.28	0.38	0.27	0.33
$g_5^{2'}$	0.29	0.23	0.29	0.31	0.33	0.30	0.35	0.36	0.27	0.35
$g_6^{2'}$	0.25	0.28	0.26	0.34	0.36	0.33	0.30	0.27	0.35	0.32
$g_7^{2'}$	0.25	0.23	0.25	0.33	0.35	0.33	0.31	0.36	0.27	0.36
$g_8^{2'}$	0.26	0.30	0.28	0.30	0.28	0.29	0.35	0.38	0.33	0.29
$g_9^{2'}$	0.37	0.37	0.38	0.32	0.32	0.30	0.30	0.23	0.39	0.28
$g_{10}^{2'}$	0.36	0.32	0.36	0.32	0.31	0.31	0.31	0.31	0.32	0.32

Table A5. Standardized decision matrix in the operation stage.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}
g_1^3	0.19	0.29	0.26	0.30	0.28	0.14	0.05	0.24	0.21	0.24
g_2^3	0.16	0.17	0.13	0.32	0.30	0.18	0.18	0.32	0.32	0.32
g_3^3	0.11	0.41	0.13	0.29	0.26	0.29	0.03	0.06	0.17	0.24
g_4^3	0.70	0.49	0.68	0.28	0.06	0.81	0.19	0.71	0.49	0.27
g_5^3	0.45	0.50	0.38	0.31	0.26	0.13	0.11	0.39	0.43	0.39
g_6^3	0.22	0.22	0.22	0.30	0.34	0.19	0.41	0.20	0.24	0.29
g_7^3	0.16	0.15	0.12	0.33	0.38	0.21	0.39	0.20	0.19	0.31
g_8^3	0.40	0.35	0.46	0.30	0.31	0.21	0.62	0.24	0.50	0.33
g_9^3	0.02	0.18	0.09	0.25	0.41	0.21	0.07	0.10	0.21	0.36
g_{10}^3	0.06	0.06	0.06	0.45	0.41	0.14	0.46	0.18	0.14	0.37

Appendix C

Table A6. Weighted standardized decision matrix in the planning and design stage.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}
g_1^1	0.02	0.02	0.02	0.02	0.02	0.01	0.01	0.57	0.02	0.02
g_2^1	0.01	0.01	0.01	0.02	0.02	0.01	0.03	0.01	0.02	0.01
g_3^1	0.02	0.02	0.02	0.02	0.01	0.01	0.02	0.03	0.02	0.01
g_4^1	0.02	0.02	0.02	0.02	0.01	0.02	0.01	0.06	0.02	0.01
g_5^1	0.02	0.02	0.02	0.02	0.01	0.03	0.01	0.07	0.02	0.02
g_6^1	0.01	0.01	0.01	0.02	0.02	0.01	0.04	0.02	0.01	0.02
g_7^1	0.03	0.03	0.02	0.02	0.02	0.02	0.01	0.04	0.01	0.03

Table A7. Weighted standardized decision matrix in the construction stage.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}
$g_1^{2'}$	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.02	0.03	0.03
$g_2^{2'}$	0.03	0.03	0.03	0.03	0.03	0.04	0.03	0.03	0.03	0.03
$g_3^{2'}$	0.04	0.04	0.04	0.03	0.03	0.03	0.03	0.03	0.03	0.03
$g_4^{2'}$	0.04	0.04	0.03	0.03	0.03	0.03	0.03	0.04	0.03	0.03
$g_5^{2'}$	0.03	0.02	0.03	0.03	0.03	0.03	0.04	0.04	0.03	0.03
$g_6^{2'}$	0.02	0.03	0.03	0.03	0.04	0.03	0.03	0.03	0.03	0.03
$g_7^{2'}$	0.02	0.02	0.02	0.03	0.03	0.03	0.03	0.04	0.03	0.04
$g_8^{2'}$	0.03	0.03	0.03	0.03	0.03	0.03	0.04	0.04	0.03	0.03
$g_9^{2'}$	0.04	0.04	0.04	0.03	0.03	0.03	0.03	0.02	0.04	0.03
$g_{10}^{2'}$	0.04	0.03	0.04	0.03	0.03	0.03	0.03	0.03	0.03	0.03

Table A8. Weighted standardized decision matrix in the operation stage.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}
g_1^3	0.02	0.02	0.03	0.02	0.01	0.04	0.00	0.03	0.01	0.01
g_2^3	0.02	0.01	0.01	0.02	0.01	0.05	0.01	0.04	0.02	0.02
g_3^3	0.01	0.03	0.01	0.01	0.01	0.08	0.00	0.01	0.01	0.01
g_4^3	0.09	0.03	0.08	0.01	0.00	0.23	0.02	0.09	0.03	0.01
g_5^3	0.06	0.03	0.04	0.02	0.01	0.04	0.01	0.05	0.03	0.02
g_6^3	0.03	0.01	0.03	0.02	0.02	0.05	0.03	0.03	0.01	0.01
g_7^3	0.02	0.01	0.01	0.02	0.02	0.06	0.03	0.03	0.01	0.02
g_8^3	0.05	0.02	0.05	0.02	0.02	0.06	0.05	0.03	0.03	0.02
g_9^3	0.00	0.01	0.01	0.01	0.02	0.06	0.01	0.01	0.01	0.02
g_{10}^3	0.01	0.00	0.01	0.02	0.02	0.04	0.04	0.02	0.01	0.02

Appendix D

Table A9. Relative error values of the prediction results between the proposed model and the BPNN.

Actual Values	Output Values of BPNN	Output Values of RBFNN	Relative Error Values of BPNN	Relative Error Values of RBFNN
0.9800	0.9521	1.0900	0.0279	−0.1100
1.1900	1.1380	1.1897	0.0520	0.0003
1.2100	1.1747	1.1507	0.0353	0.0593
1.1200	1.1834	1.0375	−0.0634	0.0825
1.1900	1.1920	1.0945	−0.0020	0.0955
1.1100	1.2778	1.1549	−0.1678	−0.0449
1.1600	1.0989	1.1832	0.0611	−0.0232
1.0800	1.0006	1.0751	0.0794	0.0049
1.3600	1.4022	1.3614	−0.0422	−0.0014
1.9600	2.0879	1.9323	−0.1279	0.0277
1.2000	1.1899	1.3179	0.0101	−0.1179
0.8200	1.0116	0.9543	−0.1916	−0.1343
1.2300	1.1564	1.1231	0.0736	0.1069
2.2500	2.2566	2.1982	−0.0066	0.0518
1.2500	1.2288	1.1290	0.0212	0.1210
1.5000	1.3052	1.4355	0.1948	0.0645
2.1300	2.0880	1.8895	0.0420	0.2405
1.0800	1.1728	1.0947	−0.0928	−0.0147
1.3300	1.3569	1.2713	−0.0269	0.0587
1.0200	1.0928	0.9867	−0.0728	0.0333
1.9600	1.7885	1.7603	0.1715	0.1997
1.2300	1.1765	1.0475	0.0535	0.1825
0.7900	0.9120	0.7626	−0.1220	0.0274
1.0000	1.0871	1.1768	−0.0871	−0.1768
1.4200	1.3900	1.4431	0.0300	−0.0231
0.9900	1.1447	1.1798	−0.1547	−0.1898
1.1300	1.1399	1.2387	−0.0099	−0.1087
1.1700	1.1153	1.1677	0.0547	0.0023
1.1900	1.2479	1.2427	−0.0579	−0.0527
1.4400	1.3321	1.2392	0.1079	0.2008
0.9700	0.9448	1.0518	0.0252	−0.0818
2.0900	2.2407	2.0757	−0.1507	0.0143
0.9200	0.9813	0.9042	−0.0613	0.0158
0.9900	0.9051	0.8601	0.0849	0.1299
1.1300	1.1601	1.2547	−0.0301	−0.1247
1.7400	1.6851	1.7114	0.0549	0.0286
0.5000	0.7636	0.6007	−0.2636	−0.1007
2.0700	2.0294	1.8513	0.0406	0.2187
1.1800	1.0961	1.1553	0.0839	0.0247
1.3500	1.3791	1.5813	−0.0291	−0.2313
1.2500	1.0244	1.1158	0.2256	0.1342
1.0000	0.9799	1.0817	0.0201	−0.0817
1.5200	1.2802	1.3564	0.2398	0.1636
1.3900	1.1613	1.1884	0.2287	0.2016
1.1400	1.0689	1.1294	0.0711	0.0106
1.3900	1.3504	1.4680	0.0396	−0.0780
1.8900	2.0206	1.9008	−0.1306	−0.0108
0.9100	1.3543	1.0336	−0.4443	−0.1236
1.0100	1.2122	1.0191	−0.2022	−0.0091
1.1000	1.1368	1.0640	−0.0368	0.0360
1.3900	1.3620	1.3101	0.0280	0.0799
1.0700	1.0816	1.1190	−0.0116	−0.0490
1.1200	1.0386	1.0448	0.0814	0.0752
1.5300	1.3138	1.5072	0.2162	0.0228

Table A9. *Cont.*

Actual Values	Output Values of BPNN	Output Values of RBFNN	Relative Error Values of BPNN	Relative Error Values of RBFNN
1.2500	1.2986	1.1342	−0.0486	0.1158
1.2000	1.1433	1.1205	0.0567	0.0795
1.4400	1.3374	1.4255	0.1026	0.0145
0.8900	1.1490	1.0062	−0.2590	−0.1162
1.1700	1.1521	1.1028	0.0179	0.0672
1.2400	1.2509	1.2788	−0.0109	−0.0388
1.9800	2.0370	2.0432	−0.0570	−0.0632
2.0400	2.0517	1.8715	−0.0117	0.1685
1.3700	1.2948	1.4287	0.0752	−0.0587
2.3800	2.3321	2.3916	0.0479	−0.0116
1.1600	1.2237	1.0040	−0.0637	0.1560
1.2700	1.1847	1.0562	0.0853	0.2138
0.9000	0.9607	0.9512	−0.0607	−0.0512
0.9600	0.9954	0.8493	−0.0354	0.1107
1.1300	1.1655	1.0474	−0.0355	0.0826
1.2900	1.0987	1.2319	0.1913	0.0581
1.1100	1.2858	1.3339	−0.1758	−0.2239
1.2100	1.1786	1.1110	0.0314	0.0990
2.2000	2.2190	2.0603	−0.0190	0.1397
1.3300	1.1784	1.3149	0.1516	0.0151
1.2700	1.1509	1.1895	0.1191	0.0805
0.9300	0.9304	0.9463	−0.0004	−0.0163
1.3600	1.3078	1.2528	0.0522	0.1072
1.5800	1.3526	1.6036	0.2274	−0.0236
1.2700	1.2531	1.3412	0.0169	−0.0712
1.2000	1.1818	1.1589	0.0182	0.0411
1.4200	1.3338	1.3318	0.0862	0.0882
1.5700	1.5527	1.6451	0.0173	−0.0751
1.1300	1.1617	1.0983	−0.0317	0.0317
2.0300	2.0325	1.9836	−0.0025	0.0464
1.0000	1.0010	0.9248	−0.0010	0.0752
1.0100	1.0969	0.9753	−0.0869	0.0347
1.2200	1.1918	1.3066	0.0282	−0.0866
1.4800	1.2954	1.4187	0.1846	0.0613
0.8100	0.9475	0.8569	−0.1375	−0.0469
1.0200	1.1531	1.2389	−0.1331	−0.2189
0.9900	1.0547	0.9880	−0.0647	0.0020
1.7600	1.9894	1.8339	−0.2294	−0.0739
1.0100	0.9898	0.9540	0.0202	0.0560
1.9600	1.9500	1.8288	0.0100	0.1312
0.9500	1.1686	1.2000	−0.2186	−0.2500
1.2500	1.0847	1.1801	0.1653	0.0699
0.9700	1.0013	0.9234	−0.0313	0.0466
1.0200	1.0616	1.0782	−0.0416	−0.0582
1.1300	0.9276	1.0588	0.2024	0.0712
1.1700	1.1769	1.2337	−0.0069	−0.0637
1.2500	1.1449	1.2217	0.1051	0.0283
1.3700	1.2074	1.1732	0.1626	0.1968
0.9700	1.2438	1.2788	−0.2738	−0.3088
1.3700	1.2068	1.1614	0.1632	0.2086
0.9300	1.0412	1.0218	−0.1112	−0.0918
1.1500	1.1814	1.3224	−0.0314	−0.1724
1.8600	1.6594	1.5578	0.2006	0.3022
2.2200	1.9975	2.0903	0.2225	0.1297
1.0900	1.1303	1.1700	−0.0403	−0.0800
1.4000	1.3716	1.4414	0.0284	−0.0414

Table A9. *Cont.*

Actual Values	Output Values of BPNN	Output Values of RBFNN	Relative Error Values of BPNN	Relative Error Values of RBFNN
1.4200	1.3179	1.2338	0.1021	0.1862
2.0700	2.1933	2.0753	−0.1233	−0.0053
1.2300	1.1660	1.2268	0.0640	0.0032
1.2600	1.2067	1.1826	0.0533	0.0774
2.1800	2.0790	2.2379	0.1010	−0.0579
1.0800	1.0224	1.0669	0.0576	0.0131
2.3200	2.1990	2.1975	0.1210	0.1225
0.9100	0.9485	1.0132	−0.0385	−0.1032
1.4000	1.3618	1.3486	0.0382	0.0514

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