Financial management of Public Private Partnership projects using artificial intelligence and fuzzy model

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Public Private Partnership has been popular, as an infrastructure delivery model. However, due to the long-term of these contracts, often the initial financial estimates will be changed during operation period. In these circumstances, successful implementation of these projects needs to renegotiation between the main stakeholders including the government, the private sector and end users and then, the additional costs should be divided in forms of annual subsidy, contract extension and toll adjustment, respectively. The key issues are: (1) estimation the future cash flows, in which future demand and operation and maintenance costs as stochastic variables and (2) fair allocation of excess cost between the stakeholders. This paper applied Local Linear Neuro Fuzzy and Multi-Layer Perceptron methods to forecast the stochastic variables. In addition, a fuzzy multi-objective model is proposed to identify the most feasible and satisfactory solution.

Keywords: Public Private Partnership stakeholders; financial management; renegotiation; artificial intelligence; local linear neuro fuzzy; multi-layer perceptron; fuzzy multi-objective model.

Nomenclature

PPP : Public private partnership.
LLNF : Local linear neuro fuzzy.
MLP : Multi-layer perceptron.
NPV : Net present value.
BOT : Build-operate-transfer.
BOOT : Build-own-operate-transfer.
BROT : Build-rent-own-transfer.
1. Introduction

Public infrastructure and services projects are the most important factors in creating social welfare and development of the countries. Until the last few decades, the public sector being the owner and the responsible entity for these infrastructures. Recently, as method of construction projects became more complicated, the governments believed that private sector investment, innovation and skills should play a significant role in the delivery of public infrastructure and services. The 1990s witnessed significant growth in private investment in both developed and emerging countries infrastructure which was named PPP. According to the Treasury [1], PPPs are a form of long-term relationship between the public and private sector for the benefit of both parties and cover a wide range of business partnership arrangements including joint ventures, concessions, sale of equity stakes in state-owned businesses, franchises and outsourcing of public services.

The most common PPP models (such as BOT, BOOT and BROT) are the methods for granting the concession period in which the right of utilization is given exclusively to private investor. The process of implementing these contracts can be divided into four major stages: project feasibility study, construction, operation, and post transfer [2]. Government and private sector participation is usually related to the last three rounds which is shown in Fig. 1 in the form of a NPV chart.

During the operation period, the private sector utilizing the project and anticipated revenues will be realized. In this period, private sector investment must be return and expected profit earned. However, due to the long-term of this period, there is a possibility of some changes in project scope, risk assignment, contract conditions along with other unforeseeable (endogenous or exogenous) issues and this topic create some concerns about the successful implementation of these projects [3].

![NPV Chart](image-url)  
**Fig. 1.** Major cycles in PPP contracts with concession periods.
In order to reduce these concerns and attract private sector, governments guarantees a certain level of return on investment to the private sector and allow renegotiations of the concession terms when some serious scenarios occur [4, 5].

Empirical data also indicate that renegotiations are not exceptional in PPP contracts [4, 6, 7]. Renegotiation can occur in each period of the project life cycle and due to long-term of operation period, the probability is very high in this period. Guasch et al. [7] stated that about 45% of renegotiations occur during the concession period and frequently repeated in a same project. Most of these differences occur due to financial issues and would lead to added cost of projects. Guasch et al. [7, 8] found that from 1990 to 2013 more than 1700 PPP projects reached financial closure in Latin American countries and the Caribbean (54.7% of in transportation sectors and 74.4% in water and sanitation sectors).

When computing the future cash flows in a PPP project, there are many stochastic variables, among which future demand and O&M costs are the most important. During the operation period and with the passage of time, the key issue is to estimate these stochastic variables based on the actual performance of project. In this paper, using review and analysis of previous methods and determine their weaknesses, the concepts of artificial intelligence is proposed. These concepts are more accurate than the estimation methods in literature. LLNF and MLP are proposed to forecast the demand and O&M costs, respectively.

After estimating the future cash flow, decision makers should identify a viable scheme to share the excess costs/profits between the stakeholders involved in PPP project. In this purpose, with identification of stakeholders and their goals, a fuzzy multi-objective model is proposed to identify the most feasible and satisfactory solution.

The remainder of the paper proceeds as follows. Section 2 provides the theoretical basis for the framework, its development and application. In addition, the proposed models for forecasting future cash flow and cost allocation between stakeholders is presented in this section. An illustrative example and the numerical results is presented in Sec. 3. Finally, some concluding remarks is presented in last section.

2. Cash Flow Forecasting and Renegotiation Framework

2.1. Literature background

As mentioned in previous section, future estimation of demand and O&M costs is the most important issue during the operation period. In this situation, actual project performance data is available from the beginning of the operation and using different methods the demand and O&M costs is estimated for the future years. Table 1 shows the main studies related to this issue. In the latest paper, Xiong and Zhang [5] proposed a Time-series model to forecast the future revenue and costs of project. They used an ARMA model to represent the time-lagged relationship of auto correlated observations.
Table 1. A summary of main previous studies related to demand and O&M estimation.

<table>
<thead>
<tr>
<th>Method</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant growth rate</td>
<td>Ranasinghe [9]</td>
</tr>
<tr>
<td>Using data from similar projects</td>
<td>Akpan and Igwe [10]</td>
</tr>
<tr>
<td>Univariate and multivariate regression</td>
<td>Shane et al. [11]</td>
</tr>
<tr>
<td>Monte Carlo simulation</td>
<td>Hanaoka and Palapus [12]</td>
</tr>
<tr>
<td>PERT analysis</td>
<td>Zhang [13]</td>
</tr>
<tr>
<td>Analysis of economic characteristics</td>
<td>Doan and Menyah [14]</td>
</tr>
</tbody>
</table>

The demand and O&M costs functions in the PPP projects have some special features that are not considered in previous studies. These features include:

(i) Seasonality of demand in periods: PPP projects often are used by the public sector and certainly the rate of demand is not the same during short time periods. For example in a highway project, the level of demand on holidays and weather conditions is dramatically promote. Therefore, evaluating short-term demand, increases the accuracy of forecasts, while the previous studies have not this ability.

(ii) The trends in demand and cost: Pantelias and Zhang [15] and Xiong and Zhang [5] showed that demand and cost in PPP project have trend. However, most of previous studies considered a constant rate or analyzed or used qualitative methods to predict them.

(iii) Dependence the O&M costs to the demand: In the all previous studies, a same model has been proposed for demand and O&M costs. However, in addition to the discussed factors in previous studies, these costs, are dependent on demand.

2.2. Cash flow forecasting

Given the shortcomings noted in previous studies, this paper proposed the LLNF models to forecast the demand. Local linear modeling technique is based on dividing a complex modeling problem into a number of smaller and simpler sub models such as linear models, which are identified independently and simply [16]. Many researches have been shown that the LLNF has a good ability in time series prediction and nonlinear system identification [17].

According to the features mentioned for the O&M cost function, the prediction model should be used the historical data along with the demand values as an effective parameter. So we need a predictor that involves the forecasting of future trends in a time series of data given current and previous conditions and have the ability to learn through time. Many researchers showed that MLP has good abilities for prediction these models [18]. MLP utilizes a supervised learning technique called back propagation for training the network. The architecture of a multilayer perceptron is variable but in general will consist of several layers of neurons. In addition to one input layer, a multilayer perceptron may have one or more hidden layers.
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and finally an output layer. The hidden layer(s) is consist of many simple nonlinear transfer functions that enables the multilayer perceptron to approximate extremely non-linear functions. By selecting a suitable set of connecting weights and transfer functions, it has been shown that a multilayer perceptron can approximate any smooth, measurable function between the input and output vectors [19]. Therefore, the actual O&M data along with projected demand of LLNF methods enter to the MLP network as the inputs and the future O&M costs is estimated as outputs.

Here we use the NPV method to represent the cash flow of the PPP projects. Assuming a PPP project has a concession period of $T_c$ years and $m$ years have passed. With forecasting the demand and O&M costs for remaining years, the expected NPV based on actual performance to the current period, $NPV^{(1)}$, can be calculated as follow.

$$NPV^{(1)} = \sum_{t=1}^{m} NPV_t + \sum_{t=m+1}^{T_c} \frac{P_tD_t - C_t}{(1 + r)^t},$$  

where $C_t = $ planned costs, $P_t = $ planned toll rate, $D_t = $ planned demand and $r = $ planned discount rate.

2.3. PPP renegotiation framework

During the operation period, if renegotiation is occurred, different stakeholders of project should be taken to divide the excess costs. Based on the literature, there are essentially two categories of stakeholders that effect on the performance and success of PPP projects: internal stakeholders, who are actively involved in project execution; and external stakeholders, who are affected by the project [20, 21]. Researchers categorized the government and the private sector as the most important internal stakeholders and the end users as the most important external stakeholders [22, 23].

By applying a PPP approach, governments usually provide various guarantees to encourage private sector which can be measured by certain quantitative financial indicators such as minimum revenue or least present value of revenue [2]. If one or more risk scenarios occur and push these financial indicators below the corresponding threshold, renegotiation will be opened. The dispute value can be expressed (2).

$$\Delta NPV = NPV^{(0)} - NPV^{(1)},$$

where $NPV^{(0)}$ is the guaranteed minimum accumulated NPV of the cash flow.

Various forms can be imagined for renegotiation process results. According to researchers, three common compensation results are toll adjustment, contract extension and annual subsidy or unitary payment adjustment. During the operation period, each of these results, affect on satisfaction of key stakeholders including the government, the private sector and end users [8, 22].

Decision makers should identify a viable scheme that could cover $\Delta NPV$ and simultaneously satisfy social consideration, commercial interests and public
accountability of the government, investor, and community, respectively. In practice, a combination of the results may be taken depending on the actual situation of the PPP project. So, the stakeholders should identify the most feasible alternative and sign an agreement. However, the diverse purposes of the stakeholders interact, making it difficult to directly obtain the most feasible alternative. As a result, fuzzy set theory is applied, which is an effective approach to solving multi-objective problems. From the perspective of the government, the decision objective is to provide an amount of annual subsidy that is as low as possible. The decision objective for the private sector is to obtain the minimum guaranteed NPV \( NPV(0) \) as soon as possible. So, from the perspective of the private sector, the decision objective is the minimum contract extension. Moreover, from the perspective of the end users, lower value of toll is better. Consequently, the diverse interests of the government, private sector, and public can be defined as the following multi-objective decision making problem.

\[
\begin{align*}
\min \text{ annual subsidy} \\
\min \text{ contract extension} \\
\min \text{ toll adjustment}
\end{align*}
\]

If \( X \) is a collection of objects denoted generically by \( x \), then a fuzzy set \( \tilde{A} \) in \( X \) is \( \tilde{A} = \{ x, \mu_{\tilde{A}}(x) | x \in X \} \), where \( \mu_{\tilde{A}}(x) \) is a membership function taking values from \([0,1]\) specifying to what degree \( x \) belongs to \( \tilde{A} \). According to Zadeh [24], for a fuzzy multi-objective decision problem, where the objectives are conflicting, makes it difficult to obtain an optimal solution.

\[
\max \{ \mu_{\tilde{f}_i}(x) | x \in X, i = 1, 2, \ldots, m \},
\]

where \( \tilde{f}_i \) is a fuzzy set in field \( X_i = \{ x | f_i_{\inf} \leq f_i(x) \leq f_i_{\sup}, x \in X \} \), \( f_i_{\inf} \) and \( f_i_{\sup} \) are the inferior and superior boundaries of \( f_i(x) \) respectively; \( \mu_{\tilde{f}_i}(x) \) is the degree of membership that \( x \) belongs to \( \tilde{f}_i \). For the maximization objectives, the membership function is determined by:

\[
\mu_{i}(x) = \left[ \frac{f_{i_{\sup}} - f_{i}(x)}{f_{i_{\sup}} - f_{i_{\inf}}} \right]^{p_i},
\]

where \( p_i \) is an exponential parameter. \( f_{i_{\inf}} \) is equal to zero for the stakeholder involved in PPP project. Ho and Asce [25] showed that due to the political costs, the governments can justify the payment of annual subsidy up a certain level \( f_{G_{\sup}} \) which is depends on internal and environmental projects factors. About private sector, \( f_i(x) \) is done by increasing or decreasing the concession period. As shown in Fig. 1, during the operation period, NPV slope gradually decreases and becomes zero at the end of economic life. As such, \( f_{P_{\sup}} \) can be given by end of economic life. Most of PPP contracts are infrastructure projects and there are alternatives for them. By increasing tariffs, public tendency exponentially decreases and the earned income related to the tariff, will be parabolic. Therefore, \( f_{U_{\sup}} \) can be calculated using this function.
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Fig. 2. The proposed framework for cash flow forecasting and dispute management of PPP contracts.

To solve the fuzzy multi-objective decision problem, many researchers proposed a max–min composition approach [26, 27]. The max–min composition approach can avoid non-inferior solutions from having a minimal membership value. Therefore, the non-inferior solution is deduced by the max–min composition as (6). Figure 2 illustrates the framework of proposed approach in forecasting the cash flow and renegotiation management.

\[
\mu_{ij}^* = \max_j \min_i \{\mu_i(x_j)\}.
\]  

(6)

3. An Illustrative Example

In this section, we used the project information presented in Xiong and Zhang [5] with some additional information to evaluate the proposed model. This Project is a harbor tunnel road crossing procured through a BOT contract and its information are summarized in Table 2. Over 14 years of operation period, 1998–2011, the
Table 2. Summary of data about presented project.

<table>
<thead>
<tr>
<th>Project index</th>
<th>Quantity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Construction period</td>
<td>5 years (1993–1998)</td>
</tr>
<tr>
<td>Construction cost</td>
<td>7000 million $</td>
</tr>
<tr>
<td>Concession period</td>
<td>25 years (1998–2023)</td>
</tr>
<tr>
<td>Minimum guaranteed NPV</td>
<td>3320 million $</td>
</tr>
<tr>
<td>Economic life time</td>
<td>40 years (until 2038)</td>
</tr>
<tr>
<td>Annual discount rate (r)</td>
<td>10%</td>
</tr>
</tbody>
</table>

Fig. 3. The autocorrelation coefficient for weekly demand data during: (a) 4 years before and (b) 15 years before.

demand and costs information have been collected weekly. Based on this information, the accumulated NPV was −4,573 million $, until 2011.

In order to determine the seasonal nature of the data, the autocorrelation coefficient for weekly data demand is measured using MATLAB software. As shown in Fig. 3, the highest correlation is related to 1, 2, 51, 52, 53, 103, 104, 105 data before. Following the LLNF model with one-step ahead estimating is applied to forecast future demand. The 8 mentioned weekly data is used as input. These data is divided into two subsets, namely the training data set (first 13 years) and the test data set (last 2 years).

Prevalent statistical metrics including MAPE, $R^2$ and RMSE are employed to evaluate the estimation performance of the proposed neuro-fuzzy model. These metrics are defined by:

$$MAPE = \frac{1}{N} \sum_{i=1}^{n} \frac{|d_i - \hat{d}_i|}{d_i},$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (d_i - \hat{d}_i)^2}{\sum_{i=1}^{n} (d_i - \bar{d})^2},$$
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Table 3. The LLNF results to predict demand according to the prevalent indices.

<table>
<thead>
<tr>
<th>Prevalent indices</th>
<th>MAPE</th>
<th>$R^2$</th>
<th>RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>LLNF model</td>
<td>0.087</td>
<td>0.088</td>
<td>0.065</td>
</tr>
</tbody>
</table>

\[
RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{n} (d_i - \hat{d}_i)^2},
\]  

(9)

where \(d_i\) and \(\hat{d}_i\) represent the actual and estimated values of the \(i\)-th data, respectively. These three metrics are used to measure the deviation between the actual and predicted values. The overall comparative results to the proposed model for the test data are presented in Table 3. The results reveal that the proposed model can be implemented to predict the future demand.

In order to forecasting the future O&M costs, a two-layer perceptron network is defined consist of \textit{tansig} and \textit{linear} functions for the first and second layers, respectively. Also 14 neurons are considered for the middle layer. Similar to LLNF, 676 and 104 data (Weekly O&M costs in 15 years) is considered as the training and test data, respectively. Table 4 shows the results of running MLP model.

Based on forecasted future demand and cost and using (1), it is expected that at the end of concession period, the NPV reaches to 197 million $ which is much lower than the minimum guaranteed NPV (3320 million $). Therefore, the amount \(\Delta NPV = 3123\) million USD should be divided between the main stakeholders (government, private sector and end users).

The required components related to the proposed multi-objective fuzzy model, is defined in Table 5. Suppose that according to the exogenous and indigenous conditions, the government can pay the annual subsidy up to $2000 million until the end of concession period (2023). Suppose also that based on the analysis of alternative methods of transportation, the maximum amount of increase in tariffs is 100%. In addition, as shown in Table 2, the economic life of the project is 40 years and with extending the concession period, 15 years could be add to contract.

Table 4. The MLP results to predict O&M costs for the test data.

<table>
<thead>
<tr>
<th>Prevalent indices</th>
<th>MAPE</th>
<th>$R^2$</th>
<th>RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>MLP model</td>
<td>0.146</td>
<td>0.226</td>
<td>0.167</td>
</tr>
</tbody>
</table>

Table 5. The components related to the proposed multi-objective fuzzy model.

<table>
<thead>
<tr>
<th>Component</th>
<th>Options</th>
</tr>
</thead>
<tbody>
<tr>
<td>Set of objective functions</td>
<td>{\text{annual subsidy, contract extension, tool increase (%)}}</td>
</tr>
<tr>
<td>Set of possible solutions</td>
<td>{(904, 5, 45%), (336, 6, 70%), (591, 8, 30%), (0, 10, 38%),}</td>
</tr>
<tr>
<td></td>
<td>(1003, 10, 0), (1823, 0, 0), (0, 12, 0), (0, 0, 95%)}</td>
</tr>
</tbody>
</table>
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Set of 8 possible solutions also presented in Table 5. For example, in order to cover $\Delta NPV = 3123$ million USD, the first solution is annual subsidy of $1604$ million by government, 5 years extension to contract period and 45% increase in tariff, simultaneously.

Using (5), each of these solutions receive special membership value for the three purposes objectives. Here we assumed that the exponential parameter, $p_i$, is equal to 2 for all stakeholders. Finally, the best solution is introduced using (6). According to following calculation, the first solution is the best.

$$\mu^*_{ij} = \max_j \min_i \{\mu_i(x_j)\}$$

$$= \max_{1 \leq j \leq 8} \min_{1 \leq i \leq 3} \begin{pmatrix} 0.30 & 0.69 & 0.50 & 1 & 0.25 & 0.08 & 1 & 1 \\ 0.44 & 0.36 & 0.22 & 0.11 & 0.11 & 1 & 0.04 & 1 \\ 0.30 & 0.09 & 0.49 & 0.30 & 1 & 1 & 1 & 0.01 \end{pmatrix}$$

$$= 0.30.$$

4. Conclusion

Public Private Partnership (PPP) has been popular, due to its objectives in transferring risk, reducing cost, solving budgeting constraints problems, providing higher quality and saving time. However, Changes in financial estimates of public-private partnerships are inevitable, due to the long-term of these contracts and existence of different internal and external factors. During the operation period, the key issue is to estimate the future demand and O&M costs based on the actual performance of project. This paper proposed LLNF and MLP models to forecast the demand and O&M costs, respectively.

If the project financial estimates are differing from predicted values, renegotiations should be occurred between the main stakeholders involved including government, private sector and end users. In these circumstances, additional costs should divide between stakeholders in form of annual subsidy, contract extension and toll adjustment. The stakeholders should identify the most feasible alternative and sign an agreement. However, the diverse purposes of the stakeholders interact, making it difficult to directly obtain the most feasible alternative. As a result, fuzzy set theory is applied, which is an effective approach to solving this multi-objective problem.

The combined features of the artificial intelligence techniques and fuzzy multi-objective decision models enable the scenario most likely to result in a win–win–win concession scheme to be identified. A hypothetical example is used to illustrate the proposed models.

References

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