Evaluating subcontractor performance using Evolutionary Gaussian Process Inference Model

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Abstract: "Subcontractor Evaluation" is one of the methods which general contractors use to evaluate subcontractor performance. The result is often used as a reference index for subcontractor choice during the outsourcing of activities within a project. Inappropriate subcontractor choice would have a direct impact on the duration, cost, quality, and safety of a project, leading to failure in achieving its goals and target profits. Therefore, this paper establishes a set of Evolutionary Gaussian Process Inference Model, which utilize a Gaussian Process to map the relationships between data input and output and uses Bayesian inference together with Particle Swarm Optimization to optimize the hyper-parameters of the Gaussian Process covariance function to obtain the best inference predictive ability. The model provides construction managers with quantitative measures of subcontractor performance in their selection process.

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1. Introduction

The construction industry is one of the key parts of a nation's economic development. The production processes in construction are constrained by contracts, design illustrations, construction specifications and site conditions. Since projects require a variety of resources to achieve final construction, contractors are unable to perform all tasks by themselves, as many of them are highly complex or specialist activities. In order to do so, they must source specialized labor from outside themselves. Therefore, except for activities that contractually cannot be outsourced, contractors usually subcontract out activities and only oversee the overall planning and management of the project [1] .

This sub-contractual form of project management is a way to reduce costs and improve efficiency and, contractors in Taiwan generally outsource a high percentage of their projects. In this context, the decision-making process for subcontractor choice to gain a better competitive advantage is a key issue of study. The evaluation of subcontractors usually happens during the construction period. Key criteria of evaluation include how contractor will cooperate with other subcontractors, both in the present and in future. However, current methods do not clearly map out the relationships between individual construction factors and a subcontractor's overall performance (a review of the total score) In order to improve such circumstance, many artificial wisdom technologies have been developed in recent years, assisting in processing large amount of data, which could analyze and find out the rules and patterns to predict future behavior and in assistance of decision making. Ulubeyli Presents a study of subcontractor selection practices of Turkish contractors in international projects[2]. Cheng was to propose support model using Evolutionary Support Vector Machine Inference model (ESIM) that would improve current subcontractor performance evaluation practices [3].

In this research establishes an Evolutionary Gaussian Process Inference Model (EGPIM) which utilizes the Gaussian Process (GP) to map out the relationship between data input and output and uses Bayesian inference together with particle swarm optimization (PSO) to optimize the hyper-parameters in covariance functions so as to obtain the best predictive ability. The objective of EGPIM learning was to map the relationships between the primary scores and the final scores with the learned results potentially being used to assess subcontractor performance directly from primary to final scores. By using the model's prediction, the expected value and variance that are needed in decision-making can establish a data confidence interval to serve as references for decisions.

This dynamic production model boasts quick training, short execution times, and accurate predictions which place it in good stead to provide managers with a practical basis for subcontractor performance evaluation.

2. Review of Approaches

2.1. Gaussian process regression

Gaussian process (GP), a widely utilized AI technique, has been widely applied in chemistry, construction, medicine and other fields[4] . GP provides a statistical advantage and is easy to learn[5] . It uses probability theorems to predict unknown input data and estimates prediction accuracies (estimation variances) to greatly improve the statistical significance of such predictions[6] [7] . GP is a combination of random variances in which capricious and limited numbers of random variances all obey Gaussian distribution:

$$F(\mathbf{X}) = \{f(X_1), f(X_2), \dots, f(X_N)\} \sim N(\mu, K) \qquad (1)$$

Where **X** is the variance of the input data, and the mean function is m(**X**) = E[f(**X**)], and the covariance function is k(X,X') = E[(f(X)-m(X))(f(X')-m(X'))]. From the previous description, as GP can explain multi-dimensional Gaussian distributions, with the trait that the random process f(X) could dominate and control random variances and with the explanation of the random process with probability distribution, a flexible non-parameter probability model can be defined; μ is the mean of variances, and K is the covariance matrix of the covariance function. GP can be described via mean function m(**X**) in $f(X_i)$ and covariance function k(X,X') in the random process.

$$f(X) \sim GP\big(m(X), k(X, X')\big) \qquad (2)$$

In real situations, however, data prediction is often accompanied by noise, and therefore, when the value Y is calculated by the estimation of the function, an error parameter ϵ should be considered. Likewise, ϵ also coincides with the Gaussian distribution. Y is calculated as follows:

$$\mathbf{Y} = F(\mathbf{X}) + \epsilon \qquad (3)$$

Joint distribution calculated under Gaussian distribution:

$$\begin{bmatrix} \mathbf{Y} \\ Y_* \end{bmatrix} | X, \theta \sim N\left(0, \begin{bmatrix} K + \sigma^2 I & k \\ k^T & \kappa + \sigma^2 \end{bmatrix}\right) \qquad (4)$$

Hence, the conditional of probability distribution can also be calculated with expected value together with noise, the X_* represents the new input data:

$$Y_* | Y, X, \theta, \sigma^2 \sim N(m(X_*), v(X_*)) \qquad (5)$$

In the end, based on conditional probability distribution, the mean and variance of expected value Y_* can be calculated:

$$m(X_*) = k^T (K + \sigma^2 I)^{-1} Y \qquad (6)$$

$$v(X_*) = \kappa + \sigma^2 - k^T (K + \sigma^2 I)^{-1} k \qquad (7)$$

2.2. Bayesian Inference

Bayesian inference uses distribution information from unknown parameters in addition to model and data information[8]. This information (called "prior") exists prior to the experiment and is expressed by the probability distribution of unknown parameters[9][10]. Bayesian theorem uses known information to construct a posterior probability density for system status variances. It utilizes the model to predict prior estimated status variance density and then makes rectifications based on the latest observation information. Using observation information to calculate status variances increases trust in the accuracy of different values and delivers the best model estimation [11].

2.3. Particle Swarm Optimization algorithm (PSO)

The Particle Swarm Optimization (PSO) algorithm is a relatively new algorithm derived by J. Kennedy and R.C. Eberhart in 1995 from a simplified social model simulation. (8) PSO algorithms mimic mechanisms used by birds to share information in flight.(9) The particle concept requires members in groups without mass and volume and with designated speed and acceleration. The first version of PSO added neighboring speed values and considered multi-dimensional search and distance-based acceleration. Inertia weight, introduced later, enhanced the algorithm's exploitation and exploration and paved the way to form a standard version of the algorithm(10) (11).

3. Evolutionary Gaussian Process Inference Model (EGPIM)

The EGPIM is a Gaussian process combined with Particle Swarm Optimization (PSO) and Bayesian inference that is based on historical data. EGPIM uses GP to reveal the intricate relationship between variance input and output.

Bayesian inference structure gives the posterior probability for the entire function and serves as the reference for parameter optimization. PSO searches the best hyper-parameter GP and required Bayesian analysis. Figure. 1 illustrates the model structure and its three component parts.

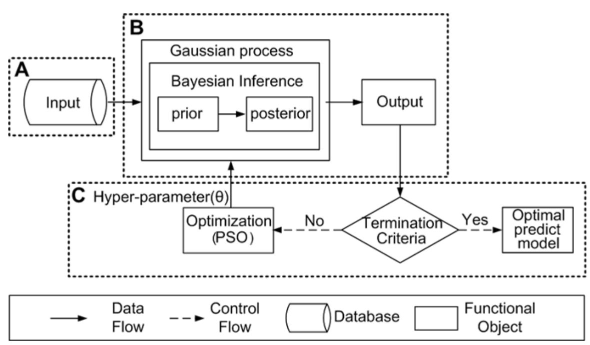

Figure 1. EGPIM structure

A. Data Input

This stage involves collecting and arranging input data **X** and output data **Y**, and establishing database D={**X**,**Y**}. **X** is the collection of data input factor of N dimensions and **Y** is the collection of m pieces of output. Thus, any Y_i is the output value of its case input value $\{X_{1i},X_{2i},\ldots,X_{Ni}\}$.When the database is coordinated, data are separated into training data and test data, with training data identifying reflection relationships between input and output data and test data used to check model prediction accuracy (5).

The corresponding function value of any input factor X_j is $f(X_j)$: F(X)= $\{f(X_1), f(X_2),\ldots, f(X_N)\}$; F(X) is the function congregation demonstrating the relationship between X and Y, with a Gaussian process used to describe function distribution. Assuming that function F(**X**) coincides with Gaussian distribution and makes work easier, the expected value m(**X**) would be 0 and probability would meet the normal distribution

$$P(F) = \frac{1}{(2\pi)^{\frac{N}{2}}|K|^{\frac{1}{2}}}\exp\left[-\frac{1}{2}F^TK^{-1}F\right] \sim N(0,K) \qquad (8)$$

where K is the matrix constructed from covariance function , and the equation above the probability of the set function F is regarded to be controlled by covariance matrix K.

B. Gaussian process and Bayesian inference

i. Covariance matrix and parameter

After determining a stationary pattern, the covariance function is chosen to construct the covariance matrix. Parameter model and quantity vary according to function. This study adopts the Squared Exponential, the most common covariance function.

ii. Gaussian process and Bayesian inference

A covariance function is then chosen to construct the covariance matrix. Parameter model and quantity vary according to function. As we adopted the Squared Exponential covariance function, the formula is as follows:

$$k_{SE}(X_i,X_j) = \sigma_f^2\exp\left[-\frac{1}{2}\left(\frac{X_i-X_j}{r_i}\right)^2\right] + \sigma_n^2\delta_{ij} \qquad (9)$$

In eq(8), σ_f controls overall function volatility, σ_n indicates overall function error, r_i shows the relationship between variances X_i and X_j in function space, and N represents data input dimensions. σ_f, σ_n, $r_1, r_2,\ldots,r_n$ represent matrix hyper-parameters and θ is their aggregate.

According to the chosen covariance function, and utilizing Bayesian theorem, we infer the posterior probability of the entire function P(F | **X**,**Y**) as:

$$P(F|\mathbf{X},\mathbf{Y}) = \frac{P(\mathbf{Y}|F,\mathbf{X})P(F)}{P(\mathbf{Y}|\mathbf{X})} \qquad (10)$$

Minimizing the Negative Log-Marginal Likelihood (NLML) and combining PSOs help maximize posterior probability in order to obtain the most likely hyper-parameter during the minimization process.

C. Hyper-parameter Optimization

Applying PSO to EGPIM optimizes the hyper-parameter in function space. This is the best model function. This step includes three steps, as follows:

i. Initial Stage

After setting up PSO parameters, particle groups, particle speed and positions are started randomly to initiate and implement iteration. These include (1) group scale m, (2) maximum speed V_{max}, (3) acceleration constant c_1 and c_2, (4) maximum inertia weight W_{max}, (5) minimum inertia weight W_{min}, (6) maximum iteration times, and (7) terminating accuracy requirement NLML (Negative Log Marginal Likelihood).

ii. Optimization stage

A fitness calculation of particles discriminates between good and bad particles. Adaptation value depends on NLML.

$$-\log P(\mathbf{Y}|\mathbf{X},\theta) = \frac{1}{2}Y^T(K(X,X)+\sigma^2I)^{-1}Y) + \frac{1}{2}\log|K(X,X)+\sigma^2I| + \frac{N}{2}\log 2\pi \qquad (11)$$

Particle search speed and direction are calculated as follows:

Particle speed calculation:

$$V_{id}^{t+1} = W^{t+1} \times V_{id}^t + c_1 \times rand(\,) \times (pBest_{id} - S_{id}^t) + c_2 \times rand(\,) \times (gBest_{id} - S_{id}^t) \qquad (12)$$

Particle weight

$$w = w_{max} - \frac{w_{max}-w_{min}}{iter_{max}} \times iter \qquad (13)$$

New search direction calculation

$$S_{id}^{t+1} = S_{id}^t + V_{id}^{t+1} \qquad (14)$$

Where V is the speed of the particle; S is the current location of the particle; pBest is the optimization found by the particle itself, i.e., body extrema; gBest is the optimization of the whole swarm, i.e., global extrema. R and ( ) are the random numbers within (0, 1); c1 and c2 are called learning factors. The search process ends once particles fly into the optimum location of the space after multiple learning sessions and renewals of location and speed. The final output, gBest, is the best optimization.

iii. Termination Stage

With gBest identified as the best solution, fitness value is compared against the global solution. If fitness value>global solution, the search continues.

The search ends only when requirement accuracy (NLML) and search Itermax are achieved.

EGPIM can be optimized through the adaption process with 3 phases (Figure 2). Each model result is evaluated using NLML. The process uses PSO to search simultaneously for optimum hyper-parameters.

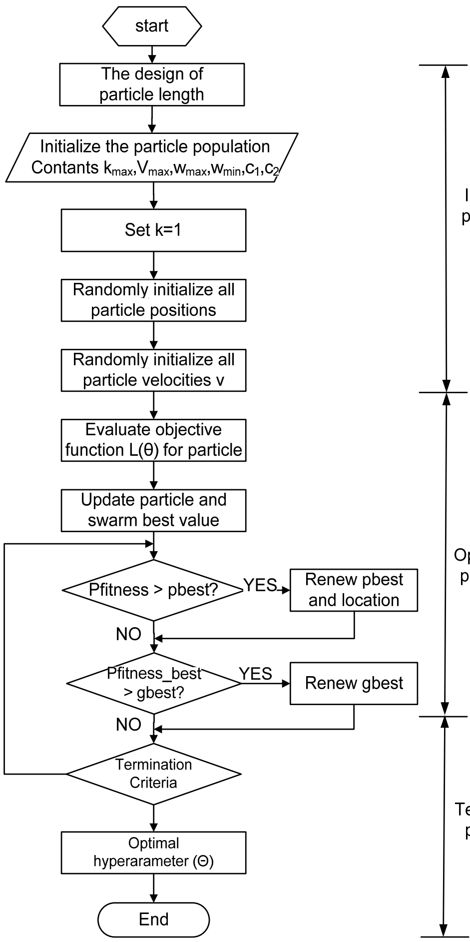

Figure 2. EGPIM Adaptation Process

4. EGPIM for subcontractor performance assessment

Performance is as an important index used by contractors to select optimal subcontractors (12). The use of this index assumes that a subcontractor's performance history can be used to predict their future performance. 'Subcontractor performance, however, can be affected by various expected and unexpected factors, such as management ability, worst conditions, such as weather, natural environment problems, or a bad workplace environment and subjective assessments [13]. This shows significant complexity in the prediction of subcontractor performance since there are uncertainties that require judgment calls based on human expert knowledge and experience [14]. Subcontractors are generally categorized into four types based on the services they provide. These are: 1) labor, 2) labor and materials, 3) materials, and 4) equipment, each with their particular characteristics. In practice, subcontractor performance is evaluated using two scores, namely a primary score and a final score with various contributing factors. Primary scores are evaluated by field superintendents. Final scores are assigned by the contractor's project management using the primary score as one point of reference. Problems that occur with this evaluation approach include: 1) there is difficulty in generalizing performance indicators for the different types of sub-contractors; 2) both the primary and final scores are independently determined by human experts based on personal knowledge and experience; and 3) the relationship between primary and final scores is not well defined.

This study gathered subcontractor data from an actual construction engineering general contractor that was established in 1956 and was valued at the time of this study to be about 11 million US dollars. Using a questionnaire survey, this study identified twelve key factors used by this general contractor to assess potential subcontractors (see Table 1). Each subcontractor was scored by the relevant field superintendent against twelve key factors. Each factor was quantified by giving a score based on qualitative ranks as follows: excellent (8 points), good (6 points), normal (4 points), poor (2 points), and bad (0 points). Final scores for subcontractor evaluation were then conducted by the general contractor's managers. The range of the final scores varied between 56 and 88 (see Table 2). The objective of EGPIM learning was to map the relationships between the primary scores and the final scores with the learned results potentially being used to assess subcontractor performance directly from primary to final scores.

Table 1. Subcontractor assessment factors.

NO.	Factors
1	Construction technique
2	Duration control abilities
3	Cooperative managers
4	Material wastage
5	Services provided after work completion
6	Collaboration with other subcontractors
7	Safe working environment
8	Self-owned tools
9	Clean working environment
10	Effective management capabilities
11	Manager personality
12	Financial condition

Table 2. Training and test data examples for subcontractor performance.

subcontractor	Contract NO.	Factor NO. 1	2	3	4	5	6	7	8	9	10	11	12	Final Score
Training Data														
A	A_01	6	6	4	6	6	4	6	6	6	4	8	8	72
	A_02	6	6	6	8	6	6	4	6	6	6	6	8	76
	A_03	6	6	6	6	6	6	6	6	6	6	8	8	76
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
M	M_03	6	8	6	8	4	6	6	6	6	4	8	8	76
	M_04	8	6	6	8	6	6	4	6	6	6	8	8	76
Test Data														
N	N_01	6	8	4	4	4	4	4	4	6	6	6	6	62
	N_02	6	6	4	6	4	6	6	4	4	4	8	6	56
	⋯	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋯	⋮
	N_14	8	8	6	6	8	6	6	8	6	6	8	8	86
	N_15	8	8	6	8	8	6	8	8	8	6	8	8	88

4.2. EGPIM parameter settings for subcontractor performance assessment

All the data shown in Table 2 were normalized to the range [0, 1] prior to EGPIM learning. As activities accomplished by subcontractor N were treated as testing data, 61 sets of data of the 76 were used as training data, with 15 remaining for testing. The EGPIM parameters were set to appropriate values in order to calculate optimal learning results, as in Table 3.

4.2. Subcontractor performance assessment result

The learned subcontractor performance (NLML) and the hyper-parameters of the model after 500 iterations are displayed in Table 4, while a graph of the testing results for EGPIM and other methods appears in Figure. 2. From these, it is clear that the EGPIM results were significantly more accurate than those achieved using ESIM [15] [3] and the original GP. For comparison, the testing root-mean-square error (RMSE) for ESIM was 5.35 and for GP it was 5.83, which were improved by EGPIM at 2.06. The longest time taken by the training courses for the Subcontractor Evaluation Performance was 1 minute, 51 seconds) the reliability of these EGPIM predictions of subcontractor performance can assist managers to select the appropriate subcontractors with greater precision and accuracy.

One of the main goals of this paper was to provide improvements to the existing EGPIM by using linear or non-linear relationships amongst the data. These improvements allow EGPIM to provide more accurate predictions for subcontractor performance evaluations than ESIM and GP. Ultimately, this paper proposes an EGPIM which integrates GP, Bayesian inference, and PSO to work with problems in the field of construction management.

Table 3. EGPIM parameter settings for subcontractor performance assessment.

	EGPIM parameter	Value
1	Particle group scale m	50
2	Maximum speed Vmax	0.9
3	Acceleration constant c1 and c2	2.0
4	Maximum inertia weight Wmax	0.7
5	Minimum inertia weight Wmin	0.4
6	Maximum iteration times	500
7	Terminate accuracy requirement NLML	−200

Table 4. Training results of EGPIM.

NLML	−105.712
Elapsed Time (sec)	111.8
Maximum iteration	485

5. Conclusions

This study applied the EGPIM to subcontractor performance data and utilized a model for evaluating subcontractor performance by collecting and extracting the rules from the actual measured data through a training algorithm. Knowledge of the data of the subcontractor evaluation model can have a direct impact on the quality of the model's results. We suggest that further studies try to evenly collect and collate a number of training cases for model training and testing in order to compare various model training approaches. To improve accuracy and better represent the model's results, construction managers should take care when conducting subcontractor evaluation and be more efficient in making more records in the database.

This paper builds a model for evaluating subcontractor performance by utilizing the EGPIM to effectively extract the knowledge and experience of engineering personnel to reduce the influence of subjective judgment, hence also reducing uncertainty. The EGPIM is based on regression and can obtain maps of the relationships between input and output values in a short time, so that it can build a real-time prediction model.

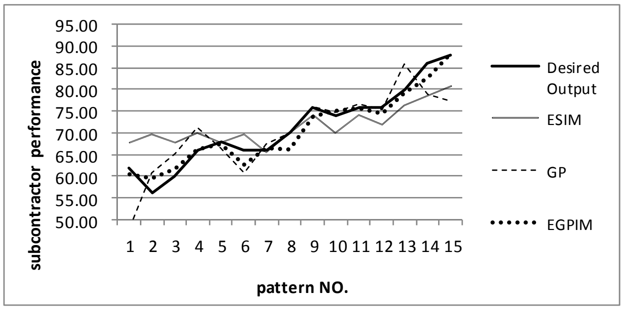

Figure. 3. A graph of the testing results for subcontractor performance using several methods.

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