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PREDICTING PRODUCTIVITY LOSS CAUSED BY CHANGE ORDERS USING THE EVOLUTIONARY FUZZY SUPPORT VECTOR MACHINE INFERENCE MODEL

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Abstract. Change orders in construction projects are very common and result in negative impacts on various project facets. The impact of change orders on labor productivity is particularly difficult to quantify. Traditional approaches are inadequate to calculate the complex input-output relationship necessary to measure the effect of change orders. This study develops the Evolutionary Fuzzy Support Vector Machines Inference Model (EFSIM) to more accurately predict change-order-related productivity losses. The EFSIM is an AI-based tool that combines fuzzy logic (FL), support vector machine (SVM), and fast messy genetic algorithm (fmGA). The SVM is utilized as a supervised learning technique to solve classification and regression problems; the FL is used to quantify vagueness and uncertainty; and the fmGA is applied to optimize model parameters. A case study is presented to demonstrate and validate EFSIM performance. Simulation results and our validation against previous studies demonstrate that the EFSIM predicts the impact of change orders significantly better than other AI-based tools including the artificial neural network (ANN), support vector machine (SVM), and evolutionary support vector machine inference model (ESIM).

Keywords: change orders, productivity loss, fuzzy logic, support vector machine, fast messy genetic algorithm.

Introduction

Changes during construction projects are very common, making construction one of the most complex industries. Changes can involve adding to or reducing the scope of project work or correcting or modifying an original design. Change orders in the construction industry have negative effects in aspects such as cost, quality, time, and organization. While most change order items (e.g. material, scheduling, rework, equipment) can be relatively easy to measure, quantifying the impact on labor productivity is typically more complicated (Hanna *et al.* 1999a).

Many studies have reported on the impact of change orders on labor productivity. The methods used in the literature to calculate productivity loss can be grouped into the 3 categories of (1) regression analysis (Leonard 1988; Moselhi *et al.* 1991; Ibbs 2005), (2) artificial neural network (ANN) (Moselhi *et al.* 2005), and (3) statistical-fuzzy (Hanna *et al.* 2002). Previous studies (Hanna *et al.* 2002; Moselhi *et al.* 2005) have reported that ANN and statistical-fuzzy methods outperform regression analysis. However, no method is suitable for calculating

productivity loss because prediction accuracies are outside of acceptable limits.

Construction projects are complex undertakings full of uncertainty and vagueness. Developing a deterministic mathematical model to predict productivity loss is difficult and expensive. An inference model (Cheng, Wu 2009) offering high accuracy and low cost is one feasible approach to predicting productivity loss. Inference models derive new facts from historical data. The human brain can learn previous information and deduce new facts from that information. Artificial intelligence (AI) can be employed to develop models that simulate human brain functions. AI is concerned with computer systems able to handle complex problems using techniques such as Artificial Neural Network (ANN), Support Vector Machine (SVM), and Fuzzy Logic (FL). AI-based inference models thus offer a promising solution to predicting productivity loss.

Several AI hybrid systems have been developed in recent years that have solved various construction management problems (Cheng, Wu 2009; Cheng, Roy 2010).

In an AI hybrid system, fusing different AI techniques can achieve better results than a single AI technique because the advantages of one technique can compensate for another's disadvantages (Cheng, Wu 2009). The Evolutionary Fuzzy Support Vector Machine Inference Model (EFSIM) (Cheng, Roy 2010) was proposed to further improve prediction accuracy. EFSIM is an artificial intelligence (AI) hybrid system that fuses fuzzy logic (FL), support vector machine (SVM), and fast messy genetic algorithm (fmGA). In EFSIM, FL deals with vagueness and uncertainty; SVM acts as a supervised learning tool; and fmGA works to optimize FL and SVM parameters. EFSIM significantly reduces the level of human intervention and can be used by professionals who do not have background in AI (Cheng, Roy 2010).

The objective of this research is to use EFSIM to predict productivity loss caused by change orders. Feasibility and capability of the proposed method are evaluated and compared with other methods, including ANN, SVM, and ESIM (Cheng, Wu 2009). Validation with previous studies (Moselhi *et al.* 2005) is also carried out to demonstrate proposed model performance.

1. Literature review

1.1. Productivity loss caused by change orders

Change can be defined as any modification in the original scope, time, or cost of the work (Hester *et al.* 1991). A change order is issued to formally announce the change and modify the contract between the contractor and owner (Hester *et al.* 1991). Keane *et al.* (2010) grouped causes of change into four categories: owner-related, consultant-related, contractor-related, and non-party-related, and effects of change into five categories: cost-related, quality-related, time-related, organization-related, other effects (Keane *et al.* 2010).

Preliminary research into calculating the effects of change orders on labor productivity was accomplished by Leonard (1988). This research attempted to identify the effects of change orders on labor productivity in 90 cases facing change-order-related productivity losses. Results indicated a significant correlation between change orders and productivity loss. However, there were limitations to Leonard's study, including limited number of variables and subjective evaluation (Hanna *et al.* 1999a, b). This preliminary study motivated other researchers to develop research in this field further.

Two studies used a statistical method to quantify the impact of change orders on labor productivity in mechanical and electrical construction projects (Hanna *et al.* 1999a, b). These studies used the delta method as an efficiency indicator and regression analysis to analyze questionnaire data. Hanna *et al.* (2002) improved the method by using the statistical-fuzzy technique to quantify the cumulative impact of change orders. Unfortunately, the technique is difficult for stakeholders to implement due to complicated calculation steps and poor prediction results.

A neural network model (Moselhi *et al.* 2005) was developed to estimate the impact of change orders on labor productivity, including the timing effect of change orders. Analysis results showed this model estimated the impact of change orders on productivity more accurately than those previously described. However, this method could gain better prediction results by fusing the neural network model with an AI technique.

1.2. Fuzzy logic (FL)

FL is a popular AI technique invented by Zadeh in the 1960s. FL has been used in forecasting, decision making, and action control in environments characterized by uncertainty, vagueness, presumptions, or subjectivity (Bojadziev, G., Bojadziev, M. 2007). In general, FL systems have four major components: fuzzification, fuzzy rule base, inference engine, and defuzzification. Fuzzification is a process that uses membership functions (MFs) to convert the value of each input variable into a corresponding linguistic variable degree. Fuzzy rules represent relations between input and output fuzzy sets and form the basis for fuzzy logic to obtain fuzzy output. The result of fuzzification, which is used by the inference engine, stimulates the human decision-making process based on fuzzy implications and available rules. Lastly, defuzzification reverses the fuzzification process and converts the fuzzy set into crisp output.

The advantages of FL related to vagueness and uncertainty depend heavily on the appropriate distribution of membership functions (MFs), number of rules, and selection of proper fuzzy set operations. Greater problem complexity increases the difficulty of MF construction and rules (Ko 2002). Some researchers have treated this drawback as an optimization problem because determining MF configurations and fuzzy rules is complicated and problem-oriented. To overcome such difficulties, some researchers have tried to fuse FL with AI optimization techniques such as GA and ant colony (Ishigami *et al.* 1995; Martinez *et al.* 2008). These optimization methods have demonstrated their ability to minimize time-consuming operations and reduce the level of human intervention necessary to optimize MFs and fuzzy rules.

1.3. Support vector machine (SVM)

SVM (Vapnik 1995) is an AI paradigm already used in a wide range of applications. SVM is a learning tool for solving classification and regression problems. SVM works by plotting input vectors into a higher dimensional feature space. The optimal hyperplane is identified within this feature space with the help of a kernel function, $K(x_i, x_j)$. A radial basis function (RBF) kernel has been recommended for general users as a first choice due to its ability to analyze higher-dimension data, use of only one hyperparameter in searches, and fewer numerical difficulties (Hsu *et al.* 2003).

SVM has achieved performance levels comparable to or higher than traditional learning tools (Borges

1998; Yongqiao *et al.* 2005). However, SVM’s generalization ability and prediction accuracy are determined by the optimal penalty (C) and kernel (γ) parameters. To overcome this drawback, an optimization technique (e.g. fmGA) may be used to identify the optimum values of parameters simultaneously (Cheng, Wu 2009).

1.4. Fast messy genetic algorithm (fmGA)

fmGA is a recently developed machine learning and optimization tool based on a genetic algorithm approach (Goldberg *et al.* 1993). fmGA is an improvement on messy genetic algorithms (mGAs), which were initially developed to overcome linkage problems in simple genetic algorithms (sGAs) resulting from a parameter coding problem that sometimes generates suboptimal solutions (Deb, Goldberg 1991). Unlike sGAs, which use fixed length strings to represent possible solutions, fmGA applies messy chromosomes to form strings of various lengths that can efficiently find optimal solutions for large-scale permutation problems (Feng, Wu 2006).

The fmGA contains two loop types: inner and outer (Fig. 1). The process starts with the outer loop. Firstly,

a competitive template (randomly generated or problem-specific) is generated. In the inner loop, the fmGA operation is three-phase, including an initialization phase, primordial phase, and juxtapositional phase. In the initialization phase, an adequately large population contains all possible building blocks (BBs) of order k . fmGA performs the probabilistic complete initialization (PCI) by generating n chromosomes randomly and evaluating their fitness value. The primordial phase contains two operations, namely threshold selection and building-block filtering. In this phase, “bad” genes that do not belong to BBs are filtered out so that, in the end, the result encloses a high proportion of “good” genes belonging to BBs. In the juxtapositional phase, fmGA operations are similar to sGA operations. The selection for “good” genes is used together with a cut-and-splice operator to form a high-quality generation that may contain the optimal solution. The next outer loop begins after the respective inner loop is finished. The competitive template is replaced by the best solution found so far, which becomes the new competitive template for the next outer loop. The whole process is performed until the

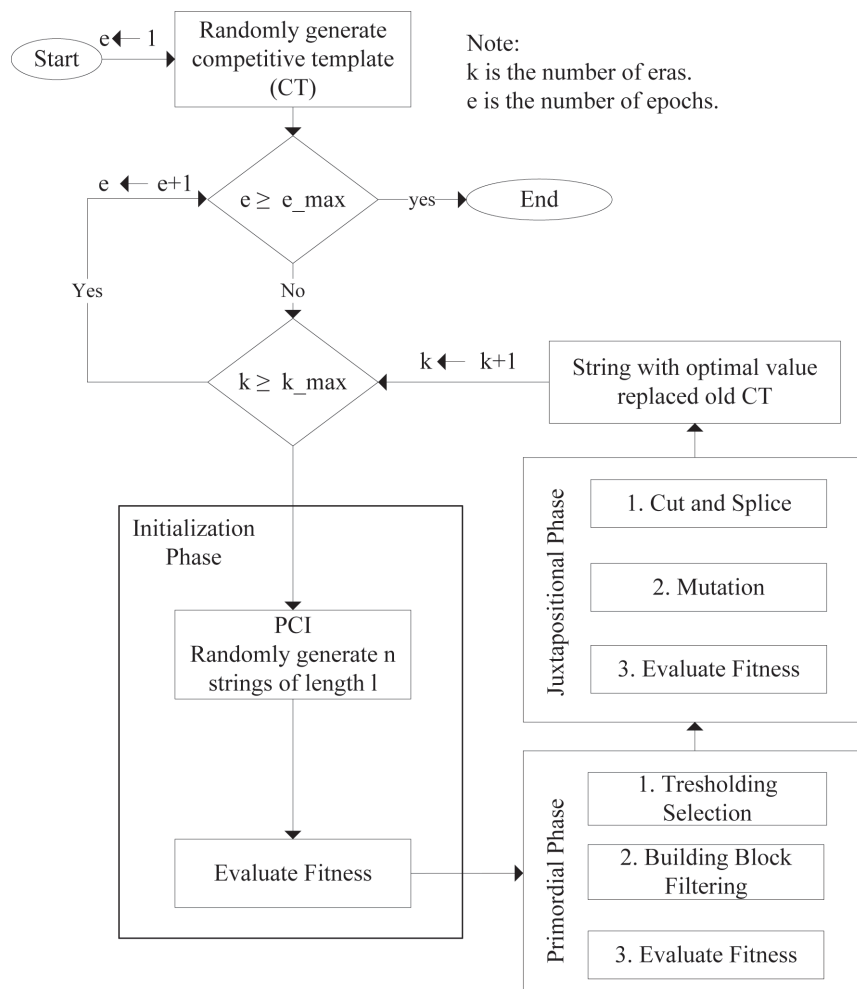


Fig. 1. Illustration of fmGA

maximum number of eras (k_{max}) is reached. The fmGA can also be performed over epochs (e_{max}). An epoch is the complete process between first era and the maximum number of eras (k_{max}). Epochs can be performed as many times as desired. The algorithm is terminated once a good-enough solution is obtained or no further improvement is made.

2. Evolutionary fuzzy support vector machine inference model

The evolutionary fuzzy support vector machine inference model (EFSIM) is a hybrid AI system developed by Cheng and Roy (2010) that fuses the three different AI techniques of fuzzy logic (FL), support vector machine (SVM), and fast messy genetic algorithm (fmGA). In this complementary system, FL deals with vagueness and approximate reasoning; SVM acts as a supervised learning tool to handle fuzzy input-output mapping; and fmGA works to optimize FL and SVM parameters.

In EFSIM, the fuzzy inference engine and fuzzy rules based on the FL system have been replaced by SVM. However, SVM's generalization ability and prediction accuracy are determined by the optimal penalty (C) and kernel (γ) parameters. Improper tuning of the parameters will affect the accuracy of the prediction model. To overcome this shortcoming, EFSIM utilizes fmGA to search simultaneously for optimum SVM parameters and FL parameters. The architecture of EFSIM is shown in Figure 2.

The EFSIM involves eight major steps, beginning with training data and ending with the optimal prediction model. An explanation of major steps involved in EFSIM is given below:

1) Training data

Final data for training are obtained from data preprocessing output. Data preprocessing used in this study included data cleaning, attribute reduction and data transformation.

2) Fuzzification

Each normalized input attribute from the previous step is converted into membership grades corresponding to the specific membership function (MF) set generated and encoded by fmGA. This model uses trapezoidal and triangular MF shapes (see Fig. 3) that, in general, may be developed by referencing summit points and widths. This study used the Summit and Width Representation Method (SWRM) (Ko 2002) to encode complete MF sets (Fig. 3 (c)). Figure 4 illustrates the fuzzification process.

3) SVM training model

SVM addresses the complex relationship between fuzzy input and output variables. Fuzzification process output, in the form of membership grades, is fuzzy input for SVM. SVM trains the dataset to obtain the prediction model, with penalty (C) and kernel (γ) as its parameters, which are randomly generated and encoded by fmGA. This study used the RBF kernel as a reasonable first choice (Hsu *et al.* 2003).

4) Defuzzification

This is a fuzzification reverse process. Once SVM finishes the training process, output numbers are expressed in terms of a fuzzy set. Output numbers are then converted into crisp numbers. Employing fmGA, the model generates a random defuzzification parameter (dfp) substring and encodes it for conversion into SVM fuzzy output. This evolutionary approach is simple and straightforward, as it uses dfp as a common denominator for SVM output.

5) fmGA parameter search

fmGA is utilized to search simultaneously the fittest shapes for MFs, dfp , penalty parameter (C), and RBF kernel parameter (γ). In fmGA, the chromosome that represents the possible solution for searched parameters consists of four parts: the MFs substring, dfp substring, penalty parameter substring, and kernel parameter substring (Cheng, Roy 2010). The chromosome is encoded into a binary string. Chromosomes consist of two segments: FL and SVM. Figure 5 illustrates the chromosome

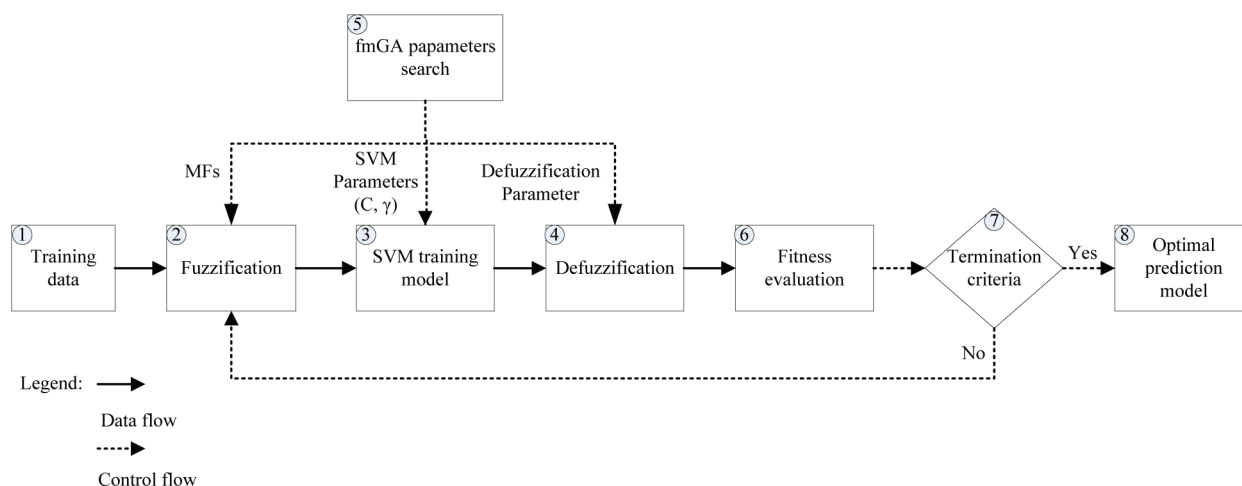


Fig. 2. Architecture of EFSIM

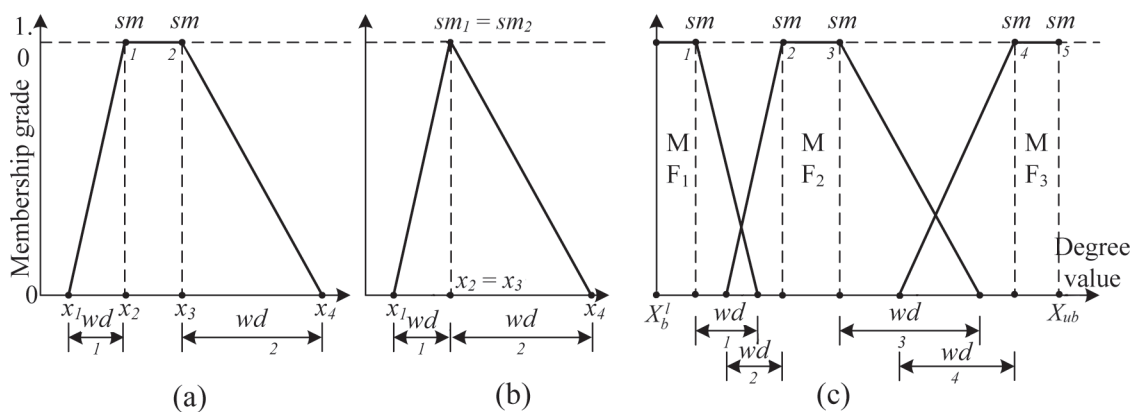


Fig. 3. Membership function: trapezoidal (a), triangular (b), complete MF set (c) (Ko 2002)

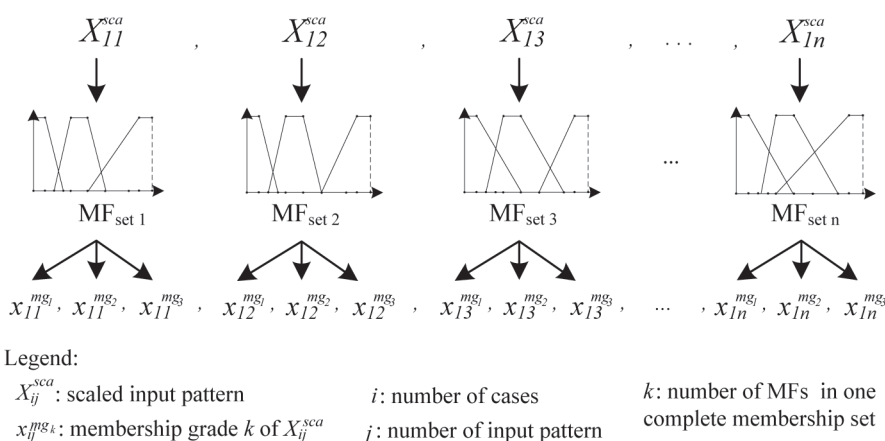
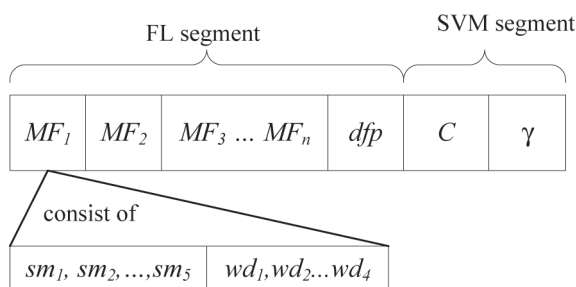


Fig. 4. Fuzzification process



Legend:

- MF_i : membership function i -th
- dfp : defuzzification parameter
- C : penalty parameter
- γ : RBF kernel parameter
- sm_j : summit point j -th of MF_i
- wd_j : width j -th of MF_i

Fig. 5. EFSIM chromosome structure

structure. Table 1 summarizes the parameter settings and number of bits required for the chromosome design. For more details about fmGA parameter search, readers are referred to the previous work of Cheng and Wu (2009) and Cheng and Roy (2010).

Table 1. Summary of EFSIM parameter settings

Parameter	Upper bound	Lower bound	Number of bits
MF set	–	–	27 ^a
C	200	0	5
γ	1	0.0001	10
dfp	1	0.5	9

^a Number of bits required for one complete MF set.

6) Fitness evaluation

A fitness function, a function designed to measure model accuracy and good generalization properties (Ko 2002), is now developed to evaluate fitness value. This function describes the fittest shape of MFs, optimized dfp number, and SVM parameters. The fitness function consists of parameters to calculate accuracy and model complexity, as expressed in Eqn (1):

$$f^{fi} = \frac{1}{c^{aw} \times s^{er} + c^{cw} \times mc}, \quad (1)$$

where c^{aw} represents the accuracy weighting coefficient; s^{er} represents the prediction error between actual output

and desired output; c^{cw} represents the complexity weighting coefficient; and mc represents model complexity, which can be quantified by counting the number of support vectors.

7) Termination criteria

The process terminates when the termination criterion is satisfied. While still unsatisfied, the model will proceed to the next generation. As EFSIM uses fmGA, the termination criterion used in this study was either era number (k) or epoch number (e).

8) Optimal prediction model

The loop stops when the termination criterion is fulfilled. This condition means that the prediction model has identified the input/output mapping relationship with optimal C , γ , and dfp parameters and is ready to predict new facts.

3. Productivity loss prediction using EFSIM

3.1. Historical data

Data used in this research were drawn from 102 cases cited in Assem's thesis (2000) and covered 33 cases from Assem's (2000) investigation of the adverse effects of change orders and 69 cases from Leonard's (1988) investigation of change order impacts. A summary of cases is shown in Table 2.

3.2. Data preprocessing

Data preprocessing is an important stage in data analysis that resolves the "unclean" nature of real-world data (Zhang *et al.* 2003). Several data preprocessing techniques such as data cleaning, attributes reduction, and data transformation were employed in this study. A systematic

Table 2. Summary cases

Parameter	Min	Max	Mean
Work type	(Architectural, Civil, Electrical, Mechanical)		
Change orders number	7	2150	106.784
Frequency of change orders a	0.389	195.454	8.614
Average size of change orders b	3.214	1595.238	161.964
Change orders hours	100	83000	10528.688
Change orders hours ratio to the planned hours	0.009	2.660	0.323
Change orders hours ratio to the actual hours	0.006	0.573	0.198
Type of impact	(1, 2, or 3) ^c		

^a frequency of change order: ratio change orders number to the actual duration in months;

^b average size of change orders: ratio of change orders hours to the number of change orders;

^c 1 represents change-order causes of productivity loss only; 2 or 3 represents change order plus 1 or 2 additional major causes of productivity loss.

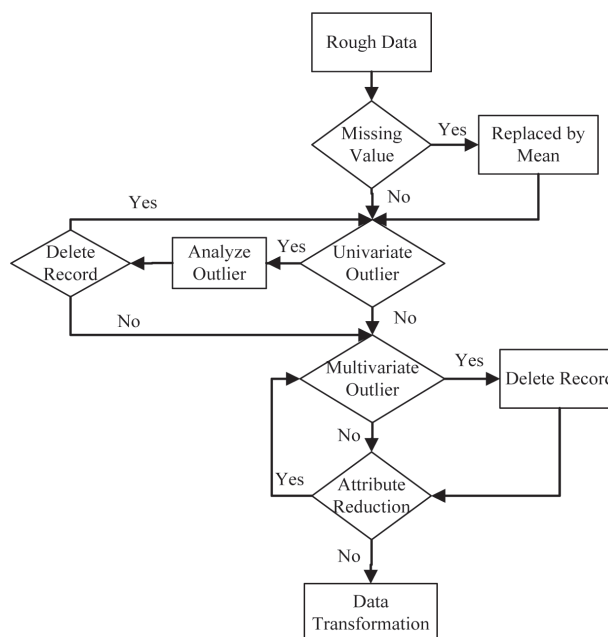


Fig. 6. Flowchart of data preprocessing

data-preprocessing flowchart (Fig. 6) was developed to obtain better prediction results. Historical data was analyzed using this flowchart to obtain training data.

Data cleaning can be applied to fill in missing values and remove noisy data (univariate and multivariate outliers) (Han, Kamber 2007; Shahi *et al.* 2009). Attributes reduction was applied to reduce the dimensionality of data attributes and help reduce computational time by eliminating unnecessary attributes. Two methods, correlation analysis (CA) and principal component analysis (PCA), were employed to compare attributes reduction method results. CA is the simplest way to assess input-output relationships. PCA is used to identify strong predictor variables in a dataset. Data transformation techniques such as normalization, where attribute data are scaled to fall within a small specified range, may improve the accuracy and the efficiency of mining algorithms involving distance measurements (Han, Kamber 2007; Shahi *et al.* 2009). The function used to normalize data in this study is shown in Eqn (2):

$$x_{norm} = \frac{(x_i - x_{min})}{(x_{max} - x_{min})}, \quad (2)$$

where: x_{norm} is the normalized data; x_i is the observed data; x_{min} is the minimum data; and x_{max} is the maximum data.

3.3. Final data

A total of 96 records were used to train the prediction model. Two kinds of analyses were done to compare performance of attribute reduction methods. Analysis 1 used CA to reduce attributes and Analysis 2 used PCA to do the same. As shown in Table 3, CA and PCA identified 6 and 4 attributes, respectively, as significant factors. Both analyses transformed the data into values ranging

Table 3. Summary of training data

	Analysis 1 (CA)	Analysis 2 (PCA)
Significant attributes	Work type	Work type
	Frequency of change orders	Type of impact
	Average size of change orders	Frequency of change orders
	Change order hours	Time related
	Change order hours ratio to the planned hours	Relative size of change orders
	Change order hours ratio to the actual hours	

between 0 and 1. Table 4 shows example input and output data from Analysis 1.

3.4. Cross-validation

Cross-validation is a statistical technique that assesses how accurately a predictive model will perform by dividing data into two segments, of which one is used to learn or train the model and the other is used to test or validate the model. 10-fold cross-validation resulted in the best performance in the simulation (Borra, Di Ciaccio 2010). In 10-fold cross-validation, original data was randomly portioned into 10 equally (or approximately equally) sized segments. Consequently, 10 independent performance estimations of training and testing were performed such that, within estimation, a different fold of the data was alternately used for testing while the remaining 9 folds

were used for training (Fig. 7). We then calculated the average of each performance measure to obtain cross-validation accuracy.

3.5. Performance measures

This research used the following four performance measures to evaluate EFSIM:

1. Root mean square error

Root mean square error (RMSE) is the square root of the average squared distance of predicted values by the model and the observed values. RMSE can be used to calculate the variation of errors in a prediction model and is very useful when large errors are undesirable. The RMSE is expressed using the following equation:

$$RMSE = \sqrt{\frac{1}{n} \sum_{j=1}^n (y_j - \hat{y}_j)^2}, \quad (3)$$

where y_j is the actual value; \hat{y}_j is the predicted value; and n is the number of data samples.

2. Mean absolute error

Mean absolute error (MAE) is the average absolute value of the residual (error). MAE is a quantity used to measure how close forecasts or predictions are to eventual outcomes. The MAE is expressed using the following equation:

$$MAE = \frac{1}{n} \sum_{j=1}^n |y_j - \hat{y}_j|. \quad (4)$$

Table 4. Input and output data for Analysis 1

No.	Actual % productivity loss	Work type	Frequency	Average size	Change order hours	Change order hours/planned hours	Change order hours/actual hours
1	23.7	1	1.54545	33.41176	568	0.08686	0.06494
2	24.5	1	1.36000	165.02941	5611	0.11567	0.08492
3	31.8	1	1.20000	69.75000	837	0.13368	0.08745
4	11	3	9.75000	25.35897	989	0.08074	0.07122
5	27	3	0.47619	138.80000	1388	0.68850	0.42382
6	19	3	1.81818	71.15625	5692.5	0.12291	0.09728
...
41	18.4	2	12.04762	129.64427	32800	0.41362	0.33745
42	22.81	2	21.11111	113.15789	21500	0.48864	0.37719
43	14.18	2	0.80000	191.66667	2300	0.10000	0.08582
44	17.75	2	0.73333	272.72727	3000	0.05769	0.04745
45	19.03	2	0.71429	190.00000	1900	0.13333	0.10795
46	21.05	2	6.25000	189.33333	14200	0.13524	0.10677
...
92	38.71	4	34.00000	135.29412	23000	0.68047	0.39792
93	44.31	4	4.64286	61.53846	4000	0.66116	0.53121
94	48.95	4	6.47059	156.36364	17200	1.01176	0.51652
95	35.09	4	2.42857	63.23529	4300	0.11406	0.07713
96	45.34	4	2.92857	336.58537	13800	0.31364	0.17143

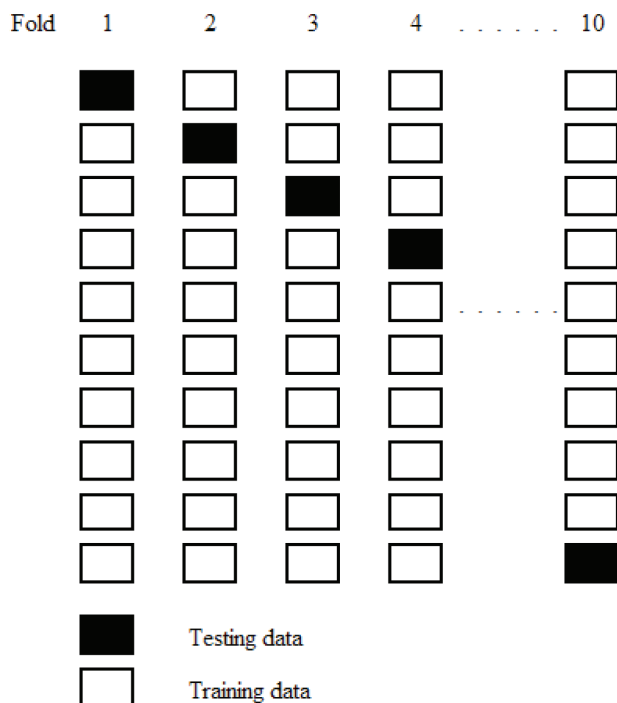


Fig. 7. 10-fold cross-validation

3. Mean absolute percentage error

Mean absolute percentage error (MAPE) is a measurement of prediction accuracy. It represents prediction percentage error. Small denominators can cause problems in MAPE value because small denominators generate large MAPE values that impact overall value. The MAPE is expressed using the following equation:

$$MAPE = \frac{1}{n} \sum_{j=1}^n \left| \frac{y_j - \hat{y}_j}{y_j} \right| \times 100\%. \quad (5)$$

4. Training time

Training time represents time taken by the proposed model to train data and obtain the optimum prediction model.

To obtain an overall comparison, a normalized reference index (RI) (Chou *et al.* 2011) was created by combining the four performance measures (RMSE, MAE, and MAPE, and training time). The RI was obtained by calculating the average of each normalized performance measure. Performance measure values ranged from 1 (best) to 0 (worst). The equation of RI can be described as follows:

$$RI = \frac{\sum_{i=1}^n \frac{x_i^{\max} - x_i}{x_i^{\max} - x_i^{\min}}}{n}, \quad (6)$$

where: x_i is the measurement indicator (RMSE, MAPE, MAE, training time); x_i^{\max} is the maximum value of the indicator among all prediction methods; x_i^{\min} is the minimum value of the indicator among all prediction methods; n is the number of measurement indicators.

4. Results and discussion

4.1. Model performance

A systematic methodology was previously established to calculate prediction performance. Database records contain several attributes related to productivity loss caused by change orders. Data preprocessing was done to improve data quality. In the data preprocessing stage, two kinds of analysis relate to attributes reduction methods. We performed Analyses 1 and 2 to compare the performance of each. Analysis 1 employed the CA method and Analysis 2 employed the PCA method, with each implementing training and testing processes in accordance with 10-fold cross-validation.

In the testing process, each fold validates the performance of the proposed model. A comparison with other methods such as ESIM (Cheng, Wu 2009), ANN, and SVM was developed to show EFSIM as more accurate and reliable. Several performance measures (RMSE, MAE, MAPE, and training time) were employed to evaluate the proposed model.

Table 5 summarizes our comparison of Analyses 1 and 2 results. Optimal EFSIM parameter of Analysis 1 is $C = 31$ and $\gamma = 0.574$, founded in fold 3. Meanwhile, $C = 31$ and $\gamma = 0.566$ of fold 9 is regarded as the optimal EFSIM parameter in Analysis 2. In Analysis 1 earned better results in all EFSIM and ESIM performance measures except for MAPE. On the other hand, Analysis 2 obtained better results in SVM and ANN. Analysis 1 had a higher EFSIM training time than Analysis 2 because of its larger number of attributes.

However, the difference between the two analyses in terms of the MAPE performance measure was not significant. Table 5 shows EFSIM results found both Analysis 1 and Analysis 2 to be significantly more accurate than other AI techniques. Longer computation time is required for the EFSIM model due to the FL paradigm. The more attributes in a training process, the more training time is needed to obtain the prediction model.

Table 6 shows average Analysis 1 and 2 performance values. The best model with the smallest RMSE value is EFSIM (2.98%). Moreover, Table 6 shows a

Table 5. Performance of predictive techniques for Analyses 1 and 2

Analysis	Predictive technique	RMSE (%)	MAE (%)	MAPE (%)	Average training time (s)
Analysis 1	EFSIM	2.83	2.25	30.44	7065.73
	ESIM	6.57	5.62	55.40	231.3
	ANN	9.24	8.00	76.43	1
	SVM	9.12	7.78	60.70	1
Analysis 2	EFSIM	3.13	2.51	23.85	5146.83
	ESIM	7.12	6.07	48.12	138.2
	ANN	8.79	7.55	72.82	1
	SVM	8.61	7.23	65.16	1

direct relationship between RMSE and MAE. MAE values are always smaller than RMSE values. EFSIM obtains the smallest MAE value (2.38 %) of all models. MAPE values are inadequate in all models due to the series of small denominator values. MAPE values are consistent with other performance measures (RMSE and MAE). The best model is obtained by EFSIM (27.15%).

Table 6. Average performance values of the predictive techniques

Predictive technique	RMSE (%)	MAE (%)	MAPE (%)	Average training time (s)	RI
EFSIM	2.98	2.38	27.15	6106.28	0.7500
ESIM	6.84	5.84	51.76	184.75	0.5423
ANN	9.01	7.77	74.62	1	0.2500
SVM	8.86	7.70	62.93	1	0.3303

In terms of training time, both ANN and SVM train data relatively quickly, while ESIM requires more time and EFSIM requires the most time. This is due to the FL paradigm that requires more computational time during the training process and to the status of ESIM and EFSIM as hybrid AI techniques. Longer computational time is a trade off necessary to obtain greater accuracy. Figure 8 illustrates the performance described in Table 6.

The normalized RI obtained a general measurement by combining all performance measures. Based on RI values, EFSIM is the best model, followed in order by ESIM, SVM, and ANN. Although EFSIM requires the longest training time, it consistently obtains the best results on most other performance measures. Thus, by fusing FL, SVM, and fmGA, EFSIM predicts change-order-related productivity loss more accurately than the other models considered.

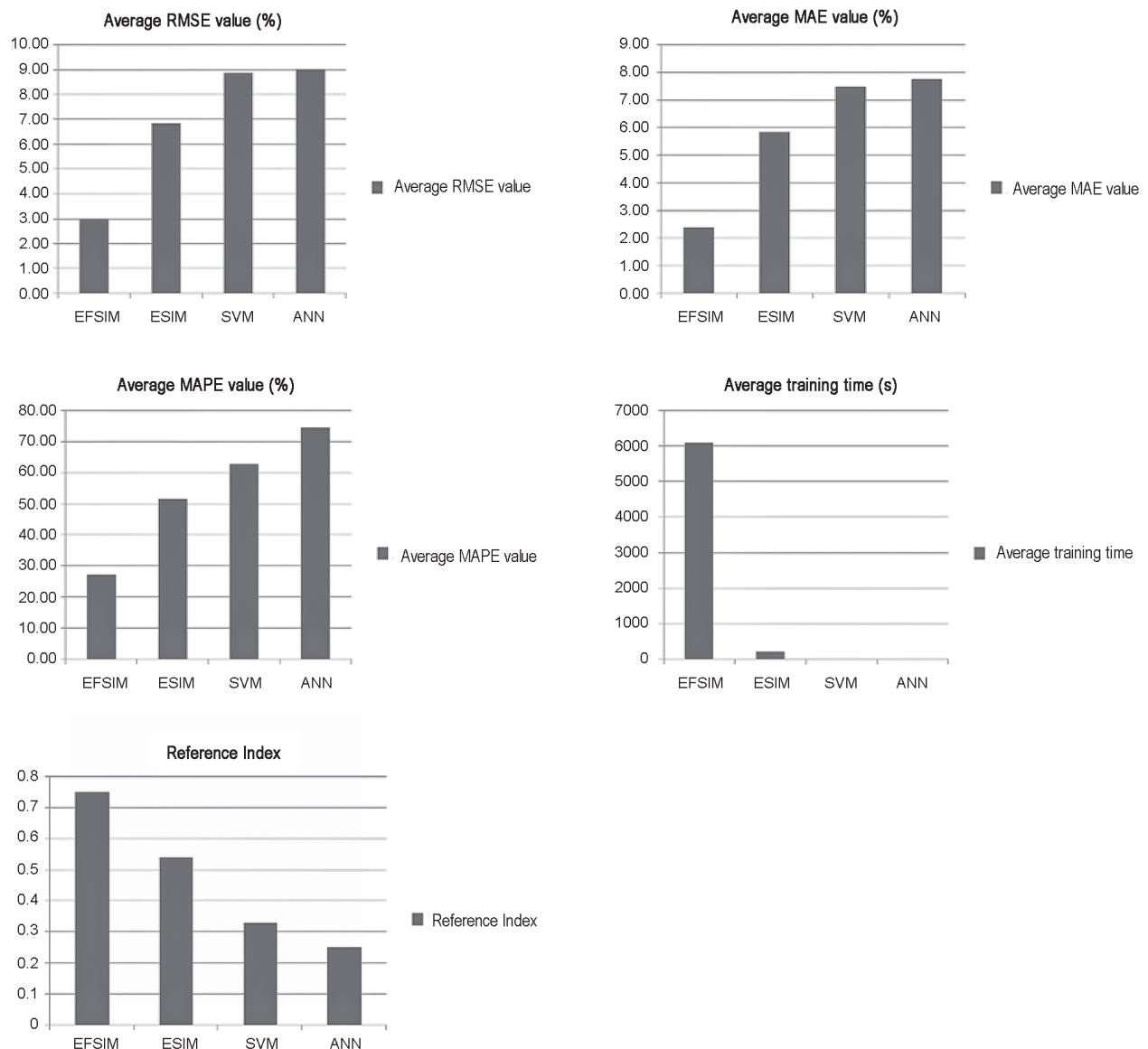


Fig. 8. Average result for performance measures with 10-fold cross-validation

4.2. Validation with previous studies

We compared the performance of EFSIM against other methods such as the general regression model (Moselhi *et al.* 1991), electrical regression model (Hanna *et al.* 1999b), and neural network model (Moselhi *et al.* 2005). Our validation used a dataset of 33 records from Assem (2000) as training data and change-order data from the literature (Bruggink 1997) as testing data. Attributes used in this dataset were (1) timing impact of change orders (TP_i); (2) work type; and (3) type of impact (TI), which could be either change orders only or change orders plus 1 or 2 additional causes of productivity related impact. TP_i represents the ratio of actual change order hours to planned hours in each of the five construction periods ($i = 1$ to 5) as shown in following equation:

$$TP_i = \frac{HCO_i}{PH_i}, \quad (7)$$

where: TP_i is the timing impact of change orders in period i ; HCO_i is the actual change order hours during period i ; PH_i is the planned hours during period i ; and i is the period when change orders occur, where the value of i can range from 1 to 5. This data set used NECA (1983) distribution for electrical work and the trapezoidal distribution of Bent and Thuman (1994) for other types of work to distribute the planned hours in each of the five construction periods.

The cases were analyzed using EFSIM and results were compared with previous studies found in Moselhi *et al.* (2005). Table 7 shows comparisons among all methods. Results demonstrate that the EFSIM model proposed in this study outperforms all other models in terms of estimating the impact of change orders on productivity. EFSIM obtained the smallest average error (7.90%) and lowest average absolute error of any model. This shows that EFSIM improves prediction model accuracy and reliability.

Conclusions

This research proposes a hybrid AI technique, EFSIM, to predict productivity loss caused by change orders. The EFSIM, developed by fusing complementary AI techniques including FL, SVM, and fmGA, achieves prediction results superior to traditional techniques.

The developed model reduces the level of human intervention necessary to elicit MF shapes from questionnaire surveys and expert judgment; it also successfully identifies optimum penalty and kernel parameters. EFSIM is easy to apply and convenient for new users, and may be used by professionals without AI domain knowledge.

Test results show that EFSIM prediction performance is superior to other prediction methods such as ESIM, ANN, and SVM. Although EFSIM requires

Table 7. Actual versus estimated productivity loss (Moselhi *et al.* 2005)

Case No. (j)	Actual productivity loss (h)	Moselhi <i>et al.</i> (1991)		Hanna <i>et al.</i> (1999)		Moselhi <i>et al.</i> (2005)		Proposed model (EFSIM)	
		Estimated productivity loss (h)	Estimating error ^b (%)	Estimated productivity loss (h)	Estimating error ^b (%)	Estimated productivity loss (h)	Estimating error ^b (%)	Estimated productivity loss (h)	Estimating error ^b (%)
1	801	731	8.74	650	18.85	940	-17.35	822	-2.68
2	1,073	1,050a	2.14	713	33.55	1,245a	-16.03	1,113	-3.75
3	1,593	884	44.51	1,467	7.91	1,240	22.16	1,749	-9.78
4	1,741	2,070	-18.90	2,041	-17.23	2,674	-53.59	1,799	-3.32
5	2,660	1,744	34.44	2,966	-11.50	2,699	-1.47	2,550	4.14
6	5,139	N/A	N/A	2,485	51.64	5,078a	1.19	4,912	4.42
7	13,713	11,469	16.36	10,644	22.38	15,169	-10.62	13,822	-0.79
8	10,575	5,073	52.03	2,438	76.95	7,077	33.08	8,350	21.04
Average error ^c (%)		30.45		40.50		17.83		7.90	
Average absolute error ^d (%)		25.30		30.00		19.44		6.24	

Notes: N/A = not applicable (i.e. off model range);

^aTwo additional types of impact are considered in the estimate (i.e. TI = 3);

^b Estimating error_j = $\frac{(Actual\ loss_j - Estimated\ loss_j)}{Actual\ loss_j}$, where j represents case 1 to 8;

^c Average error = $\frac{\sum_{j=1}^8 |Actual\ loss_j - Estimated\ loss_j|}{\sum_{j=1}^8 Actual\ loss_j}$;

^d Average absolute error = $\frac{\sum_{j=1}^8 |Estimated\ loss_j|}{8}$.

more computation time, EFSIM prediction results are significantly more accurate than competing methods. Validation results with previous studies in predicting the impact of change orders on productivity loss also indicate that EFSIM provides the smallest margin among competing methods. These results exhibit great potential for EFSIM as a tool to accurately predict change-order-related productivity loss. Moreover, the developed model manages to help the project manager to make an adjustment related to productivity loss caused by change order. Furthermore, this research paper succeed in demonstrating a hybrid Artificial Intelligence paradigm, FL-SVM-fmGA, for facilitating the decision making in the construction industry.

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