Forecasting construction cost escalation

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Escalation can account for a substantial part of construction costs. Therefore forecasts of the amount of escalation are required for budgetary and bidding purposes. This paper examines methods for forecasting construction escalation using statistical time series methods. Time series of construction cost indices are used as a proxy of construction cost escalation. The application of time series methods, their limitations, and their effect on the risk of cost escalation are demonstrated and evaluated. The analytical methods available are only useful in forecasting for short construction projects in stable conditions. This is because none of the methods can forecast escalation caused by unpredictable occurrences such as outbreak of war or certain government action. Construction cost escalation remains a risk to be borne by either the contractor or the owner, or both, depending on the terms of the contract; any logical approach to minimize the risk is worthwhile.

Key words: construction cost escalation, cost indices, time series forecasting, exponential smoothing. Box–Jenkins methods, dynamic regression, Statistics Canada.

Une bonne partie des coûts de construction est attribuable à l'escalade de ceux-ci. Par conséquent, la prévision de l'ampleur de cette escalade est nécessaire à des fins budgétaires ou d'appel d'offres. Cet article examine des méthodes de prévision de l'escalade des coûts de construction à l'aide de méthodes chronologiques statistiques. Les séries chronologiques des indices des coûts de construction sont utilisées comme substitut à l'escalade des coûts de construction. L'application des méthodes chronologiques, leurs limites ainsi que leur effet sur le risque d'escalade sont traités et évalués. Les méthodes analytiques existantes ne sont utiles que dans le cas de projets de construction de courte durée dans des conditions stables. Cela s'explique par le fait qu'aucune méthode ne peut prévoir l'escalade causée par des événements imprévisibles comme la guerre ou certaines décisions gouvernementales. L'escalade des coûts de construction est un risque qui doit être assumé par l'entrepreneur, le propriétaire ou les deux, selon les modalités du contrat; toute méthode logique en vue de minimiser ce risque est souhaitable.

Mots clés : escalade des coûts de construction, indice des coûts, prévision chronologique, lissage exponentiel, méthode Box–Jenkins, régression dynamique, Statistique Canada.

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Introduction

Websters dictionary defines the term escalate as "to gradually increase ... to raise and go up ...." Escalation in construction costs is the increase in the costs of any construction elements required for original contract works occurring during construction. The amount included in any construction cost estimate or construction cost breakdown to account for escalation in construction costs is an important component of total construction costs.

The financial success of construction projects can be uncertain and at risk because of the possibility of drastically changing escalation rates during construction. At the beginning of any given project, there can be a number of different possible future escalation rates. The use of an erroneous escalation rate when estimating construction costs can have adverse effects on economic decision making. As an example, Fig. 1 illustrates the impact of changing escalation rates on a hypothetical construction project with an unescalated cost of \$30 000 000. The cost flow profile of the project is expected to form the predetermined S-shaped curves shown in Fig. 1 (Tham 1980). The project is to be constructed over a period of 2 years starting 3 months from the date of tender. Figure 1 indicates that if an annual escalation rate of 10% is experienced during construction instead of a prior estimated rate of 3%, then an additional \$3 000 000 expenditure would be incurred. The party who bears the escalation risk can be devastated by it.

This problem could be minimized or eliminated by inclusion of a mutually agreed "escalation clause" in the contract documents. This is the practice in many offshore and international construction projects, but unfortunately is not common in North America.

It is therefore necessary to forecast the amount in monetary terms of escalation costs that will be incurred during the execution of a construction project for budgetary and bidding purposes. To forecast the amount of cost escalation, one can forecast an applicable escalation rate and apply this rate to the estimated cash flow. Forecasting the applicable escalation rate can be achieved by forecasting the future value of an appropriate cost index. Cost indices are indicators of the amount of cost escalation. Indices describe how the cost of a particular construction unit changes with time. Cost indices are time series because they are generally produced at regular time intervals. Methods for analyzing

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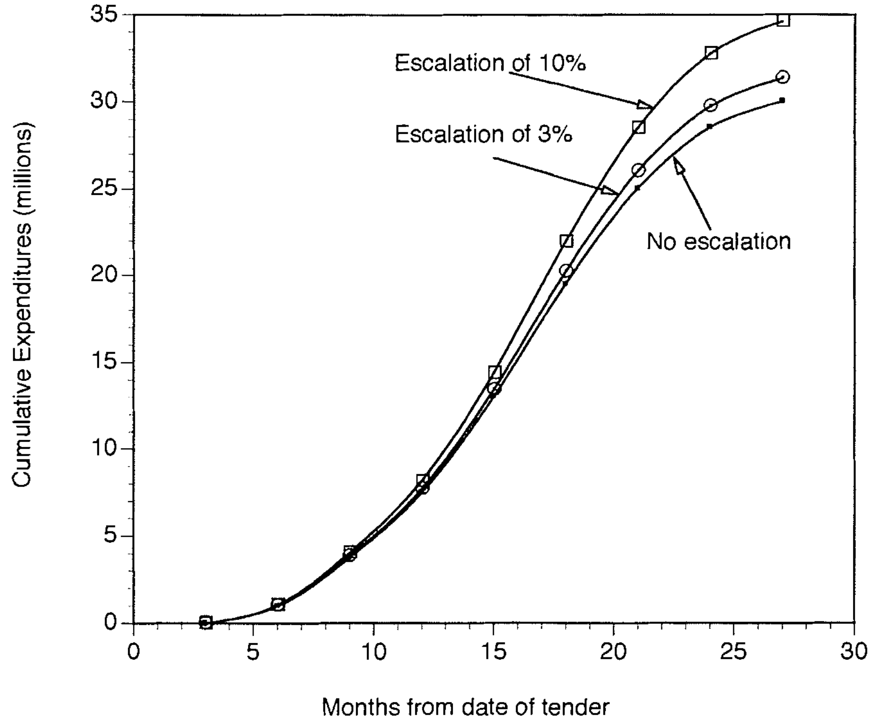

FIG. 1. Effect of various escalation rates on construction costs.

and forecasting time series can thus be used to forecast the rate of escalation of a given construction project (Taylor and Bowen 1987).

A number of methods are available for forecasting time series. Many of these methods require a substantial degree of mathematical dexterity and can be time consuming. In the past, the parties to a contract were often advised to hire a consultant to apply these techniques (Stevenson 1984). The current availability of user friendly computer forecasting software packages, such as FORECAST PRO (BFS 1988), has now reduced the amount of mathematical manipulation necessary for a practitioner. The key requirement in applying the various forecasting methods using these packages is the ability to interpret the computer output and to understand the limitations of the techniques used. The growth of computer utilization, even among small- and medium-sized contractors, leads us to believe that the computational techniques will soon be commonplace.

This paper examines the analytical techniques available to forecast the rate of escalation of construction costs by forecasting the values of a typical cost index. The cost index chosen is the "output" index for the prefabricated wood building industry. The technique for development of this index is fully documented in Catalogue 62.007, Construction Price Statistics, published by Statistics Canada. A brief outline of the theory underlying the various forecasting methods applicable to construction cost forecasting is given. Forecasting the values of the typical cost index using FORECAST PRO is used as an example of the application of each of the applicable forecasting methods. From these examples, and from the outline of the underlying theory, the benefits and limitations of each method are discussed and a general strategy for choosing between various methods is given. Finally, the usefulness of the various forecasting methods to the owner and the contractor of a given construction project is evaluated. Particular attention is given to whether or not these methods of forecasting future values of cost indices significantly reduce the risk of financial loss due to cost escalation.

Forecasting methods

Empirical studies have shown that there is no single best forecasting method applicable to all situations (Goodrich 1989). To decide on which forecasting method is best for a given situation, it is necessary to critically examine the available data. This and an understanding of the fundamentals of the various forecasting procedures are prerequisites for obtaining realistic forecasts.

Forecasting methods can be classified into three categories: subjective methods, univariate methods, and multivariate methods (Chatfield 1975).

Subjective methods

Subjective methods are based on human judgement of the various factors that may have an impact on the required forecast (Firth 1977). These methods may range from intuitive and subjective decision made by the decision makers (Nelson 1973) to highly refined rating schemes that turn qualitative information into quantitative estimates.

Subjective forecasts are based on judgement, intuition, commercial knowledge, and any other information the forecaster deems relevant. A wide range of factors may be taken into account, depending on the knowledge and the experience of the forecaster. This makes subjective forecasts unique to the individual forecaster and therefore not reproducible.

Subjective methods and intuitive estimates are widely used in construction estimating and are most useful when there are insufficient historical data on the appropriate cost index. Mathematical methods cannot generally be used to make long range forecasts, that is, forecasts of duration over 2 years (Firth 1977). For such forecasts, subjective methods have to be used.

The forecaster's intuition may often prove to be more reliable than any mathematical method (Chatfield 1975). As such, subjective methods can be used as a basis of judging the accuracy of other methods by comparing the forecasts obtained using mathematical methods with the forecaster's intuitive estimates. Since subjective forecasts are not reproducible, they will not be analyzed and compared to other methods discussed herein.

Univariate methods

Univariate methods are based on fitting a model to the historical data of a given time series and extrapolating to obtain forecasts. The reasons for using univariate time series methods are provided in Taylor and Bowen (1987). There are many univariate methods available. They include extrapolation of trend curves, averaging, stepwise autoregression, and adaptative filtering. Some of these simpler techniques have been examined by Taylor and Bowen (1987) for building price-level forecasting. Extrapolation of trend is inherent in all the other univariate methods. Exponential smoothing encompasses averaging and is comparable to adaptive filtering (Sullivan and Claycombe 1977). Stepwise autoregression can be regarded as some form of the Box–Jenkins method (Granger and Newbold 1977). For these reasons, an examination of the use of the Box–Jenkins method and exponential smoothing to forecast construction cost indices should reveal the benefits and limitations of using univariate methods to forecast construction cost escalation.

Exponential smoothing

The most commonly used exponential smoothing methods are the Holt–Winters family of models (Goodrich 1989). These model time series use up to three components, representing level, trend, and seasonal influences. Recursive equations are used to obtain smoothed values for the model components. Each smoothed value of any model component is a weighted average of current and past data with the weights decreasing exponentially. The Holt–Winters family of exponential smoothing models can be classified into three classes, namely, simple exponential smoothing, Holt's two-parameter smoothing, and Winters' three-parameter smoothing (Goodrich and Stellwagen 1987).

Simple exponential smoothing uses an equation to model the level of the series of the form:

$$[1] \quad L_t = \alpha Y_t + \alpha(1-\alpha)Y_{t-1} + \alpha(1-\alpha)^2 Y_{t-2} + \ldots$$

where α is the level smoothing parameter, Y_t is the observed value of the time series at time t, and L_t is the smoothed level at time t. This equation reduces to the recursive form:

$$[2] \quad L_t = \alpha Y_t + (1-\alpha)L_{t-1}$$

The forecasting equation is

$$[3] \quad \hat{Y}_{t(m)} = L_t$$

where $\hat{Y}_{t(m)}$ is the forecast for lead time m from time t; and m is the lead time of interest, usually in months.

Holt's two-parameter smoothing uses two equations to model level and trend. These are given in their recursive form by

$$[4] \quad L_t = \alpha Y_t + (1-\alpha)(L_{t-1} + T_{t-1})$$

$$[5] \quad T_t = \gamma(L_t - L_{t-1}) + (1-\gamma)T_{t-1}$$

where T_t is the smoothed trend at time t, γ is the trend smoothing parameter, and other parameters are as previously defined. The forecasting equation is

$$[6] \quad \hat{Y}_{t(m)} = L_t + mT_t$$

The multiplicative Winters three-parameter smoothing involves three smoothing parameters for level, trend, and seasonal effects. The smoothing equations are of the form:

$$[7] \quad L_t = \alpha\frac{Y_t}{S_{t-p}} + (1-\alpha)(L_{t-1} + T_{t-1})$$

$$[8] \quad T_t = \gamma[L_t - L_{t-1} + (1-\gamma)T_{t-1}]$$

$$[9] \quad S_t = \delta\frac{Y_t}{L_t} + (1-\delta)S_{t-p}$$

where S_t is the smoothed seasonal index at time t, p is the number of periods in the seasonal cycle, and δ is the seasonal index smoothing parameter; other parameters are as previously defined. The forecasting equation is of the form:

$$[10] \quad \hat{Y}_{t(m)} = (L_t + mT_t)\hat{S}_{t(m)}$$

where $\hat{S}_{t(m)}$ is the last available smoothed seasonal index for time $t + m$.

Simple exponential smoothing is appropriate for data that fluctuate around a constant or have a slowly changing level and neither are seasonal nor have any trend. The use of the Holt's two-parameter model is appropriate for data that fluctuate about a level that changes with some nearly constant linear trend. The Winters' three-parameter model is used for data with trend and seasonal effects. The relevant exponential smoothing equations can be adjusted to represent data that have a damped exponential rather than linear trend (Goodrich 1989).

All exponential smoothing equations give more weight to more recent values of data. The larger the values of the smoothing parameters the more emphasis on recent observations and less on the past. This is intuitively appealing for forecasting applications.

The smoothing parameters are normally obtained by either using iterative least squares or a grid search for the parameters that give the minimum squared error over the historical data. This calculation process requires a great number of computations which are normally incorporated into a computer program.

Exponential smoothing models are robust in that they are insensitive to changes in the data statistical structure (Goodrich 1989). No assumptions about the statistical distribution of data are made in exponential smoothing, and there is therefore no need to analyze the diagnostic statistics given with most computer programs.

One of the main advantages of using exponential smoothing is that once the smoothing parameters have been estimated, only the previous forecast and the most recent observation have to be stored or are necessary to make a new forecast. This makes the calculation of a new forecast computationally very convenient.

Box–Jenkins method

The Box–Jenkins method models time series by making strong and explicit distributional assumptions about the underlying data generating process (Box and Jenkins 1976). The method uses a combination of autoregressive (AR), integration (I), and moving average (MA) operations in the general autoregressive integrated moving average (ARIMA) model to represent the correlational structure of a univariate time series.

An autoregressive operation of order p develops a forecast based on a linear weighted sum of previous data represented by

$$[11] \quad \hat{Y}_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \ldots + \phi_p Y_{t-p} + e_t$$

where $\hat{Y}_t$ is the forecasted value of the series at time t, Y_{t-i} is the observed value of time series at time $t - i$, ϕ_i is the weighting coefficient of the ith previous period, and e_t is the error term at time t. The coefficients are found by minimizing the sum of squared errors usually using a nonlinear regression routine.

A moving average operation of order q develops a forecast which is a function of the previous forecast errors using an equation of the form:

$$[12] \quad \hat{Y}_t = e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \ldots - \theta_q e_{t-q}$$

where θ_i is the weighting coefficient for the ith previous period, and the other terms are as previously defined.

The autoregressive and moving average operations can only be applied to stationary time series. That is, they can only be applied to data that have constant mean and standard deviation with time. If a time series is non-stationary, it has to be transformed to a stationary series by a differencing operation before the AR and MA operations can be performed. Forecast values have to be transformed back to the original non-stationary state by the integration (I) operation.

A three-step procedure of identification, estimation, and diagnostic checking was originally proposed by Box and Jenkins (1976) to select a model from the general class of ARIMA models. This iterative process is depicted in Fig. 2. The identification process is deciding the best ARIMA (p, d, q) model to fit the data. This means identifying the degree of differencing d, the AR order p, and the MA order q. The estimation process involves statistically estimating the model parameters. The diagnostic step involves an examination of the residuals to ensure that the ARIMA modeling assumptions of independence, homoscedasticity, and normality of the residuals are not violated.

To use the Box–Jenkins method, the data must have a strong correlational behavior, and there should be sufficient data to permit reasonably accurate estimates of the parameters. It is suggested that there should be at least 50 observations for good estimates (Box and Jenkins 1976).

The selected Box–Jenkins model, which satisfies the diagnostic checks, will generally fit the historical data well; the parameters estimated describe the data on which they are estimated. These parameters are estimates of unknown parameters. Therefore when the forecasts using the model are compared with future data not used in estimating the model parameters, the fit may not be as good (Abraham and Ledolter 1983).

Multivariate methods

Choice of the type of multivariate method

Multivariate methods forecast a given time series taking into account observations of other variables. Generally, these models use equations developed by regression to represent the relationship between the dependent or endogenous variable and the exogenous or explanatory variables. Multivariate methods are either single-equation models or simultaneous-equation models.

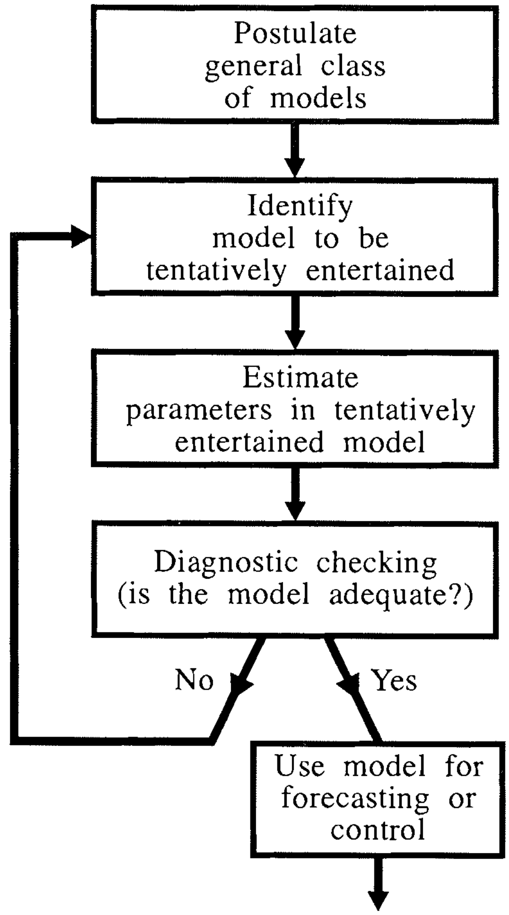

FIG. 2. Stages in the iterative approach to Box–Jenkins model building (from Box and Jenkins 1976).

In single-equation models, the values of the explanatory variables determine the value of the dependent value and the explanatory variables are not influenced by the values of the dependent variable. Simultaneous-equation models take into account the simultaneous dependency between the dependent and explanatory variables.

The construction costs of any given single normal-sized construction project[1] seldom have any significant influence on the market forces which cause changes in cost. As such, single-equation models are most applicable to construction. Therefore in this paper, only single-equation models will be discussed.

Single-equation models can be of either nonlinear or linear specification. A linear specification means that the dependent variable or some transformation of the dependent variable can be expressed as a linear function of the explanatory variable or some transformation of the explanatory variable. A model with a linear specification is the most appropriate to use with construction cost indices because construction cost components are generally additive.

The multivariate method most applicable to construction costs is therefore the single-equation linear regression model.

[1]A normal-sized construction project is defined as a project of between \$2 and \$5 million, with a completion time of less than 3 years (R.S. Means Estimating Guides).

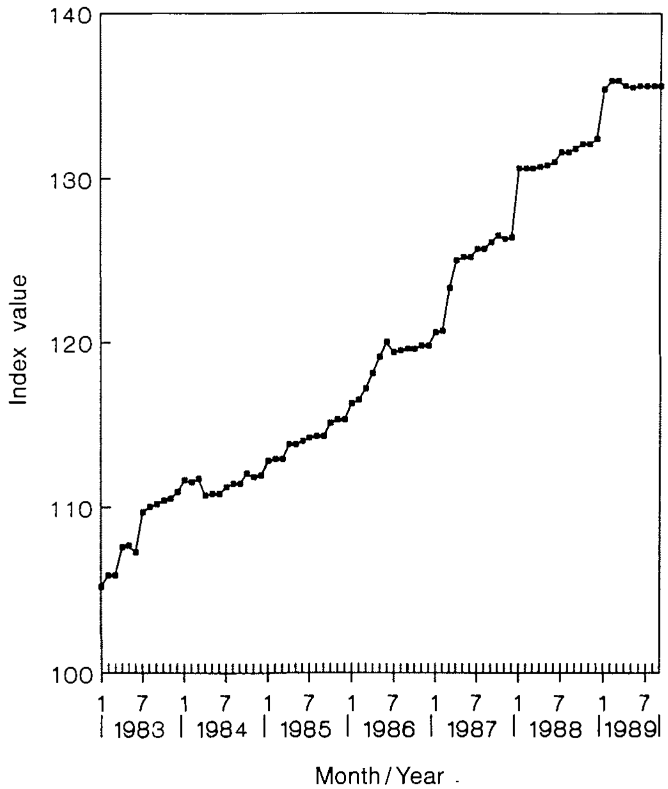

FIG. 3. Plot of the prefabricated wooden building industry index (PWBII).

This regression model is of the form (Pindyck and Rubinfeld 1976):

$$[13] \quad Y_t = \beta_0 + \beta_1 X_{1t} + \beta_2 X_{2t} + \ldots + \beta_i X_{it} + e_t$$

where Y_t is the dependent variable at time t, β_i are the coefficients of X_{it}, X_{it} is the observed value of the ith explanatory variable at time t, and e_t is the error term at time t.

Requirements for the use of regression models

The single-equation linear regression model assumes that the residuals are normally distributed random variables with a mean of zero and a constant variance. It is also required that the explanatory variables are linearly related to the dependent variable (or can be transformed into some linear relation), and that explanatory variables are not collinear, that is, they are not correlated to one another.

Building regression models requires theoretically plausible explanatory variables and sufficient historical data to estimate the model parameters. The models have to be tested through the examination of various statistical diagnostics to ensure that the assumptions on which the models are based hold.

Improvement to the linear regression model

The true relationship between the explanatory variables and the dependent variable is rarely known. Use is therefore made of empirical evidence to develop an approximate relationship. Thus, the explanatory variables may not sufficiently account for the variation in the dependent variable, in which case the use of dynamic regression may improve the model.

The term dynamic regression is adopted to represent multivariate models that combine the time series oriented dynamic features of autoregression and the effects of explanatory variables. In dynamic regression, the dynamic portion of the model, that is, the lagged dependent variables and the autoregressed error terms, must be determined term by term by hypothesis testing. The specification of the explanatory variables must be such that all the necessary explanatory variables are included. It should further be verified that all variables included in the model are statistically significant and that underlying assumptions are not violated.

Dynamic regression is generally used when the data available are long enough or stable enough to support a correlational model and the explanatory variables result in a definite increase in accuracy. The various measures of accuracy will be given in the examples that follow.

Attributes of regression models

Regression models have the advantage of being amenable to the investigation of various "what-if" scenarios. This is appealing because one can tell the influence of a change in an explanatory variable of interest, whether known, foreseen, or probable.

One shortcoming of regression models is that if some crucial explanatory variable has not been varying in the past, it is not possible to include it in the model. Thus the effect of a change in such a variable cannot be assessed.

Problems are encountered in the use of regression models in cases where the values of the explanatory variables for use in obtaining forecasts are not known or required to be forecast. This will occur when there is no lag relationship between the explanatory and dependent variables or when the lag is not sufficient.

Application of forecasting techniques

From the above discussion of the various forecasting methods, it would appear that statistical expertise would be required to apply these methods. Fortunately, available computer software reduces the application process to the interpretation of the computer output and running various trials to obtain the best forecasting model. One such advanced statistical forecasting package is FORECAST PRO (BFS 1988) developed by Business Forecast Systems, Inc., which is used in the examples that follow.

The data used consist of 81 monthly values of the prefabricated wooden building industry index (PWBII) published by Statistics Canada for the period January 1983 to September 1989. This is an output index based on industry selling price for completed structures. The authors feel that this index could not be materially changed by new technology or code changes in the brief period (6 years) considered. A time plot of the data used is shown in Fig. 3. The first 72 observations are initially used for fitting the various models and the last 9 observations are used to compare the forecasts obtained using various methods. From a visual inspection, it can be seen that the series is non-stationary, has an upward trend, and appears to be seasonal in the last half of the data. For such data, both Winters three-parameter exponential smoothing and Box–Jenkins models are applicable. Dynamic regression can also be applied to obtain forecasts if suitable explanatory variables can be found. All these methods will be used and the best method will be chosen from the resulting forecasts. The use of analytical methods to forecast a construction cost index will thus be demonstrated by these examples.

TABLE 1. Computer output for exponential smoothing model

Historical fit of exponential smoothing model	
Dependent variable:	PWBII
R-squared:	0.992
Adjusted R-squared:	0.992
Standard forecast error:	0.710986
F-statistic:	3020.771 (1.000)
Durbin–Watson:	1.784
Ljung–Box:	14.733 (0.744)
Standardized AIC:	0.725630
Standardized BIC:	0.760876
Three-parameter Winters smoothing parameter values	
Level:	0.872749
Trend:	0.048131
Seasonal:	0.484918

Measures of goodness-of-fit and diagnostic statistics

To aid the selection of the best forecasting model, some form of objective statistical criteria are required. The statistical criteria fall into two categories: goodness-of-fit statistics and diagnostic statistics. The goodness-of-fit statistics used in FORECAST PRO are the R-squared, adjusted R-squared, and the standard forecast error. The R-squared statistic indicates the percentage of variance that is explained by the model. An R-squared of 1.00 (100%) would indicate a perfect fit of the model to the historical data. The adjusted R-squared statistic adjusts the R-squared value to reflect the number of parameters used in the model. For univariate time series models, the adjusted R-squared may be the same as the R-squared value. Another indication of model fit is the standard forecast error which is calculated by taking the square root of the average of the squared one-step ahead forecast error. The smaller the standard forecast error the better the fit. A standard forecast error of 0.0 would indicate perfect fit.

The diagnostic statistics used in FORECAST PRO include the F-statistic, Durbin–Watson statistic, Ljung–Box statistic, the Akaike information criterion (AIC), and the Bayesian information criterion (BIC). The F-statistic which is the result of a F-test indicates whether the null hypothesis that the actual model parameters are 0 holds. The percentage value of the test statistic is given in parentheses in the output tables. A percentage value greater than 0.95 would indicate that the actual model parameters are statistically different from 0 at the 95% confidence level. The Durbin–Watson statistic and the Ljung–Box statistic test whether or not the residuals are autocorrelated. Interpretation of the Durbin–Watson and the Ljung–Box statistics requires reference to statistical tables. The Durbin–Watson statistic indicates the acceptance of the null hypothesis that there is no serial correlation in the first lag. A value close to 2 is desirable. While the Durbin–Watson test checks for first-lag autocorrelations, the Ljung–Box test checks for autocorrelations up to the maximum of lag L. The percentage value of the Ljung–Box test statistic is given in parentheses in the output tables. A percentage value less than 0.95 would indicate that the residuals are not correlated. The two tests should be used as complements of each other (Box and Jenkins 1976). The AIC and BIC statistics evaluate how well a given model will perform relative to another. They reward goodness of fit to historical data and penalize model complexity. Based on

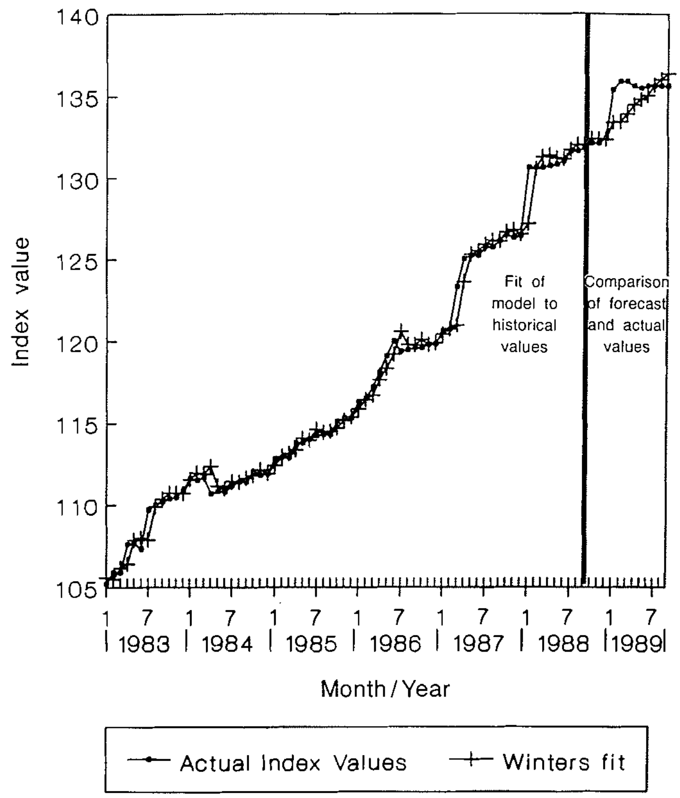

FIG. 4. Forecast comparison: Winters three-parameter exponential smoothing model.

empirical research, the model with the lowest AIC or BIC will generally be the most accurate (Goodrich and Stellwagen 1987).

Exponential smoothing modelling

Winters three-parameter exponential smoothing model was fitted to the data using FORECAST PRO. The results are shown in Table 1. Since no statistical distribution assumptions have been made about the data, it is not necessary to closely scrutinize all the diagnostic statistics produced by the software package.

The smoothing parameter values are obtained by FORECAST PRO using an iterative search method to minimize the squared errors over the historical data. The computerized iterative search employs the simplex method of nonlinear optimization.

Examining the exponential smoothing parameters reveals that the seasonal parameter value is close to 0.5, indicating that the best forecast for the next seasonal effect is half the last seasonal effect and a weighted average of preceeding seasonal effects. The small trend parameter value of 0.05 indicates that the smoothing model has a long memory of trend, and distant trends have an effect on the forecasted trend component. The large value of the level parameter indicates that the model is highly adaptive to the last observed level of the series.

Figure 4 shows the plot of the fitted and forecasted values as compared to the actual figures. Though the model gives a visually good fit to the historical data, it does not forecast the turning point after the last fitted value. A 1-month lag between the fitted and actual values is apparent. This shows the strong influence of the previously observed level.

TABLE 2. Computer output for Box-Jenkins model

Historical fit of Box-Jenkins model	
Dependent variable:	PWBII
R-squared:	0.991
Adjusted R-squared:	0.990
Standard forecast error:	0.763177
F-statistic:	7298.051 (1.000)
Durbin-Watson:	2.066
Ljung-Box:	11.454 (0.510)
Standardized AIC:	0.768608
Standardized BIC:	0.781052
Box-Jenkins model parameters	
B[1]:	0.956028
Simple difference:	2

TABLE 3. Computer output for dynamic regression model: initial trial

Historical fit of dynamic regression model	
Dependent variable:	PWBII
R-squared:	0.965
Adjusted R-squared:	0.962
Standard forecast error:	1.564319
F-statistic:	303.379 (1.000)
Durbin-Watson:	0.557
Ljung-Box:	120.896 (1.000)
Standardized AIC:	1.627879
Standardized BIC:	1.789863

Variable	Coefficient	Standard error	T-statistic	Probability
UWRI	0.361754	0.073729	4.907	1.000
CBMPI	0.351710	0.137117	2.565	0.990
CBLR	0.064706	0.044185	1.464	0.857
S&PMPI	0.000548	0.039341	0.014	0.011
AMI	0.120562	0.129265	0.933	0.649
Constant	7.109199	5.230716	1.359	0.826

Box-Jenkins modelling

Without software packages like FORECAST PRO, considerable skill and judgement is required to identify a suitable Box-Jenkins model to fit the data. The originally proposed method of identification through an examination of autocorrelations and partial autocorrelations requires specialist knowledge (Firth 1977). This specialist knowledge would have to be provided by professional statisticians. FORECAST PRO identifies an appropriate model automatically by the BIC statistic.

The use of these criteria in a computer package relieves the user from the lengthy identification, estimation, and diagnostic steps in the Box-Jenkins methodology. The results of an application to the PWBII are shown in Table 2. Because of the strict distributional assumptions in the Box-Jenkins model, an examination of the diagnostic statistics is required.

The R-squared statistic of 0.991 indicates that 99% of the variation of the index is explained by the model. This shows that the model fits the historical data very well. The F-statistic is highly significant (as indicated by the number 1.000 in parentheses). This rejects the null hypothesis that the actual model parameters are 0.

The Ljung-Box statistic is not significant at both the 95% confidence level and the 99% confidence level. There is therefore no evidence of serial correlation in the first several lags of the residuals.

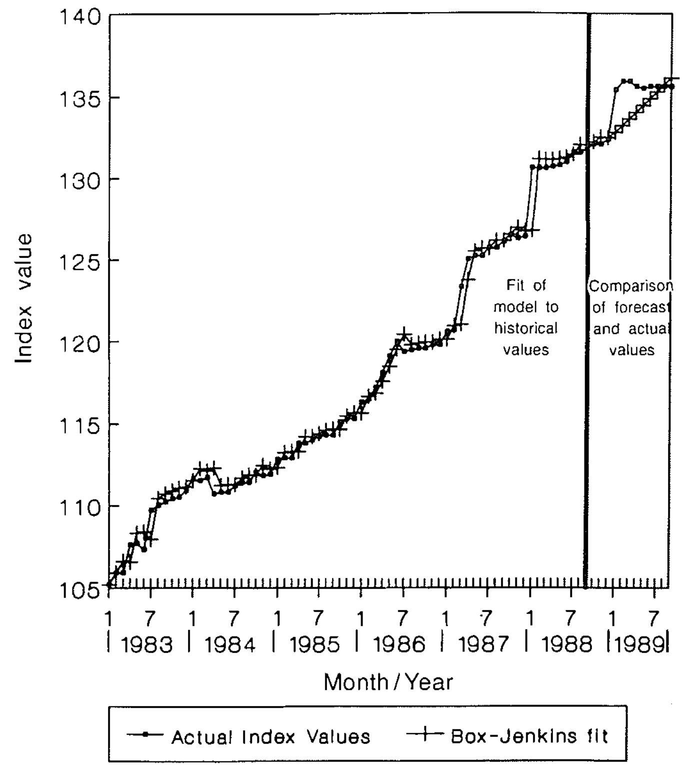

FIG. 5. Forecast comparison: Box-Jenkins model.

The autocorrelations of the residuals were examined using FORECAST PRO and were found to exhibit no systematic pattern. They were also small in magnitude, being less than 2 times the standard error.

A comparison of the AIC and BIC for the Box-Jenkins and exponential smoothening models indicates that on the basis of these criteria the exponential smoothing model is probably more accurate. However, this is not conclusive because the most important criterion in forecasting is how good the forecasted values fit the actual values and not the goodness of fit to historical data.

Figure 5 shows the plot of the actual, fitted, and forecast values. The model gives a visually good fit to the historical data, but does not forecast the turning point in the data right after the last fitted value.

Dynamic regression modelling

Dynamic regression requires additional variables which are correlational significant and theoretically plausible to explain the dependent variable. In this example, various indices published in Statistics Canada Catalogue 62-007 were used as possible explanatory variables to forecast the PWBII. These include the union wage rate index (UWRI), the construction building materials price index (CBMPI), the commercial bank lending rate index (CBLR), the sawmill and planing mill products index (S&PMPI), and the architectural materials index (AMI). These variables were plotted and their plots compared with the PWBII. Possible lag relationships and possible transforms were sought through a visual inspection of the plots.

Table 3 shows the results of the initial trial. The value of the R-squared statistic is quite high (97%). This is probably due to trying to develop a model using a large number of explanatory variables. Each additional explanatory variable can only increase the R-squared value, but may not improve the model's forecasting accuracy.

TABLE 4. Computer output for dynamic regression model: final trial

Historical fit of dynamic regression model	
Dependant variable:	PWBII
R-squared:	0.992
Adjusted R-squared:	0.992
Standard forecast error:	0.658523
F-statistic:	2456.983 (1.000)
Durbin-Watson:	2.032
Ljung-Box:	14.390 (0.724)
Standardized AIC:	0.674757
Standardized BIC:	0.711028

Variable	Coefficient	Standard error	T-statistic	Probability
UWRI[– 5]	0.082996	0.033897	2.448	0.986
AMI[– 12]	0.111773	0.031417	3.558	1.000
PWBII[– 1]	0.797042	0.059730	13.344	1.000

The Durbin–Watson and Ljung–Box statistics indicate problems of serial correlation. This means the model has to be adjusted because the assumptions on which it is based do not hold.

The coefficients of four of the explanatory variables are not significant at the 95% confidence level, implying that these variables should be omitted, transformed, or lagged. Some of these explanatory variables may appear not to be statistically significant because of multicollinearity, that is, these explanatory variables may be correlated with one another. FORECAST PRO, however, does not provide tests for multicollinearity.

Various trials using lagged dependent and transformed explanatory variables were performed until a near optimum regression model was obtained as one possible solution. There are a number of available selection strategies that can be used to empirically construct the required regression model. For this example, the backward elimination procedure, whereby the selection process started with the largest possible model, was used. Other selection strategies include forward selection and stepwise regression (Abraham and Ledolter 1983). The choice of the search strategy to use depends on the forecaster's individual preference, since all methods produce a regression model with the necessary statistical attributes. The result of the backward elimination selection strategy is given in Table 4. The explanatory variables found to give the statistically satisfactory model shown in Table 4 are the following:

- UWRI[– 5], the UWRI lagged 5 months; AMI[– 12], the AMI lagged 12 months; and PWBII[– 1], the dependent variable lagged 1 month.

This model implies that the value of the PWBII at any given time can be forecast using values of the AMI 12 months before, the UWRI 5 months before, and the PWBII 1 month before. These results seem to indicate the time periods for the input variables to affect the output variable, and are not unrealistic given the time for material inventory to work through.

The signs of the coefficients of the explanatory variables are all positive. This agrees with a priori expectations that the PWBII will increase with increases in the UWRI and the AMI. In this model there is no problem of serial correlation, as evidenced by the Durbin–Watson and Ljung–Box statistics. All independent variables are significant at the 95% confidence level. This model explains 99% of the variation in the PWBII, as indicated by the R-squared statistic, and therefore fits the historical data well. Figure 6 shows the plot of the fitted and forecast values as compared with the actual values. The regression model appears to attempt to account for the turning point in the data after the last fitted value. This example demonstrates some of the problems of using regression models. Though, from theoretical considerations, interest rates affect construction costs, the CBLR was not found statistically significant enough to be used in the model to forecast or explain the variation in the PWBII. Thus factors that are known to affect construction costs may not be found useful in forecasting by regression models even when data on the variation of these factors exist.

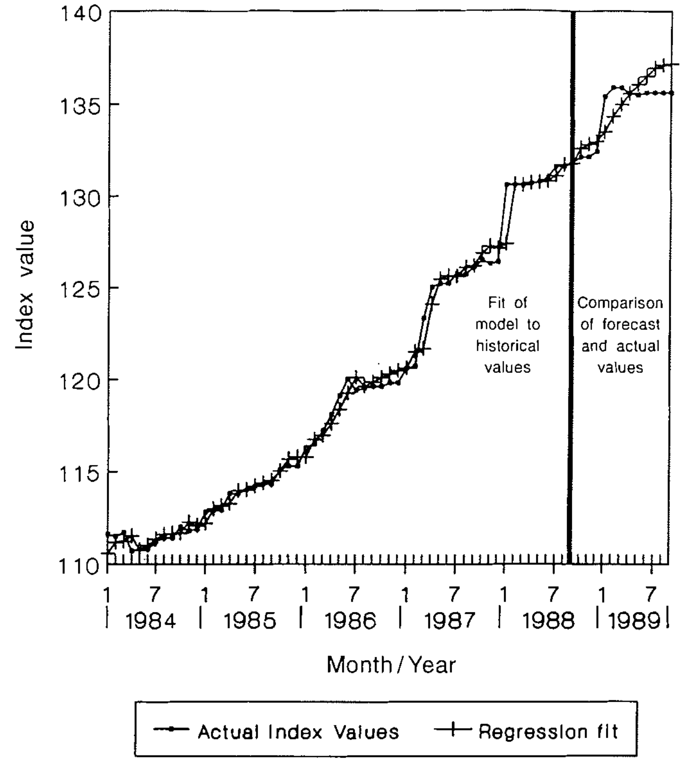

FIG. 6. Forecast comparison: dynamic regression.

Choice of the forecasting model

In order to decide which of the three fitted models would be best to use for forecasting the PWBII, the following criteria are used:

1. The accuracy of the forecasts and not the historical fit to the data will be considered.
2. A more complex model will only be recommended if it undoubtedly improves the forecasting accuracy.

Various methods of measuring forecast accuracy exist. Mahmoud (1984) surveys the following: the mean square error, the mean percentage error, the mean absolute percentage error, Theil's U-statistic, the root mean square error, the mean error, the mean absolute deviation, turning points, and hits and misses.

In forecasting construction cost escalation, it is most convenient to use a measure of accuracy consistent with the normal measure of accuracy used in construction cost estimation. The measure of accuracy used in construction cost estimation is normally the percentage error of the estimate. Of particular interest to the cost estimator would also be the turning points in the time series where the rate of cost

TABLE 5. Mean absolute percentage error of various forecast models and scenarios*

Period	Actual PWBII	Exponential smoothing forecast	Absolute error	Box–Jenkins forecast	Absolute error	Regression forecast	Absolute error
Jan. 1989	135.40	133.40	2.00	132.81	2.59	133.46	1.94
Feb. 1989	135.90	133.43	2.47	133.23	2.67	134.30	1.60
Mar. 1989	135.90	133.90	2.00	133.64	2.26	134.97	0.93
Apr. 1989	135.60	134.48	1.12	134.05	1.55	135.58	0.02
May 1989	135.50	134.81	0.69	134.47	1.03	136.06	0.56
June 1989	135.60	135.04	0.56	134.88	0.72	136.48	0.88
July 1992	135.60	135.67	0.07	135.30	0.30	136.92	1.32
Aug. 1992	135.60	136.01	0.41	135.71	0.11	137.07	1.47
Sept. 1992	135.60	136.36	0.76	136.12	0.52	137.17	1.57
M.A.P.E.†			0.83		0.96		0.84

*Nine-month forecast beginning with January 1989.
†M.A.P.E., mean absolute percentage error.

TABLE 6. Mean absolute percentage error of various forecast models and scenarios (continued)*

Period	Actual PWBII	Exponential smoothing forecast	Absolute error	Box–Jenkins forecast	Absolute error	Regression forecast	Absolute error
July 1988	131.60	131.66	0.06	131.47	0.13	131.07	0.53
Aug. 1988	131.60	132.07	0.47	131.94	0.34	131.28	0.32
Sept. 1988	131.80	132.46	0.66	132.41	0.61	131.50	0.30
Oct. 1988	132.10	133.04	0.94	132.88	0.78	132.44	0.34
Nov. 1988	132.40	133.34	0.94	133.35	0.95	133.13	0.73
Dec. 1988	135.40	133.58	1.82	133.82	1.58	133.83	1.57
Jan. 1989	135.40	134.58	0.82	134.30	1.10	134.68	0.72
Feb. 1989	135.90	134.70	1.20	134.77	1.13	135.33	0.57
Mar. 1989	135.90	135.21	0.69	135.24	0.66	135.81	0.09
M.A.P.E.†			0.61		0.62		0.44

*Nine-month forecast beginning with July 1988.
†M.A.P.E., mean absolute percentage error.

TABLE 7. Mean absolute percentage error of various forecast models and scenarios (continued)*

Period	Actual PWBII	Exponential smoothing forecast	Absolute error	Box–Jenkins forecast	Absolute error	Regression forecast	Absolute error
Oct. 1988	132.10	132.38	0.28	132.25	0.15	132.68	0.58
Nov. 1988	132.10	132.66	0.56	132.69	0.59	133.32	1.22
Dec. 1988	132.40	132.88	0.48	133.14	0.74	133.98	1.58
Jan. 1989	135.40	133.84	1.56	133.58	1.82	134.81	0.59
Feb. 1989	135.90	133.94	1.96	134.03	1.87	135.44	0.46
Mar. 1989	135.90	134.42	1.48	134.47	1.43	135.92	0.02
Apr. 1989	135.60	135.00	0.60	134.92	0.68	136.38	0.78
May 1989	135.50	135.35	0.15	135.36	0.14	136.73	1.23
June 1989	135.60	135.62	0.02	135.81	0.21	137.05	1.45
M.A.P.E.†			0.59		0.63		0.65

*Nine-month forecast beginning with October 1988.
†M.A.P.E., mean absolute percentage error.

escalation changes. As such, to measure the accuracy of forecasts, the mean absolute percentage error and the precision with which a method forecasts turning points is examined.

In terms of complexity, exponential smoothing is the simplest method to apply. The other methods should therefore be tested to examine whether they are undoubtedly more accurate and forecast the turning points much better than exponential smoothing.

To guard against spurious accuracy, three forecasting scenarios were used. These scenarios were obtained by fitting the different models to the data and forecasting 9 months ahead but using three different last fitted values. The three forecasting scenarios are forecasting 9 months ahead beginning with January 1989, July 1988, and October 1988. The various forecasts are given in Tables 5–7. These tables show that Winters three-parameter exponential smoothing yields superior forecasts in two of the three forecasting scenarios and the regression model gives a superior forecast in the other.

Exponential smoothing is the simplest of the three types of forecasting models. From the evidence in Tables 5–7, none of the more complex models give undoubtedly better forecasts of the PWBII than the Winters three-parameter model. Based on the previously stipulated criteria, exponential smoothing would be the best method to use in these circumstances to forecast the PWBII.

It should be noted that due to the specification of the regression model, forecasts of the PWBII can only be made 5 months ahead without having to first obtain forecasts of the UWRI. In obtaining the 9-month forecasts given in Tables 5–7, actual values for the UWRI were used up to 4 months ahead. This gave the regression forecast for the last 4 months of the 9-month forecast period unrealistic accuracy. Nonetheless, the regression forecasts were less accurate than those from exponential smoothing in two of the three scenarios. It is therefore not necessary to investigate the accuracy of the regression model when 4-month forecasts instead of actual values of the UWRI are used.

Nevertheless, the regression model could still be useful in some circumstances, such as in the case when the forecaster knew of ongoing labour union negotiations which were likely to increase the UWRI by some estimated amount. The regression model could be used to forecast the effect of this increase on the PWBII. This illustrates one of the benefits of developing a regression model.

Conclusion

Forecasting construction cost escalation is important because escalation accounts for a substantial part of the costs of many construction projects. With the availability of user friendly forecasting software, many complex statistical forecasting techniques can now be used to forecast construction cost escalation. This can be done provided the practitioner can interpret the results produced by these software.

Univariate time series are based on the assumption that existing patterns in the data will continue. Therefore they cannot usually predict turning points. They are not recommended if there is reason to believe existing conditions will change dramatically.

Multivariate forecast methods are dependent on the accuracy of the explanatory variables used in the forecasts. One of the main difficulties in their use is the identification of statistically significant explanatory variables. The accuracy of the multivariate forecasts produced depends on the accuracy of the explanatory variables used to make the forecasts.

The analytical forecasting techniques discussed herein are only valid for short-term forecasting, generally less than 1 year ahead. No analytical forecasting technique reviewed is capable of long-term forecasting of cost escalation.

Being able to give quantitative forecasts of escalation does not eliminate the risk caused by cost escalation. This is so because none of the discussed techniques can forecast escalation caused by unpredictable occurrences, which include major events like the outbreak of war or government action. The analytical methods available are only useful in forecasting for short construction projects in stable conditions. Construction cost escalation, with or without the use of these forecasting methods, still remains a risk to be borne by either the contractor or the owner, or both, depending on the terms of the construction contract.

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List of symbols and abbreviations

AIC	Akaike information criterion
AMI	architectural materials index
AR	autoregressive
ARIMA	autoregressive integrated moving average
BIC	Bayesian information criterion
CBLR	commercial bank lending rate index
CBMPI	construction building materials price index
d	degree of differencing
e_t	error term at time t
I	integration
L_t	smoothed level at time t
MA	moving average
p	number of periods in the seasonal cycle
S_t	smoothed seasonal index at time t
S&PMPI	saw mill and planing mill products index
T_t	the smoothed trend at time t
UWRI	union wage rate index

Y_t	observed value of time series at time t
$Y_{t(m)}$	forecast for lead time m from time t
Y_t	forecasted value of time series at time t
Y_{t-i}	observed value of time series at time $t - i$
X_{it}	observed value of the ith explanatory variable at time t
α	level smoothing parameter
β_i	coefficient of X_i
δ	seasonal index smoothing parameter
γ	trend smoothing parameter i
ϕ_i	weighting coefficient of the ith previous period
θ_q	weighting coefficient for the qth previous period