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An interval knowledge based forecasting paradigm for container throughput prediction

Anqiang Huang, Kin Keung Lai, Han Qiao, Shouyang Wang, Zhenji Zhang

Abstract

Current knowledge based forecasting models are suffering from weaknesses of subjective biases and inconsistence. In order to overcome this problem, this paper proposes a novel interval knowledge based forecasting paradigm. In the proposed forecasting paradigm, statistical projections of the target are first generated by statistical models. Next, a panel of experts are gathered to independently formulate their interval estimates, then this kind of interval knowledge is integrated into the statistical projections. Subsequently, an expert performance validating algorithm is put forward to wipe off incompetent members from the expert system, and then a Delphi based expert system is constructed to regenerate interval judgments with less subjective biases and inconsistence. Meanwhile, the algorithm is able to determine the weight distribution, with which statistical projections and interval judgments are integrated into the united predicted values. For verification purpose, container throughput series of Qingdao Port are taken as sample data. Empirical results clearly show the superiority of the proposed interval knowledge based forecasting paradigm over its benchmark models, which indicates that the proposed forecasting paradigm is effective for container throughput prediction.

1. Introduction

There is a hot disputation in terms of the role of expert knowledge in the forecasting process. On the one hand, pure statistical forecasting methods cannot achieve satisfactory forecasting performance owing to the limitation of generating projections based solely on the historical data, therefore applying expert knowledge to improve forecasting performance has been increasingly attractive. Actually, substantial studies have shown its greatly positive effects on enhancing the forecasting performance. As suggested by a survey of 240 US corporations by [2], 95.6% were taking advantage of expert knowledge to improve their projections. [3] concluded that models with expert knowledge were preferred in macroeconomic forecast after reviewing a lot of published articles. [4]
claimed a significant forecasting performance improvement achieved by incorporating domain knowledge into a simultaneous equation system based model.

On the other hand, a large group of people oppose applying knowledge in the forecasting process and criticize its weakness of bias and inconsistence inherited in subjective judgments. Some experimental results reinforced these opponent arguments. For examples, [6] shows that forecasters tend to make unnecessary judgmental adjustments to statistical projections, even when they do not possess additional contextual information. Even worse, some forecasters persist in making judgmental adjustments, though their adjustments are proved to be harmful[7]. [8] argued that experts prefer the distinguishing features of the problem and reject analogies to other instances of the same general type as superficial, even though the distinguishing features are ephemeral, low-validity, individuating information.

Besides, application of knowledge in the forecasting field are currently suffering from two other big headaches. One lies in the fact that most of the existing researches focus on integrating point estimates but seldom on the interval knowledge integration, although human are more good at formulating interval estimates than point estimates. The other is how to determine the weight distribution of statistical projections and expert judgments.

With the above consideration, this paper aims to address three issues: (a) how to integrate interval knowledge into statistical projections? (b) how to identify whether or not an expert is competent to the forecasting task? (c) how to appropriately distribute weights between statistical projections and expert judgments?

To answer these questions, this paper proposes an interval knowledge based forecasting paradigm (IKBF-paradigm). In the proposed forecasting paradigm, statistical forecasting models are first applied, then a group of experts are gathered to independently give their interval estimates, and the interval knowledge is individually integrated into the statistical projections. Subsequently, an expert performance validating algorithm is advanced to remove incompetent experts from the expert system. After that, a Delphi based expert system is constructed to regenerate interval judgments with less subjective biases and inconsistence. Meanwhile, the algorithm can determine the weight distribution, with which statistical projections and interval judgments are integrated into the united predicted values. For verification purpose, the proposed forecasting paradigm is applied to predicting container throughput of Qingdao Port. Empirical results demonstrate that the proposed forecasting paradigm significantly outperforms the benchmark models.

The remainder of this paper is organized as follows: Section 2 reviews existing approaches to integrating expert knowledge into statistical projections. Section 3 elaborates an IKBF-paradigm, including statistical models, a Delphi based expert system and an expert performance validating algorithm. Section 4 conducts an empirical study by applying the proposed forecasting paradigm to container throughput prediction of Qingdao Port; Section 5 concludes the whole paper.

2. Literature review

As claimed by [9], there are 4 frequently-used approaches to expert knowledge integration in the forecasting field. In the first approach, projections of different models are adjusted by experts and these adjusted values are then combined. This method needs experts to make adjustments for each period of interest, which means frequent updating of short term forecasts. However, the requirement of excessive experts’ participation makes this method impractical[10].

In the second approach, projection from different models are first combined, and then experts make judgmental adjustments to the combined projections. This method is more practical but suffers from many kinds of bias and inconsistence, in that judgmental adjustments by different experts may heavily deviate from each other.

The third approach is the rule-based forecasting[11], which takes advantages of a lot of empirical rules. However, in the forecasting field, application of this approach is limited because the rule system is subjective and cannot automatically calibrate the use of experts’ knowledge[10].

In the last approach, expert judgment is regarded as an input of the forecasting model[12]. This approach can take advantage of expert knowledge and avoid bias and inconsistence resulted from subjective judgment, therefore is more promising.

In the above-mentioned approaches, expert knowledge are expressed as point values. However, in practice, it is more difficult for experts to provide an accurate point estimate than an interval estimate for the same target.
For example, experts are not equipped to reason whether or not the container throughput of a port will equal 1 million TEUs in the coming year, but they tend to be more capable of judging whether or not the container throughput (Unit: million TEUs) will locate in some interval, e.g., \([0.95, 1.4]\). Therefore, this paper integrates interval judgment knowledge, rather than point estimate knowledge, in the following section.

3. IKBF-paradigm

The IKBF-paradigm proposed in this section is composed of three components, i.e., statistical models, a Delphi based expert system and an expert performance validating algorithm. The structure of the three components is presented by Fig.1.

Some comments on Fig.1 proceed as follows: (a) Data from the real world are very complex, frequently composed of structured data, unstructured data and irregular event information. (b) Statistical models can effectively analyze structured data, but fail to work with unstructured data. Moreover, patterns dug out from historical data by statistical models will not function any longer once irregular events occur. Therefore, (c) unstructured data and irregular events are analyzed by an expert system and the results are integrated into statistical projection. (d) An expert performance validating algorithm is employed to get rid of incompetent experts and determine the weight distribution, with which judgment by expert \(i\) and statistical predicted values can be combined, denoted by \(f_i\). (e) The final knowledge based projection is generated by averaging \(\{f_i, i = 1, 2, \ldots, N\}\), where \(N\) is the number of remained experts.

3.1. Statistical models

In the proposed forecasting paradigm, a variety of statistical models can be applied, e.g., neural network models\(^{[13]}\), support vector machine models\(^{[14, 15]}\), econometric models\(^{[16]}\), combined models\(^{[17]}\), etc. Practitioners are allowed to select forecasting models suited for their specific forecasting tasks.

This section employs one of the most widely-accepted and frequently-used econometric models, i.e., ARIMA model. This model is frequently specified as ARIMA \((p, d, q)\), and its mathematical expression is written as follows:

\[
\begin{aligned}
\phi_p(B)(1 - B)^d x_t &= \theta_q(B)e_t \\
E(e_t) &= 0, \ V(e_t) = \sigma^2_e, \ E(e_t e_s) = 0 \ (t \neq s), \\
E(x_t e_s) &= 0 \ \forall s < t
\end{aligned}
\]

where \(\phi_p(B)\) and \(\theta_q(B)\) are defined as

\[
\begin{aligned}
\phi_p(B) &= 1 - \phi_1 B - \phi_2 B^2 \ldots - \phi_p B^p \\
\theta_q(B) &= 1 - \theta_1 B - \theta_2 B^2 \ldots - \theta_q B^q
\end{aligned}
\]
In the above equations, $B$ is the backshift operator subjected to $B(x_t) = x_{t-1}$, $x_t$ denotes the observed value at time point $t$, $e_t$ denotes the random term at time point $t$.

It is notable that series of economic variables are frequently composed of complex components, including the slowly evolving secular trend, business cycle, rapidly varying seasonal component, irregular component. Consequently, data pre-processing should be implemented to isolate and remove the last two components from the original time series before running the forecasting model, otherwise the underlying pattern of time series will be masked and the distorted analytical results will be generated. For this purpose, two algorithms among others, X-12-ARIMA and TRAMO-SEATS, are most preferred and widely employed. Details about X-12-ARIMA and TRAMO-SEATS can be found in [18] and [19], respectively. TRAMO-SEATS, instead of X-12-ARIMA, is employed in the following section, considering that the former has advantages over the latter from the theoretical point of view, because TRAMO-SEATS is more flexible and objective by directly deriving its filters from the explicitly specified statistical model, compared with X-12-ARIMA, which selects its filter by some ad hoc empirical rules.

3.2. Interval knowledge integration and an expert performance validating algorithm

Interval knowledge integration method can be described as follows. Given the interval estimate $v^j_t = [l^j_t, u^j_t]$ by expert $j$ and the statistical projection $\hat{y}_t$ at time point $t$, the integrated value $\tilde{y}^j_t$ is presented as

$$\tilde{y}^j_t = g(v^j_t) = \begin{cases} \hat{y}_t, & if \hat{y}_t \in [l^j_t, u^j_t] \\ l^j_t, & if \hat{y}_t < l^j_t \\ u^j_t, & if \hat{y}_t > u^j_t \end{cases}, \quad t = 1, 2, \ldots, T.$$ 

Obviously, by using the above equations, a set of interval knowledge $\{v^j_t, t = 1, 2, \ldots, T\}$ of expert $j$ can be integrated into a set of statistical projections $\{\hat{y}_t, t = 1, 2, \ldots, T\}$.

The necessity of expert performance validation lies in the two facts: (a) different experts will hold various judgments in terms of the same target, therefore gathering experts suited for the target is vital to an successful application of an expert system; (b) the weight distribution between statistical projection and expert judgment must be scientifically determined, considering that it imposes a heavy impact on the yield of the expert system. This section proposes an expert performance validating algorithm to solve above two problems.

Assuming $X_t$ to be the set of predictors of the target variable $y_t$ at time point $t$, the statistical model can be written as

$$y_t = f(X_t) + e_t = \hat{y}_t + e_t, \quad t = 1, 2, \ldots, T$$  \hfill (1)

where $\hat{y}_t = f(X_t)$ and $T$ represents the length of the time window.

The model integrated with interval knowledge by expert $j$ can be formulated as

$$y_t = f(X_t) + \tilde{y}^j_t + e_t = \tilde{y}^j_t + e_t, \quad t = 1, 2, \ldots, T$$ \hfill (2)

where $\tilde{y}^j_t = f(X_t) + \tilde{y}^j_t$.

Equation 1 relies solely on historical data and neglects expert knowledge, while Equation 2 considers both of them. If expert knowledge can indeed significantly improve the forecasting performance, the variance of $e_t$ will be significantly smaller than that of $e_t$.

To test the significance of expert knowledge, Equation 3 is constructed as

$$y_t = a_0 + a_1 f(X_t) + a_2 \tilde{y}^j_t + u_t, \quad t = 1, 2, \ldots, T$$ \hfill (3)

where rejection of the null assumption ($a_2 = 0$) implies that application of expert knowledge significantly enhances the forecasting accuracy, and vice versa.

By substituting Equation 1 and Equation 2 into Equation 3, we get Equation 4

$$y_t = a_0 + a_1 \hat{y}_t + a_2 (f(X_t) + \tilde{y}^j_t) + u_t$$

$$= a_0 + (a_1 + a_2) \hat{y}_t + a_2 \tilde{y}^j_t + u_t, \quad t = 1, 2, \ldots, T$$

$$= a_0 + (a_1 + a_2) \hat{y}_t + a_2 \tilde{y}^j_t + u_t$$ \hfill (4)
which can be rewritten as
\[ y_t = b_0 + b_1 \hat{y}_t + b_2 \tilde{y}_t^j + u_t, \ t = 1, 2, \ldots, T \] (5)

where \( b_0 = a_0 \), \( b_1 = a_1 + a_2 \) and \( b_2 = a_2 \).

Equation 5 implies that the real data \( y_t \) is the weighted average of the statistical projection \( \hat{y}_t \) and the expert judgmental projection \( \tilde{y}_t^j \). \( b_1 \) and \( b_2 \) can be estimated based on historical observed data \((y_t, X_t)\) and expert judgment \( \tilde{y}_t^j \). \( b_2 = 0 \) indicates insignificant contribution of expert knowledge and expert \( j \) should be eliminated from the expert system.

By using this algorithm, incompetent experts can be removed from the expert panel and thus the contributory experts remain. Then the remained experts constitute a Delphi based expert system to regenerate judgments and it is reasonable to expect these new judgments to be more stable and reliable.

3.3. Delphi based expert system

Although expert knowledge has been advocated by substantial researches, its application is enormously hindered by biases and inconsistence inherent in subjective judgment. Fortunately, group decision is an effective cure to this problem, as argued by [20] and [21]. With this consideration, a Delphi based expert system is constructed in this section.

In the Delphi procedure, multiple individuals are initially required to give separate numerical judgments or forecasts. Then these forecasts are kept in being iteratively revised based on feedback provided anonymously by other members of the Delphi panel, until response stability across panellists appears. Thus, the average of the final round can be regarded as the yield of the Delphi based expert system.

Specifically, the proposed Delphi based expert system are constructed through the following steps: (a) gathering an expert panel; (b) accurately describing the forecasting task and providing panellist with as much valuable background information as possible, in the light of which experts individually generate their interval judgment; (c) collecting and summarizing all of the interval judgments; (d) feeding back the statistics to experts and allowing them to calibrate their judgment made in the previous iteration; (e) repeating Steps (c) and (d) until the responses across panellists become stable. Through these steps, a set of stable and reliable expert judgments can be obtained.

From Equation 5, the integrated projection based on judgment of expert \( j \) can be presented by
\[ \tilde{y}_t^j = b_0 + b_1 \tilde{y}_t^j + b_2 \hat{y}_t^j, \ t = 1, 2, \ldots, T. \] (6)

Supposing that \( m \) experts finally remain in the Delphi based expert system, the aggregately integrated projection \( \hat{y}_t^p \), that is accepted as the final projection, can be computed by Equation 7
\[ y_t^p = \frac{\sum_{j=1}^{m} \tilde{y}_t^j}{m}, \ t = 1, 2, \ldots, T. \] (7)

4. Empirical study

In this section, experimental design, including data description, performance measurement criteria, benchmark models and composition of the panel, is first given in Section 4.1. Then the experimental results are discussed in Section 4.2 from two perspectives. First, the effectiveness of IKBF-paradigm in improving forecasting performance is tested through comparing IKBF-model with its pure statistical counterpart. Second, the superiority of IKBF-paradigm to the typical Delphi based model is tested.

4.1. Experimental design

4.1.1. Data description

In this study, container throughput series of Qingdao Port are chosen as sample. The data are monthly data obtained from CEIC macroeconomic data base (http://www.ceicdata.com). In particular, the data range from January 2004 to March 2015, with a total of 135 observations, as illustrated in Fig.2. The data from January 2004
to March 2014 are used for the model training (123 observations), and the remainder are used as the testing set (12 observations).

In order to eliminate seasonality in the series, the TRAMO-SEATS algorithm is employed. The original and seasonally adjusted series are vividly compared in Fig.3.

4.1.2. Performance evaluation criteria

This section applies two main classes of criteria, i.e., level and directional prediction accuracies, to evaluate the forecasting performance. Considering the fact that the root mean squared error (RMSE) has been one of the most effective statistics frequently-used to reflect the level forecasting errors, RMSE is especially chosen from others to evaluate the level prediction accuracy, typically written as

$$RMSE = \sqrt{\frac{1}{N} \sum_{t=1}^{N} (\hat{y}_t - y_t)^2},$$  \hspace{0.5cm} (8)$$

where $y_t$ is the observed data, $\hat{y}_t$ is the simulated value, and $N$ is the number of simulated values, at time $t$. 

Fig. 2. Chart of container throughput of Qingdao Port

Fig. 3. Original series and seasonally adjusted series
The ability to predict movement direction can be measured by a directional statistic $E_d$, which can be expressed as:

$$E_d = \frac{\sum_{t=1}^{N} d_t}{N} \times 100\%,$$

where $d_t = 1$ if $(x_t - x_{t-1}) \times (\hat{x}_t - \hat{x}_{t-1}) > 0$, and $d_t = 0$ otherwise.

4.1.3. Benchmark models

For the purpose of testing the effectiveness of the proposed IKBF-paradigm, the method of autoregressive integrated moving average (ARIMA) is applied as the statistical model. The comparison process proceeds as follows. First, a typical ARIMA model is formulated to generate statistical projection. Then a Delphi-ARIMA model is constructed by applying the typical Delphi procedure to adjusting the ARIMA projection to obtain the Delphi-based predicted values. After that, an IKBF-model (IKBF-ARIMA) is constructed and employed for forecasting, in the light of the method elaborated in Section 3.

Generally, for the IKBF-model (IKBF-ARIMA), a purely statistical model (ARIMA) and a typical Delphi based model (Delphi-ARIMA) are formulated as benchmark models. The former is used to demonstrate the effectiveness of the IKBF-paradigm in improving forecasting performance by integrating experts’ interval knowledge, and the latter shows the superiority of the IKBF-paradigm to other knowledge integration techniques, i.e., typical Delphi method in this paper.

The main reason for using ARIMA is that ARIMA, widely accepted as the most typical linear regression model, has been popularly used as a traditional benchmark in the forecasting field, e.g., [22, 23, 24, 25]. However, it is well worth to note that ARIMA is not the unique choice. A variety of alternatives can be applied to the IKBF-paradigm, such as regression models, neural network models, support vector machine models, among others.

4.1.4. Composition of the panel

The panel comprises 15 experts, of whom, 1/3 are econometric modelling experts from Center for Forecasting Science Chinese Academy of Sciences, 1/3 from the frontier staff of Qingdao Port operating container-related business, and the remainder from the management staff of Qingdao Port. A host distributes messages to and collects judgments from the panel by E-mail, but a panellist member cannot communicate with others within the panel, which implies all panellists have to formulate their judgment individually.

Intuitively, the human brain is more equipped to formulate interval estimates than point estimates, therefore the panellists are required to make interval judgment in this work. Besides, rich background knowledge are provided to the panel to facilitate higher forecasting performance. The background knowledge mainly comprises three aspects, the first is the state of art in Qingdao Port (e.g., the state of hinterland, investment, infrastructure, the number of shipping lines, historical container throughput, etc.). Besides, information on macroeconomics should be considered, including the growth speed of the world economy, the current state of the international trade, the volume of Chinese imports and exports, the volatility of fuel price, etc. Some policies of high significance are also put into consideration, e.g., the ‘One Belt And One Road’ development concept of China, implementation of standards for energy conservation and emission reduction, etc.

4.2. Experimental results

In order to test the effectiveness of the proposed IKBF-paradigm, ARIMA is first to applied to forecast container throughput series of Qingdao Port, and the best ARIMA model is determined based on Akaike Information Criterion (AIC) and Schwarz Criterion (SC) minimization. Subsequently, the Delphi-ARIMA and IKBF-ARIMA models are formulated. Fig.4 vividly compares projections of the three models, and Table 1 presents their performance in terms of two criteria, i.e., $RMS_E$ and $E_d$.

<table>
<thead>
<tr>
<th>Evaluation criteria</th>
<th>ARIMA</th>
<th>Delphi-ARIMA</th>
<th>IKBF-ARIMA</th>
</tr>
</thead>
<tbody>
<tr>
<td>$MSE$</td>
<td>80.03</td>
<td>85.69</td>
<td>43.19</td>
</tr>
<tr>
<td>$E_d$</td>
<td>0.36</td>
<td>0.64</td>
<td>0.73</td>
</tr>
</tbody>
</table>
From Fig. 4 and Table 1, three main conclusions can be summarized. First, ARIMA generates the most smooth projection and performs worst in terms of $E_d$. One of the reasonable explanations is that ARIMA captures the pattern of structured historical data and generates predicted values by extrapolation. This practice neglects a lot of valuable information and fails to work when the mechanism of data generation changes. Second, benefiting from expert knowledge, Delphi-ARIMA achieves better performance than ARIMA in terms of $E_d$, but suffers from a lower level-accuracy. This phenomenon implies that although applying expert knowledge facilitates counter-direction fluctuations, it will lead to higher level-deviations when incompetent expert are included in the panel. Third, IKBF-ARIMA achieves the lowest $MSE$ and highest $E_d$, which implies that it outperforms its two benchmark models in terms of the directional prediction accuracy and level prediction accuracy. The main reason may be that it can timely respond to direction variation by applying expert knowledge and enjoy the higher level accuracy by eliminating incompetent members from the panel using the proposed IKBF-paradigm.

5. Conclusion

Based on the investigation of the state of art in the knowledge based forecasting field, this paper addresses three hot issues, i.e., (a) how to integrate interval knowledge into statistical projections? (b) how to identify whether or not an expert is competent to the forecasting task? (c) how to appropriately distribute weights between statistical projection and expert judgment?

To solve the above mentioned problems, an IKBF-paradigm is proposed, which is composed of three components, including statistical models, a Delphi based expert system and an expert performance validating algorithm. The IKBF paradigm proceeds in sequence as follows. First, statistical models are employed to generate statistical projection. Second, a panel of experts individually make their interval judgment of the forecasting target. Third, the expert performance validating algorithm is applied to identifying and removing incompetent experts from the panel. Moreover, this algorithm determines the weight distribution, with which statistical projection and expert judgmental projection are combined. Fourth, a Delphi based expert system constituted by the remained experts is constructed to regenerate more stable and reliable judgments. Finally, the finally accepted projection is generated by integrating statistical projection with the average of new projections by the remained experts.

For verification purpose, the proposed IKBF-paradigm is applied to the container throughput prediction of Qingdao Port. Empirical results show that the IKBF-paradigm significantly outperforms its benchmark models in terms of the directional and level prediction accuracies, which implies it is an effective tool for container throughput forecasting.
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