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Research on the Advantages of Hybrid Forecasting Method and Its Performance Under Different Forecasting Spans

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Abstract: Prediction technology is the key support for decision-making in the fields of economy, energy, environment and so on, but there are obvious limitations in a single prediction method: ARIMA and other statistical models are difficult to fit nonlinear data, and LSTM and other machine learning models rely on large samples and are easy to over fit. Through literature analysis and method comparison, combined with typical scenarios such as power load, GDP growth, population planning, this paper focuses on the core advantages of the hybrid forecasting method, and explores its performance in the short-term (1-3 months), medium-term (3-12 months), and long-term (more than 1 year) forecasting span. The results show that the hybrid method breaks through the accuracy bottleneck and enhances robustness by "basic model complementarity+fusion strategy optimization": it is good at capturing real-time fluctuations in short-term forecasting, and can balance stability and dynamic adaptability in medium and long-term forecasting. The research provides practical reference for the selection of prediction methods in different scenarios, and effectively avoids the scene adaptation defects of a single method.

Keywords: Hybrid prediction method, prediction span, prediction accuracy, statistical model, machine learning.

1. Introduction

Prediction has always been the key premise of decision-making in practical work. For example, the accuracy of power load forecasting directly affects the efficiency of power grid dispatching; The price forecast of agricultural products is related to the planting planning of farmers, and it may affect the income almost. However, the single forecasting method commonly used in the tradition has obvious shortcomings: statistical models such as Arima can capture the linear trend, but there is no way to deal with the nonlinear fluctuations such as power consumption peak and sudden price change; Although the machine learning model such as LSTM can fit complex relationships, it must be supported by a large amount of data. If there is less data, it is easy to "learn bias", which has many limitations in practical use.

With the increase of nonlinear characteristics in the data and the complexity of burst influencing factors, the shortcomings of single method are becoming more and more prominent. At this time, the academic community began to try to combine the advantages of different models. This is how the hybrid forecasting method came about - not a simple heap model, but a linear model to fill the lack of nonlinear models, and a small sample adaptation model to fill the leak of data dependent models, so as to achieve the effect of "1+1>2".

At present, with regard to the hybrid forecasting method, studies have focused on improving the accuracy of a single scene. For example, we only look at the short-term power forecasting [1], but there is no systematic comparison of its actual performance in the short, medium and long-term, and there is no clear basis for the actual application of the time-based method. This paper aims to focus on the core advantages of the hybrid forecasting method, analyze its adaptability and performance characteristics in combination with the typical scenes of different spans, and provide some theoretical and practical reference for the actual forecasting work. The data and conclusions used in the full text are all from public academic journals and industry practice, without fictitious content.

2. Definition and Core Composition of Hybrid Forecasting Method

Speaking of the hybrid forecasting method, it is not just a matter of piling several models together, but should be designed according to the logic of "selecting a basic model - building a fusion strategy - making error correction" - after all, the data features in the forecasting scenario are miscellaneous, and one link alone cannot support the accuracy. This hierarchical design allows each step to solve the problem, and ultimately forms a forecasting system that can cooperate with each other and improve the effect. In essence, its core is "complementary": for example, ARIMA model, which is good at grasping linear trends, is combined with SVM model which can extract nonlinear features; Or combine the grey prediction model (GM (1,1)) with the random forest model that is good at learning characteristics, so that it can cover the characteristics of data sources that a single model can not care about.

First look at the basic model layer. The key is "functional complementarity". Take the processing of time series data. For example, there are both linear trends of daily power consumption and nonlinear fluctuations caused by extreme weather in the power load data. A single linear model can not grasp the fluctuation law at all. If two models that can only fit the linear relationship are selected at the same time, there is still no way to deal with this kind of situation, so we have to deliberately select the ones with different functions to make up for each other's shortcomings [2]. Then to the fusion strategy layer, there are two commonly used methods: one is weighted fusion, such as adjusting the weight of each model in reverse according to the error, which is much used in short-term prediction; The other is stacking integration, which takes the output of the basic model as a new feature and uses a "meta model" to optimize the result. It is more appropriate to use it when the data dimension is complex [3]. Finally, there is the error correction layer, which generally relies on residual analysis - such as re modeling the error sequence of preliminary prediction to further reduce the deviation. This step is particularly important in medium and long-term forecasting, which can help alleviate the error accumulation caused by data uncertainty. Otherwise, the more the error accumulation, the more the prediction results will be inaccurate.

3. Core Advantages of Hybrid Forecasting Method

The essence of the advantages of hybrid forecasting method is to solve the "short board problem" of single forecasting method, which can directly deal with the pain points in forecasting in practical application [4]. First of all, the key is to break through the bottleneck of accuracy - take the short-term power load forecasting as an example. A single ARIMA model can only grasp the linear trend, but it has no way to deal with the nonlinear fluctuation of power consumption peak, and the fitting error is often stuck at 8%-12%; However, if ARIMA and SVM are combined into a hybrid model, and the fluctuation characteristics are captured by SVM, the error can be reduced to 4%-6%, which is the result verified in the short-term power load combination forecasting model based on arima-svm, issue 15, 2022, power system automation. There is also the Medium-term Forecast of agricultural product prices. The single GM (1,1) model has a slow response to changes in market policies, while the GM (1,1) - random forest mixed model adds policy characteristic variables, and the forecast accuracy can be improved by 15%-20%, which can be found in the study of agricultural economic issues, issue 8, 2023. This accuracy improvement depends on the complementarity of "linear+nonlinear" and "small sample adaptation+large sample learning", avoiding the inherent defects of a single model [5].

The second is strong anti-interference ability, that is, good robustness. For example, if a single LSTM model is used to predict, if the data missing rate exceeds 5%, the prediction accuracy will drop by more than 20%; However, the LSTM - Kalman filter hybrid model, which uses Kalman filter to correct data noise, can only reduce the accuracy by 5% to 8% under the same missing rate, which is the experimental conclusion of "missing data prediction method based on Kalman filter optimization LSTM" in the 11th issue of control and decision making in 2021.

In addition, it can also adapt to a variety of scenarios: whether it is time series data such as economic indicators or cross-sectional data such as regional energy consumption, there is no need to rebuild the model framework, just adjust the basic model combination. For example, arima+xgboost is used to calculate economic indicators, and GM (1,1)+SVM is used to calculate regional energy consumption, which saves the cost of reconstructing models for different scenarios and is more flexible in actual landing.

4. Performance of Hybrid Forecasting Method Under Short Term Forecasting Span

The core demand of short-term forecasting (1-3 months) is to grasp the real-time fluctuation of data - such as hourly power load and daily AQI. The data update is fast, and it is always affected by sudden factors such as extreme weather and temporary power demand. It is difficult for a single model to consider "fast response" and "accurate calculation" at the same time. At this time, the advantage of hybrid forecasting method is very prominent, which can not only quickly keep up with fluctuations, but also reduce the random error.

Taking short-term power load forecasting as an example, a provincial company of the State Grid tried to use arima-lstm hybrid model during the summer power consumption peak in 2024: first let Arima clarify the overall power consumption trend, such as the difference between the basic load on weekdays and weekends, and then let LSTM correct those fluctuations outside the trend, such as the temporary capacity increase of industrial enterprises and the sudden rise of residential air conditioning power consumption in high temperature days. In practice, this model helps the power grid allocate reserve capacity in advance, reducing the local power supply tension caused by inaccurate load forecasting for three times; The final results show that the prediction error of hourly load is only 3.2% -4.5%, which is almost 40% lower than that of using LSTM model alone (error 6.8% -8.1%). The data can be found in the practice of short-term power load accurate prediction of provincial power grid, issue 5 of power grid technology, 2024 [6].

Looking at the AQI short-term prediction, the Chinese Academy of Environmental Sciences uses a hybrid model of BP neural network and wavelet analysis. They first removed the high-frequency noise in AQI data by wavelet analysis, such as the sudden rise of PM2.5 caused by short-term dust, and then let BP neural network to fit the trend after cleaning. As a result, the 24-hour prediction accuracy of PM2.5 concentration can reach more than 85%, which is much higher than 72% using BP model only. This is the research result of the third issue of the Journal of Environmental Sciences in 2023.

However, it should be noted that short-term forecasting has a particularly high requirement on the timeliness of data. If the data preprocessing does not keep up - for example, the real-time data is not cleaned in time and the key features are not screened out, even if the model combination is good, the complementary advantages will not be brought into play. Moreover, the integration strategy should not be too complex. For example, stacking integration computing is slow. After all, short-term prediction often needs to support real-time decision-making, and even a few minutes of delay may affect the scheduling efficiency. Simple weighted integration is enough.

5. Performance of Hybrid Forecasting Method Under Medium Term Forecasting Span

The Medium-term Forecast (3-12 months) is different from the short-term forecast. Instead of chasing the real-time fluctuations, it needs to find a balance between "accurate" and "stable results" -- for such scenarios as quarterly GDP growth and supply and demand of agricultural products in half a year, the data is updated monthly or quarterly, which is greatly affected by policies and seasons, but has little sudden interference. A single model either keeps an eye on historical data or does not respond to new variables, so it is difficult to look at both sides. The hybrid forecasting method can pinch "trend fitting" and "variable adaptation" together, just to fill this gap.

Take the quarterly GDP growth forecast as an example. The Institute of economics, Chinese Academy of social sciences has done experiments: when using VAR model alone, it is not sensitive to policy variables such as industrial structure adjustment, and the prediction error often exceeds 5%; After changing to the VaR xgboost mixed model, let var smooth the trend of the economic foundation first, and then let xgboost add in the variables such as policy, import and export. The error is directly reduced to 2%-3%, which can be found in the research on quarterly GDP growth forecast based on VAR xgboost, issue 7, 2022, quantitative economic and technical economic research. It also provides a reliable support for macro policy regulation in advance.

Looking at the semi annual supply and demand forecast of wheat, the Institute of agricultural economics, Chinese Academy of Agricultural Sciences uses the GM (1,1) - elm hybrid model. The single GM (1,1) model is OK for small samples [7], but it has no way for climate, planting area and other variables, and the prediction deviation can reach 10% - 12%; The hybrid model allows GM (1,1) to manage the basic trend of supply and demand. Elm focuses on the impact of climate and planting area. Finally, the prediction deviation of supply-demand gap is only 3% -5%. This is the research result of the 6th issue of China rural economy in 2023, which can help the agricultural department guide farmers to optimize their planting plans.

In addition, the medium-term forecast also needs to make the results "clear" -- policy makers need to know why they predict so. The "black box" problem of a single machine learning model is very troublesome. For example, the mixed method uses linear regression to build a tree model, which not only retains the variable coefficients of the regression model (which factors can explain how much influence), but also relies on the tree model to improve the accuracy, so the results are more acceptable [8].

6. Performance of Hybrid Forecasting Method Under Long-Term Forecasting Span

Comparing the long-term forecast (more than 1 year) with the medium-term and short-term forecast, the biggest trouble is that the data uncertainty is too high - for such scenarios as regional population planning and new energy installed capacity, the data must be changed year by year, and slow variables such as urbanization, technological change and policy adjustment must be taken into account. It is easy to "take a blind eye" to a single model. For example, relying solely on historical data to push the trend can not keep up with the changes in the actual situation. Finally, the forecast deviation can be too large to be used. The role of hybrid forecasting method is to combine "grasping the basic trend" with "coping with long-term variables", which can not deviate from the general direction, but also reduce the system error.

Take the long-term prediction of regional population. When the Institute of population studies of Peking University planned a provincial capital city in the East, it initially used a single logistic model, which assumed that the population growth would slowly saturate, completely ignoring the inflow of migrant population brought by urbanization. In those years, the local high-tech zones developed rapidly, and tens of thousands of young people came to work every year. As a result, the prediction deviation of the model exceeded 10%. Later, it was replaced by the logistic Arima mixed model, which allowed logistic to determine the general trend of natural population growth first, and then Arima was used to correct the fluctuations caused by population flow. The prediction deviation in the last five years was reduced to 4%-6%, helping the urban planning department to adjust the layout of education and medical resources in advance [9]. The specific details of this data can be found in the population research 2022, issue 4, "improvement of regional population long-term prediction model under the background of urbanization".

Looking at the long-term prediction of new energy installed capacity, China Electric Power Research Institute tried a single transformer model when making 10-year wind power planning. Although this model can learn complex relationships, it is not sensitive enough to long-term variables such as policy subsidy adjustment and wind turbine cost reduction, and the prediction accuracy is only about 65%. After changing to the grey prediction transformer hybrid model, the grey prediction is used to deal with the basic growth trend of installed capacity. Transformer focuses on the factors such as policy changes and technology costs. Finally, the accuracy rate is more than 80%, which also provides a reliable basis for the planning of energy storage facilities supporting the power grid. This is the empirical result in the construction and verification of long-term prediction model for wind power installed capacity, issue 2 of renewable energy in 2024 [10].

However, it should be noted that in the long-term forecast, the mixed model should not be greedy. Generally, 2-3 model combinations are enough. If there are too many models, the noise in the long-term trend will be amplified, resulting in the problem of "over fitting". In addition, the parameters should also be adjusted regularly. For example, the weight should be adjusted every half a year. After all, in the long run, the variable changes slowly but the cumulative effect is strong. If it is not adjusted in time, the error will slowly accumulate and finally affect the decision.

7. Conclusion

Based on the analysis of the mixed forecasting method in the full text -- from the composition logic to the actual performance of different forecasting spans, we can draw several clear conclusions: first, the core value of the mixed forecasting method is "complementary integration": the basic model covers different data characteristics such as linear and nonlinear, and the fusion strategy is used to optimize the output results, and then the error is corrected to reduce the deviation, which not only significantly improves the prediction accuracy and anti-interference ability, but also adapts to more scenes and avoids the inherent shortcomings of a single model.

Secondly, in different forecast spans, its performance has different focuses: short-term forecasting can accurately grasp the real-time fluctuations, such as power load and AQI forecasting can quickly respond to sudden changes; In the medium term, we can find a balance between accuracy and stability, and retain the interpretability of the results, which is convenient for policy-making; In the long run, it can reduce the systematic error and deal with the impact of slow variables such as urbanization and technological change, and these performances can be optimized by adjusting the integration strategy and regularly updating the parameters.

In addition, it should also be clear that "the more models are not the better", and the rules of "complementary functions, simplified strategies, and controllable errors" must be observed. Otherwise, too many models will increase the calculation cost, and the results may not be explained.

However, the research has not been fully explained: under the extreme scenario of public emergencies, how to adapt the hybrid method has not been studied in detail; How to quantify the adaptation criteria of different fusion strategies is not clear. In the future, we can go to the research and development of "lightweight hybrid model", simplify the number of models and algorithm complexity, and combine with real-time data transmission technology to make it respond faster in dynamic scenes and provide support for decision-making in more fields.

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