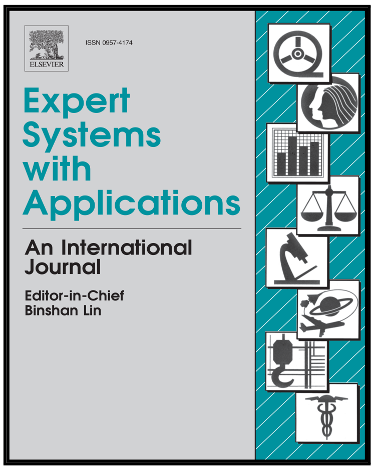

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Neural expert weighting: a NEW framework for dynamic forecast combination

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Abstract—Several empirical results on time series indicate that combining forecasts is, on average, better than selecting a single winning forecasting model. The success of the combination approach depends on how well the combination weights can be determined. Focusing on convex combinations – linear combinations with forecast weights constrained to be non-negative and to sum to unity – this paper proposes a new weight generation framework called Neural Expert Weighting (NEW). The framework generates dynamic weighting models based on neural networks, both relaxing in-sample performance dependence and abstracting statistical complexity. Assessed with 15 time series divided into two case studies – petroleum products and NN3 forecasting competition – the NEW models presented promising results.

Keywords—Forecast combination; Convex combinations; Time series; Neural networks.

1. Introduction

During the decision-making process, multiple forecasts for the same variable may be available to the planning team. In this context, as Timmermann (2006) observes, a natural question arises: what is the best way to exploit information from individual forecasts? As this paper describes, having many forecasting models should not be seen as a weakness. It allows constructing multi-forecaster systems that unite, in some manner, all available forecasting information. If properly designed, those systems lead to consensual decisions that outperform individual ones.

We here assume that multi-forecaster systems can be divided into two classes, depending on how their components interact to deliver the consensual decision: (i) *chained* (hierarchical) systems, where the output of a forecasting sub-system serves as input for some upper forecasting level (Bajo & Umgiesser, 2010; Kristjanpoller, Fadic & Minutolo, 2014) and (ii) *unchained* (non-hierarchical) systems, where independent forecasting sub-systems have their outputs combined (Aladag, Egrioglu & Yolcu, 2010; Zhang, Jin, Shan & Wang, 2012; Martins & Werner, 2012). This paper focus on the latter class of systems, for which Bates and Granger (1969) is often cited as a seminal reference.

The result of a forecast combination does not always outperform the best individual forecast but is less risky (Hibon & Evgeniou, 2005). The selection of one forecasting model relies on