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Predicting short-term bus passenger demand using a pattern hybrid approach

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ABSTRACT

This paper proposes an Interactive Multiple Model-based Pattern Hybrid (IMMPH) approach to predict short-term passenger demand. The approach maximizes the effective information content by assembling the knowledge from pattern models using historical data and optimizing the interaction between them using real-time observations. It can dynamically estimate the priori pattern models combination in advance for the next time interval. The source demand data were collected by Smart Card system along one bus service route over one year. After correlation analysis, three temporal relevant pattern time series are generated, namely, the weekly, daily and hourly pattern time series. Then statistical pattern models are developed to capture different time series patterns. Finally, an amended IMM algorithm is applied to dynamically combine the pattern models estimations to output the final demand prediction. The proposed IMMPH model is validated by comparing with statistical methods and an artificial neural network based hybrid model. The results suggest that the IMMPH model provides a better forecast performance than its alternatives, including prediction accuracy, robustness, explanatory power and model complexity. The proposed approach can be potentially extended to other short-term time series forecast applications as well, such as traffic flow forecast.

1. Introduction

With a predictive capability, the transport system will provide services in a proactive manner as opposed to a reactive manner (Smith et al., 2002). The capacity to accurately forecast demand in public transport is expected to minimize operation cost and improve bus service quality by properly allocating the constrained resources (Tirachini et al., 2013). In particular, short-term demand prediction is the prerequisite for an effective proactive real-time bus operation management (Ceder et al., 2013). As a result, short-term forecasting techniques in transport field have received a widespread attention from traffic engineers and researchers. A wide variety of methods has been proposed in the context of short-term traffic flow forecasting, depending on the implementation area, the implementation type and the conceptual output (Vlahogianni et al., 2004). These methods include regression analysis (Smith et al., 2002), time series analysis (Williams and Hoel, 2003), multivariate state space (Stathopoulos and Karlaftis, 2003), Bayesian network (Sun et al., 2006), fuzzy neuron networks (Tsai et al., 2009; Vlahogianni et al., 2005; Yin et al., 2002), intelligence computation method (Chen and Grant-Muller, 2001), and support vector machine (Zhang and Liu, 2009). However, little effort has been found in short-term bus passenger demand forecast in the literature. Current public transport demand forecasting methods are mainly applied to long-term planning practice, such as four-step sequential process, elasticity model, econometric models and long-range travel demand models (Balcombe et al., 2004).

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Each model tends to have its own advantages and limitations for different applications. It is controversial to say which model prototype can globally provide the best forecast performance among alternatives (Tsai et al., 2009). It is intuitively reasonable to capture different data characteristics by exploiting the advantage of an individual model (Sheu et al., 2009). Using a hybrid model has become a common practice in improving forecast accuracy (Zhang and Liu, 2011). A range of studies contribute to the short-term hybrid forecasting in transport area (Pohlmann and Friedrich, 2013; Tan et al., 2009; Tsai et al., 2009; Vlahogianni, 2009; Wei and Chen, 2012; Zhang, 2011; Zheng et al., 2006). Generally, the procedure of hybrid prediction includes three stages, namely pattern identification, pattern modelling, and pattern combination. Temporal pattern is widely used in time series data analysis, including trend, periodic and cycle features (Tan et al., 2009). Level shift pattern can exist when unexpected incidents or non-recurrent external conditions happen (Tsai et al., 2009). Pattern modelling methods are mainly determined by the features of the identified patterns. For example, Tan et al. (2009) applied three statistical pattern models to capture temporal patterns while Tsai et al. (2009) developed two NN pattern models to reflect the temporal and level shift patterns. For the combination stage, NN based models have been widely utilized, generally because of their good predictive ability (Karlaftis and Vlahogianni, 2011).

These NN based hybrid models always outperform simple statistical models and single pattern model, particularly in modelling multi-dimensional data (Karlaftis and Vlahogianni, 2011). However, current hybrid prediction models are largely based on the historical data information without efficient use of real-time information. The behind assumption is that the pattern of the past will continue into the future. For example, in Tan et al. (2009) study, the output of the trained NN model serves as the final prediction. Although the Autoregressive Moving Average (ARMA) model can reflect the real-time information effects, the mixture weights of different pattern models are trained based on historical data. They cannot be updated dynamically to adjust the current state. In this case, if an unexpected event happens, the repeatable pattern is not kept and the prediction accuracy is inevitably affected. Moreover, the demand usually exhibits frequent pattern transitions from time to time, especially for the short-term data (Vlahogianni et al., 2006). The pattern combinations could be different even for the same time period between two days-of-week. It is essential to dynamically update the pattern models combination for a particular time interval.

The update process can be realized by combining pattern models weighted by their corresponding representation degree of the underlying demand process. The hypothesis of this forecast strategy is that by optimizing the most probable combination of pattern models for each individual time interval one can ultimately arrive at a more accurate prediction in the whole period. Along such route, Zheng et al. (2006) proposed a Bayesian combined NNs model which provides traffic flow forecast at time interval $t+1$ by combining two NNs outputs at time interval $t+1$ weighted by the posterior probabilities at time interval t. The problem for the combination method is using the posterior probabilities at time interval t instead of those at time interval $t+1$, especially when frequent pattern transitions exist in the dataset. It is essential to estimate the probability in advance which pattern model would provide better performance in the next time interval. Additionally, the biggest obstacle for the utilization of a NN model is its limited inherent explanatory power. It cannot produce a unique solution to a problem and the designing process is rather complicated and not transparent, which is hard to use by practitioners (Karlaftis and Vlahogianni, 2011).

With three desirable properties, the Interacting Multiple Models (IMM) algorithm has been demonstrated as a cost-effective and simple prediction scheme in hybrid systems, especially widely used in manoeuvring target tracking area. The IMM is recursive, modular, and has fixed computational requirements per cycle (Zhang, 2011). More importantly, it can optimize the model combination and model forecast at time interval t using observations at time interval t. By amending the standard IMM algorithm, the combination weight of each model at time interval $t+1$ can be estimated in advance based on the optimized output at time interval t. These properties promise the IMM algorithm as a potentially effective pattern combination choice in the short-term forecast, from the perspective of prediction performance and on-line use. Zhang (2011) applied an IMM predictor in the hourly travel time index forecasting and demonstrated it can provide a large improvement in stability and robustness. To the best of our knowledge, it is the first time that the IMM algorithm is adopted to the context of short-term passenger demand prediction in public transport. This paper aims to propose an IMM algorithm based pattern hybrid method that can provide accurate, robust and efficient short-term demand forecast.

The rest of the paper is organized as follows: Section 2 describes the data structure and methodology. An amended IMM algorithm is proposed for short-term passenger demand prediction. Section 3 comprises a case study using empirical Smart Card data collected along one bus route over one year in Jinan, China. The pattern models and time-dependent transition probability matrix are calibrated using training dataset. The IMMPH model performance is validated by comparing with statistical methods and an ANN based hybrid model using an independent testing dataset. Different issues are evaluated including prediction accuracy and robustness, explanatory power and model complexity. Section 4 discusses how the IMMPH model works and the potential extension to other short-term time series prediction applications. Section 5 summarizes the main findings and future work.

2. Data structure and methodology

The source passenger demand data can be collected by a Smart Card data system and aggregated for a given time period (e.g. 15 min, 30 min, or 1 h). Vlahogianni and Karlaftis (2011) showed that the temporal aggregation would alter underlying features of the source data and suggested selecting appropriate approach for the modelling of aggregated data. The source data provided to us for this research were already aggregated for 30 min by the operators. However, the proposed demand