European Journal of Operational Research 232 (2014) 383–392

Contents lists available at ScienceDirect

European Journal of Operational Research

journal homepage: www.elsevier.com/locate/ejor

Stochastics and Statistics

Cash demand forecasting in ATMs by clustering and neural networks

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ARTICLE INFO

Article history:
Received 29 November 2012
Accepted 19 July 2013
Available online 2 August 2013

Keywords:
Time series
Neural networks
SAM method
Clustering
ATM cash withdrawal forecasting

ABSTRACT

To improve ATMs' cash demand forecasts, this paper advocates the prediction of cash demand for groups of ATMs with similar day-of-the week cash demand patterns. We first clustered ATM centers into ATM clusters having similar day-of-the week withdrawal patterns. To retrieve "day-of-the-week" withdrawal seasonality parameters (effect of a Monday, etc.) we built a time series model for each ATMs. For clustering, the succession of seven continuous daily withdrawal seasonality parameters of ATMs is discretized. Next, the similarity between the different ATMs' discretized daily withdrawal seasonality sequence is measured by the Sequence Alignment Method (SAM). For each cluster of ATMs, four neural networks viz., general regression neural network (GRNN), multi layer feed forward neural network (MLFF), group method of data handling (GMDH) and wavelet neural network (WNN) are built to predict an ATM center's cash demand. The proposed methodology is applied on the NN5 competition dataset. We observed that GRNN yielded the best result of 18.44% symmetric mean absolute percentage error (SMAPE), which is better than the result of Andrawis, Atiya, and El-Shishiny (2011). This is due to clustering followed by a forecasting phase. Further, the proposed approach yielded much smaller SMAPE values than the approach of direct prediction on the entire sample without clustering. From a managerial perspective, the clusterwise cash demand forecast helps the bank's top management to design similar cash replenishment plans for all the ATMs in the same cluster. This cluster-level replenishment plans could result in saving huge operational costs for ATMs operating in a similar geographical region.

1. Introduction

The importance of accurate forecasting of the withdrawal amounts in ATMs has the following motivation. Cash demand in ATMs needs to be forecasted accurately similar to other products in vending machines, as an inventory of cash needs to be ordered and replenished for a priory set period of time. If the forecasts are wrong, they induce costs. If the forecast is too high unused cash is stored in the ATM incurring costs to the bank. The bank pays different refilling costs depending on its policy with the money transportation company. In the first policy type, the bank pays a significant fixed fee for the refilling, independently of the amount, plus a small extra cost for each fraction of the transported money amount. In the second policy type, the bank pays a small fixed fee for refilling while the staircase costs are significant (Castro, 2009). According to Simutis, Dilijonas, Bastina, Friman, and Drobinov (2007) such cash-related costs represent about 35–60% of the overall cost of running an ATM. Wagner (2007) estimated a 28% cost saving as a result of improving the inventory policies and cash transportation decisions for an ATM network for a financial institution ranked among the world top 700 banks. On the other hand, if the ATM runs out of cash, profit is lost and customers are dissatisfied due to bad service (www.neural-forecasting-competition.com/NN5/motivation.htm). Osorio and Toro (2012) minimized the cost of a cash-management system for a Colombian financial services institution without negatively affecting the service level.

It is obvious that daily cash withdrawal amounts are time series. Hence, typical cash demand forecast models will have to use time series prediction methods. Recognizing the need, Lancaster University came up with a NN5 timeseries competition, wherein daily cash withdrawal amounts over 2 years from 111 ATM centers across the UK are posted as the input data sets and several researchers proposed various models for the task (www.neural-forecasting-competition.com/NN5). In this study, the available data from NN5 time series competition (Crone, 2008) is used. For each of the 111 time series we forecast the next cash demands as a trace forecast for a forecasting horizon of 1 week.

This paper advocates the use of clusterwise cash demand prediction as it might have two advantages: (1) improved accuracy of the cash demand forecasts due to reduction in computational complexity when predicting an ATMs daily cash demand for groups of ATM centers with similar day-of-the week cash withdrawal seasonality patterns and (2) potentially huge savings in

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http://dx.doi.org/10.1016/j.ejor.2013.07.027

operational costs as similar cash replenishment models can be used for ATM centers belonging to the same cluster.

To facilitate the cash demand forecasts, the ATM centers are (1) clustered into groups of ATM centers with similar day-of-the week cash withdrawal patterns followed by (2) a clusterwise prediction of the daily cash demands.

First, each ATM center's withdrawal time series is translated into a "day-of-the-week" cash withdrawal seasonality sequence containing seven day-of-the-week cash withdrawal seasonality parameters. For each ATM center, the continuous seasonality sequence is translated into a discrete cash withdrawal seasonality sequence. This "abstraction" transforms the continuous seasonality sequence into a high-level quality seasonality sequence facilitating the detection of ATM clusters with similar day-of-the week cash demand patterns. The similarity between the ATMs' discretized daily withdrawal seasonality parameter sequence is measured by calculating the Levenshtein distance using the Sequence Alignment Method (SAM). These distances are further processed by a clustering algorithm to produce groups of ATM centers which are relatively homogeneous with respect to the day-of-the-week cash withdrawal seasonality patterns.

Second, a predictive model is built for each cluster. For each ATM cluster four different neural networks are employed separately for forecasting purpose. We used MLP because it is universally popular in forecasting tasks. We employed GRNN, GMDH and WNN based on our experience and that of other authors (Li, Luo, Zhu, Liu, & Le, 2008; Mohanthy et al., 2010a, 2010b; Rajkiran & Ravi, 2007; Ravisankar & Ravi, 2010; Ravisankar, Ravi, Raghava Rao, & Bose, 2011; Srinivasan, 2008; Vinay Kumar et al., 2008).

The proposed approach is similar to Prinzie and Van den Poel (2006), as we also use SAM to first find ATM center clusters with similar temporal patterns. Our approach differs from Prinzie and Van den Poel (2006) in two major ways. Firstly, the sequences are represented by seven discretized day-of-the-week time series seasonality parameters rather than four discretized relative evolution turnover variables. We believe that the seasonality parameters estimated by time-series models are more precise than the calculation of relative evolution variables. Secondly, whereas Prinzie and Van den Poel (2006) include the cluster indicators as one of the predictors in the churn attrition model, this paper builds a separate cash demand forecasting model per ATM cluster.

The rest of the paper is organized as follows. In Section 2, literature review is presented. In Section 3, an overview of Sequence-alignment method is described. Section 4 presents the proposed methodology: construction of the sequential dimension; method to find effect-of-the-day parameter and its discretization; calculation of SAM distances; and the clustering procedure employing the Taylor-Butina algorithm. Section 5 presents a brief overview of the forecasting methods viz., WNN, GMDH, MLFF and GRNN. Results are discussed in Section 6. Finally, Section 7 concludes the work.

2. Literature review

In the following, we review the literature on modeling and analyzing NN5 competition data (Crone, 2008).

Bontempi and Taieb (2010) discussed the limitations of single-output approaches when the predictor is expected to return a long series of future values, and presents a multi-output approach to long term prediction. They also discussed here a multi-output extension of conventional local modeling approaches, and present and compare three distinct criteria for performing conditionally dependent model selection. Coyle, Prasad, and McGinnity (2010) employed self-organizing fuzzy neural network (SOFNN) to create an accurate and easily calibrated approach to multiple-step-ahead prediction for the NN5 forecasting competition. Lemke and Gabrys (2010) investigated meta-learning for time series prediction with the aim to link problem-specific knowledge to well performing forecasting methods and apply them in similar situations. A forecasting approach based on Multi-Layer Perceptron (MLP) Artificial Neural Networks (named by the authors MULP) is proposed by Pasero, Raimondo, and Ruffa (2010) for the NN5 111 time series long-term, out of sample forecasting competition. Good results had also been obtained using the ANNs forecaster together with a dimensional reduction of the input features space performed through a Principal Component Analysis (PCA) and a proper information theory based backward selection algorithm. Teddy and Ng (2010) proposed a novel local learning model of the pseudo self-evolving cerebellar model articulation controller (PSECMAC) associative memory network to produce accurate forecasts of ATM cash demands. As a computational model of the human cerebellum, their model can incorporate local learning to effectively model the complex dynamics of heteroskedastic time series. Andrawis et al. (2011) used Forecast combinations of computational intelligence and linear models to solve the problem. The main idea of this model is to utilize the concept of combination of forecasts (ensembling), which has proven to be an effective methodology in the forecasting literature. The models used are neural networks, Gaussian process regression, and a linear model. Wichard (2011) proposed a simple way of predicting time series with recurring seasonal periods. Missing values of the time series are estimated and interpolated in a preprocessing step. He combined several forecasting methods by taking the weighted mean of forecasts that were generated with time-domain models which were validated on left-out parts of the time series. The hybrid model is a combination of a neural network ensemble of nearest trajectory models.

None of the papers modelling NN5 data clustered the time series first on daily withdrawal trends before predicting the ATM center's cash demand. Most authors try to reduce the complexity of the cash demand forecasting by either performing a data reduction of the input features space before prediction (Pasero et al., 2010) or by employing a local learning model (Teddy & Ng, 2010). This paper reduces the forecasting problem complexity by predicting cash demand per ATM cluster containing ATM centres with similar daily cash withdrawal patterns. We thereby follow an approach similar to Prinzie and Van den Poel (2006), who first clustered customers of an International Financial-Services Provider (IFSP) into clusters with similar relative evolution in turnover using SAM and the Taylor–Butina clustering algorithm followed by a binary logistic regression model predicting the customer's churn probability. Rather than including the cluster indicators as additional predictors in the forecasting model as in Prinzie and Van den Poel (2006) we build cash demand forecast models per ATM cluster with similar day-of-the week cash withdrawal patterns.

3. Overview of sequence-alignment method (SAM)

The ATM centers are compared with respect to their daily cash withdrawal trends. Therefore, each ATM center is represented as a sequence of seven 'day-of-the-week' cash demand seasonality parameters. To facilitate the detection of ATM clusters with similar day-of-the week cash withdrawal patterns, the "day-of-the-week" seasonality parameters are discretized. Then, the Sequence-Alignment Method is used to calculate the similarity of each pair of ATM centers on this discretized sequential dimension. Subsequently, these SAM distances are input to a clustering algorithm to identify ATM centers with similar day-of-the-week cash withdrawal patterns.

The Sequence-Alignment Method (SAM) (Levenshtein, 1965) was developed in computer science and found applications in text