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A novel three-step procedure to forecast the inspection volume

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ABSTRACT

The inspection process of freight traffic at Border Inspection Posts (BIPs) generates significant time delays and congestion within the transport system. The use of forecasting methods to anticipate these situations could be a good solution. Traditional methodologies for time series prediction usually consist on: applying single techniques, combining these techniques with some others such as clustering techniques or hybridizing single prediction techniques. A novel methodology based on a three-step procedure is proposed in this paper in order to better predict the number of inspections at BIPs, integrating a clustering technique and a hybrid prediction model. Specifically, the seasonal auto-regressive integrated moving averages (SARIMA) is used first to predict the data. Then, self-organizing maps (SOM) decomposes the time series into smaller regions with similar statistical properties. Finally, Artificial Neural Networks (ANNs) are applied in each homogeneous regions to forecast the inspections volume, testing different hybrid approaches based on the inputs of the model. The experimental results show that the performance of inspection prediction can be enhanced by using the novel three-stage procedure, providing relevant information for resource planning and turning into a powerful decision-making tool, not only at the inspection process of seaports or airports, but also in the field of time series prediction.

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1. Introduction

With increasing concerns about security in border crossing and the steady growth in the exchange of goods between world countries, the inspection process has reached major importance. The European unification, in combination with the general globalization trends, has led to a significant rise in cross-border freight transport. In the case of European Union (EU), the Border Inspection Posts (BIPs) were established to guarantee that all the products coming into the EU meet the necessary conditions in terms of quality and safety. The inspections of goods performed in these facilities are a complex and lengthy process in certain cases. Thus, this problem can produce congestion and bottlenecks within the port or airport system, especially in European major ports, and may entail higher costs and delays in the supply chain. Nevertheless, strict and reliable inspections are necessary, especially in the actual context of high security. In fact, the goods that cross the UE have unrestricted freedom of movement within the member states. Just as forecast demand in traffic and transport problems are a suitable tool as mean to address congestion and decision making-problems, the prediction of the volume of inspections may become a powerful solution. In this way, a prediction of the inspection volume can be a useful tool to improve the service quality, planning operations and human resources at ports.

The number of inspections in any inspection system can be treated as a time series due to its constant changes in a period and thereby a forecasting model can be applied over the data. During past decades, many efforts have been carried out in

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order to develop and to improve prediction models for time series in any forecasting field (econometrics, statistic, artificial intelligence, etc.). A wide variety of prediction techniques have been applied to predict time series in general and traffic or transport flows in particular. In this paper, the forecasting techniques can be classified into two categories: classic statistical methods and Artificial Intelligence (AI) methods.

The first category comprises mostly the so called linear models. The main assumption of these models is that the future values have a linear relationship with past and current values of the time series under study. Some examples include classical moving average and auto regression methods (Bowerman and O'Connell, 1993), Kalman filtering methodology (Okutani and Stephanedes, 1984; Stathopoulos and Karlaftis, 2003) or the well-known Box and Jenkins (1976) methodology (e.g. Autoregressive Integrated Moving Average (ARIMA) and its improvements). Particularly, related to the maritime transport (the traffic associated to the port BIPs and consequently with the inspections), Gambardella et al. (1996) predicted export operations in a container terminal using ARIMA models. In the same way, ARIMA were proposed to predict several traffic flows of goods through a port in Klein (1998) and Babcock and Lu (2002). Besides, ARIMA models with seasonal component (SARIMA) were successfully used and then were compared with other methods for traffic flow forecasting (Smith et al., 2002) and recently for predicting container throughput volumes in ports (Peng and Chu, 2009) with promising results. An extensive review of other statistical forecasting methods can be found in the work of Stathopoulos and Karlaftis (2003).

Although classical linear models have proved to be effective in a wide range of time series, they show weakness when uncertainty or nonlinear patterns are presented. The real-world problems are complex and are typically generated by an underlying nonlinear process (Zhang, 2003). Therefore, the traditional linear models might be unsuitable if the time series shows a nonlinear behaviour, such could be the case of inspection volume forecasting.

In order to overcome the nonlinearity present in time series, several intelligent techniques have been proposed which comprise the second category of forecasting methods (AI techniques). Specifically, Artificial Neural Networks (ANNs), an extremely popular class of AI models, have constantly been applied to forecasting and planning tasks in transportation and traffic flows (Smith and Demetsky, 1994; Dougherty, 1995; Amin et al., 1998; Park and Rilett, 1998; Abdelwahab and Sayed, 1999; Faghri et al., 1999; Sayed and Razavi, 2000; Dharia and Adeli, 2003; Sarvareddy et al., 2005; Vlahogianni et al., 2005a; Lam et al., 2006; Celikoglu and Cigizoglu, 2007; Tsai et al., 2009; Gosasang et al., 2011) due to its relatively easy way to approximate a nonlinear mapping with any degree of complexity, overcoming the problem of nonlinearity (Hornik et al., 1989).

The performance of the AI techniques have constantly been compared with the one obtained from linear models. Particularly, ANNs and ARIMA models have been subject to evaluation with mixed results. Several authors make comparisons between ANNs and the corresponding traditional methods in their certain application and conclude that ANNs perform better than linear models (Amin et al., 1998; Park and Rilett, 1998; Sayed and Razavi, 2000; Qiao et al., 2001; Vlahogianni et al., 2004) including ARIMA models as linear method (Lingras et al., 2000; Zhong et al., 2005). However, although ANNs have demonstrated their ability to modelling nonlinear process in many research findings, they have also shown inconsistent performances in certain situations, as Tang et al. (1991) or Taskaya-Temizel and Casey (2005) have demonstrated. Hence, it seems to be clear that it not wise to apply ANNs blindly to any data series (Zhang, 2003).

Over the past several years, much effort have been devoted to improve and develop hybrid time series forecasting models (Khashei and Bijari, 2012). Linear and nonlinear models tend to have their own advantages and limitations for different applications (Ma et al., 2014). To overcome the disadvantages related to the use of single models, the combination or hybridization of several models have become a powerful solution in order to reduce forecast error rates (Zhang and Liu, 2011). A wide range of hybrid forecasting studies have been applied in many transport areas (Yin et al., 2002; Vlahogianni, 2009; Tsai et al., 2009; Zhang and Liu, 2011; Ma et al., 2014). The aim is to combine several models to improve forecast accuracy and to reduce the risk of failure involved in the use of an unsuitable single model.

Specifically, in recent years several hybrid models combining linear models and intelligent techniques (nonlinear models) have been proposed to forecast time series achieving good prediction performance. The reason is that real time series are not purely linear or nonlinear and exhibit both components. This scheme is based on the assumption that a hybrid methodology including models with linear modelling capabilities and models with nonlinear capabilities are able to capture the complete behaviour of a time series (Tseng et al., 2002; Hansen and Nelson, 2003; Zhang, 2003; Khashei and Bijari, 2010). One of the most popular structure of this hybrid approach consists on fuse ARIMA models with artificial neural networks. In this way, a hybrid methodology based on seasonal ARIMA (SARIMA) and ANNs was proposed by Tseng et al. (2002) to predict time series with a seasonal component. In a similar manner, Zhang (2003) presented a hybrid model combining ARIMA models and ANNs models for time series forecasting. These authors found that hybridizing ARIMA and ANNs achieve more accurate prediction performance instead of using each model in an individual way. Since then, the literature on this topic has dramatically extended. Numerous hybrid forecasting models have been proposed and applied in many areas of time series, such as stock index forecasting (Wang et al., 2012), wind speed forecasting (Cadenas and Rivera, 2010; Shi et al., 2012) or air pollution forecasting (Diaz-Robles et al., 2008) among others. However, none of them deals with the prediction of the inspection process, which is the focus of this paper. All these authors addressed the prediction problem using the traditional hybrid approach. This approach consists on decomposing the time series into its linear and nonlinear component. The prior assumption is that the relationship established between this two components is additive, and thereby it may be underestimated. To address this problem, Khashei and Bijari (2010) presented a novel hybrid approach where the forecasting values obtained

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