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An improved grey neural network model for predicting transportation disruptions

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ABSTRACT

Transportation disruption is the direct result of various accidents in supply chains, which have multiple negative impacts on supply chains and member enterprises. After transportation disruption, market demand becomes highly unpredictable and thus it is necessary for enterprises to better predict market demand and optimize purchase, inventory and production. As such, this article endeavors to design an improved model of grey neural networks to help enterprises better predict market demand after transportation disruption and then the empirical study tests its feasibility. This improved model of grey neural networks exceeds the conventional grey model GM(1,1) with respect to the fact that the raw data tend to show exponential growth and data variation is required to be moderate, demonstrating the good attribute of nonlinear approximation in terms of neural networks, setting up standards for selecting the number of neurons in the input layer of BP neural networks, increasing the fitting degree and prediction accuracy and enhancing the stability and reliability of prediction. It can be applied to sequential data prediction in transportation disruption or mutation, contributing to the prediction of transportation disruption. The forecasting results can provide scientific evidence for demand prediction, inventory management and production of supply chain enterprises.

1. Introduction

The management of disruption risk in supply chains has been a priority for enterprises and a focus of research in academia. In recent years, with trends such as global purchases by enterprises, non-core business outsourcing, single source supply and lean production, supply chains have increasingly expanded in terms of space and have significantly shorter supply cycles. The changes in space and time increase the probability of occurrence of disruption. Also, the moments of natural disasters, economic fluctuations, epidemics, terrorism, wars and others are likely to occur, which renders supply chains fragile and the probability of supply chain disruption increases. Transportation disruption is one aspect of the risk management of supply chain disruption.

In 1998, the computer breakdown at Hong Kong International Airport delayed the transport of a multitude of goods and passengers. The 911 incident resulted in movement of goods on the borders between the USA and Canada coming to a standstill and Ford Motor Company was forced to stop production at 5 assembly plants. In 2002 strikes along the western coast of USA resulted in COSCO's failure to unload cargo which returned, causing a loss of $24,000,000 in two weeks. The ice damage in China in 2008, floods in Thailand in 2011 and the Ya'an earthquake in China in 2013 led to paralysis of transportation facilities on a large scale. The frequent occurrence of various transportation disruptions directly disrupt movement of raw materials of enterprises and production cost increases, affecting the steady pace of production, health and safety of consumers, and the prosperity and stability of society.

Transportation disruption in supply chains is the direct result of various accidents such as natural disasters (e.g., ice damage, ocean disasters, and earthquakes, etc.) and social accidents (e.g., strikes and terrorist attacks), affecting supply chains and their member enterprises negatively. A number of scholars have investigated transportation disruption in terms of recognition and strategies. Sheffi (2001)

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found that transportation disruption is one of the factors generating supply chain risks. He stated that risk can be mitigated by increasing the visualization of the transportation process and optimizing the inventory decisions and partnership. Wilson (2007) examined the effects of transportation disruption on the attributes of supply chains by systematic dynamics and found that transportation disruption affects the first suppliers and their inventory most. Zhang and Lam (2015) investigate the transportation disruption caused by typhoons at ports and the loss they cause and finds that loss consists of 4 parts: reputation loss, shippers' loss, transporters' loss and port operators' loss. Taking China's railways and airline companies as examples, Ouyang, Pan, Liu, and He (2015) discuss measures to mitigate the fragility of various transportation systems in terms of the complementary relationship of the infrastructure system. Hishamuddin, Sarker, and Essam, (2013), (2015) consider the two-stage recovery model of production and inventory in transportation disruption, and find that the optimal order quantity and production can be determined and the total cost can be minimized during the recovery period. Khademi et al. (2015) take Tehran with frequent earthquakes as an example, analyze the fragility of transportation networks, and point out that after disasters the demand for tourism becomes highly uncertain and the traditional methods cannot be applied to predictions. They recommend some methods to evaluate the loss caused by earthquakes and recover the transportation. Bravo and Vidal (2013) develop an optimal model for supply chain goods by mathematical planning and provide an example and build a model in terms of abnormal transportation. The literature discussed above has shown that many researchers offer strategies for transportation disruption from multiple perspectives and note that the market demand is highly unpredictable after transportation disruption, affecting the production and inventory significantly.

The uncertainty of market demand after transportation disruption can be optimized from many aspects such as production, inventory and distribution in supply chain enterprises. Chiu, Lee, Chiu, and Cheng (2013) explore the supply chain in multinational companies to ensure that products can be sold in multiple places; quality is guaranteed; the optimal quantity of products and means of transportation can be determined, thus minimizing the cost of production, inventory and transportation of supply chain members. Based on Generic Bill of Materials (GBOM), Shu, Chen, Wang, and Lai (2014) investigate the risk control of supply chain enterprises and tackle the unpredictability of production after disruption by combining random simulation and neural networks. Costantino, Gravio, Shaban, and Tronci (2015) design the real time statistics process control (SPC) system to counteract the whip effect through control charts, hence achieving the stability of competitive inventory. The results show that SPC system can satisfy the principle of smooth complements. Pasandideh, Niaki, and Asadi (2015) consider a three-tier supply chain consisting of manufacturers, distribution centers with uncertain service and customers to achieve optimization of multiple products and multiple stages in supply chains. They deploy the model of mixed integral linear planning and the method of multiple-target decisions, to achieve minimization of total cost and maximization of average quantity of goods for customers.

Market demand is unpredictable and highly uncertain particularly after transportation disruption and thus enterprises have to manage their inventory and production accordingly. Now, if the market demand is well predicted, the cost of inventory and production as well as risk can be reduced and sales can be optimized. Little research so far has involved prediction of market demand for supply chain enterprises after transportation disruption. For this reason, this article designs an improved model of grey neural networks to help supply chain enterprises better forecast market demand after transportation disruption. Also, an empirical study is conducted to test the feasibility of the model.

2. An improved prediction model of grey neural networks

Deng (1982) proposed the grey system theory which addresses samples of some known and some unknown information and is an uncertain system of inadequate information. The advantages are a simple modelling process and concise expressions, which are extensively employed in multiple disciplines. By contrast, this prediction method is suitable for sequences with stable rates of variation. In particular, when the sequence of data changes dramatically, where deviation varies in terms of prediction results, many scholars have made improvements accordingly (Chang, Li, Huang, & Chen, 2015; Cristóbal et al., 2015; Zeng & Liu, 2011).

Neural networks refer to concurrent nonlinear dynamic systems on a large scale, with strength to handle nonlinear problems. Particularly, back propagation is most widely employed, in e-commerce, industry, environmental science and many other fields (Chi & Zhao, 2012; Ray, Mukhopadhyay, Datta, & Pal, 2013; Wang, Zeng, Feng, & Xia, 2013). In contrast, this method is likely to show flaws such as local minimizers in longer operations.

There are merits and demerits of each algorithm and thus it is common to integrate two or more methods and build a combined model (Bates & Granger, 1969). Some scholars have endeavored to incorporate the grey model with other methods to build a combined model, including particle swarm optimization (Hodzic & Tai, 2016), DEMATEL method (Rajesh & Ravi, 2015), uncertainty theory (Memon, Lee, & Mari, 2015), multivariate model (Intharathirat, Salam, Kumar, & Untong, 2015), fuzzy mathematics method (Dewangan, Gangopadhyay, & Biswas, 2015) and Markov method (Xie, Yuan, & Yang, 2015), among many others. A number of researchers have attempted to integrate grey prediction model and neural network to handle nonlinear problems, tackle unpredictable demand and increase prediction precision (Alvisi & Franchini, 2012; Hsu, 2011; Pai et al., 2015; Zhang, Xu, Cui, He, & Tian, 2012).

It can be observed that in the combination of grey model and neural network model, the number of neurons in the input layers of BP neural networks can be either 1 or random, which can control the intrinsic errors of the prediction model of neural networks, whereas the deviation of grey model and neural network model cannot be controlled at the same time. This leads to failure to optimally control the total deviation. As such, based on the grey model and the neural network model, this article designs an improved prediction model of grey neural networks, setting up the standards for choosing the number of neurons in the input layer of BP neural networks, namely, the optimal number of dimensions of the improved grey prediction model is the figure for neurons in the input layer of BP neural networks. This improved prediction model for determining the number of neurons in the input layer of BP neural networks exceeds the conventional grey GM(1,1) which has strict requirements for the sequence of raw data, demonstrating the good attribute of nonlinear approximation in terms of neural network, increasing the fitting degree and prediction accuracy, and enhancing the stability and reliability of prediction. It can be applied to sequential data prediction in transportation disruption or mutation.

2.1. A grey prediction model

2.1.1. Traditional GM(1,1) model

GM(1,1) is a fundamental prediction model based on the grey theory. GM is formed by the initial letters of the grey model; regarding (1,1), the first 1 means that the prediction model only consists of a 1-step equation and the second 1 means that there is only one dependent variable in the model. As such, GM(1.1) is based on the premise that 1-step equation and 1 dependent variable are satisfied. In the Grey prediction model GM(1,1), the original sequence is cumulatively produced as the time sequence increases progressively. The corresponding approximate differential equations are constructed to