

Effects of Extreme Weather and Economic Factors on Freight Transportation

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Abstract

The objective of this paper is to examine the impact of changes in extreme weather conditions and economic factors on freight transportation in Taiwan. To explore the effect of climate variability such as the increasing frequency and intensity of precipitation and typhoons, a climate-related freight prediction model using time series data is presented. Empirical results indicate that severe typhoons with extremely torrential rains show a significant influence on freight movements. In addition, the gross domestic product, changes in oil prices, and events of regional and global economic crises also significantly influence freight movements. Based on the findings of the analyses, some recommendations for reducing the vulnerability of freight sectors to climate change are proposed.

JEL classification numbers: Q5, R4

Keywords: Extreme weather, Economic effect, Freight , transportation
Transportation modes

1 Introduction

The impact of global climate change and changes in local weather conditions on transportation systems (e.g., road, rail, air, and water transportation) have become a worldwide concern (Eisenack et al., 2012; Molarius et al., 2014). Extreme

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weather events (e.g., severe storms, intense precipitation) may affect freight transportation because more trips are canceled or re-routed, and there are more travel delays, and traffic accidents (Suarez et al., 2005). More frequent extreme weather such as snowstorms, ice storms, severe typhoons/hurricanes, tornadoes, and heavy rainfall are more likely to cause additional disruption and loss in freight movement in all transportation modes.

The impact of climate change on freight transportation can cause changes in shipping patterns/routes and influence the design, safety, operation, and maintenance of the physical infrastructure of freight movement by road, rail, water, and air. For example, more frequent icing and extreme weather events significantly decrease safety and increase delays as well as adding to the cost of maintenance of the freight transport system (Caldwell et al., 2002). Climate change can also influence all modes of freight transportation and the affected regions are vulnerable to adverse effects, such as rising sea levels and storm surges which increase the risk of damage to roads, railways, the transit system, and runways in floodplains or coastal areas (TRB, 2008). Also, the challenges to the impact of climate change on the operation and infrastructure of freight transportation should be admitted and incorporated into the planning, design, construction, operation, and maintenance of freight transportation systems (Camp et al., 2013).

Significant damage and disruption caused by typhoons will affect the operation of the freight transportation system. For example, the damage to roads/bridges/railway lines/seaports/airports increases the reconstruction and repair costs of freight transport operators. Also, typhoons can impair the operating efficiency of freight movement, such as strong winds and large waves interrupt cargo operations of seaports, heavy rains and high winds cause delays and cancellations of flights or even the closure of airports.

Climate change may result in more extreme weather events, e.g., more frequent and intense typhoons, heavy rains, snowfall, heat waves, cold spells, flooding, or droughts. This study focused on the effects of the increasing frequency of typhoons and rainfall on freight transportation which have been the two major events of climate change in the subtropical climate of Taiwan. Other minor effects of severe weather on freight movement in Taiwan such as heat waves, cold spells, and dense fogs were not included in this study.

In addition to the effect of extreme weather on freight transportation, the growth in freight movement is significantly associated with economic growth, e.g., freight ton-miles and gross domestic product (GDP) are strongly related (Mallett et al., 2004).

The remainder of this paper is structured as follows: Section 2 introduces the related literature. Section 3 describes the data sources. Section 4 presents the methods used to assess important variables affecting freight transportation. Section 5 discusses the empirical results and the effects of extreme weather and economic factors on freight transportation. Section 6 summarizes the important findings and proposes policy recommendations.

2 Literature Review

Past studies have examined the potential impact of climate change on the transportation system. For example, Keay and Simmonds (2005) found that the impact of rainfall in Australia would decrease traffic volume by 1.35% and 2.11% on wet days in winter and spring, respectively. Traffic volume would also decrease by 2%~3% for 2~10 mm of rain during daytime and a larger reduction of 3.43% for 2~5 mm of rain in spring. Hranac et al. (2006) quantified the impact of inclement weather on the traffic stream. Light rain would cause reduction in the traffic free-flow speed and speed-at-capacity of approximately 2~3.6% and 8~10%, respectively. Snow precipitation would produce larger reduction in the traffic stream than rain. Light snow would cause reduction in both free-flow speed and speed-at-capacity of approximately 5~16%. Peterson et al. (2008) identified that changes in weather and climate extremes can have a substantial impact on transportation. As the climate warms, decreasing cold temperature extremes would probably improve the safety record for rail, air, or ships. Warm extremes are projected to increase and this change would probably increase the amount of roadbed and railroad track buckling and adversely impact maintenance work.

Regarding the modeling approaches to investigate the impact of climate change on the transportation system, Hassan and Barker (1999) developed a simple model to predict traffic activity based on yearly, monthly and daily variations as well as meteorological variables based on monthly variations. The results showed that an average reduction of 10% in weekday traffic activity when snow was on the ground. Also, there was an average reduction of 4% and 15% in weekend traffic activity on the days with the highest rainfall and when it was snowing, respectively. Suarez et al. (2005) developed a methodology that integrates projected changes in land use, demographic and climatic conditions to model the delays and lost trips caused by increased coastal and river flooding on the performance of the system of urban transportation networks. The results showed that delays and lost trips were almost twice as common. Jonkeren et al. (2011) used a GIS-based freight network planning model to estimate the change in the modal split between inland waterway and rail/road transport under several climate scenarios. The results showed that the annual quantity transported by barge would decline by about 5.4% (2.8 million tons) in the most extreme climate scenario.

Concerning methods used to forecast the changes in future climate patterns, Hoyos et al. (2006) used a statistical analysis based on the data of historical climate trends to measure the relationship between hurricane intensity and four important variables (sea-surface temperatures, specific humidity, wind shear, and zonal stretching deformation) during the period 1970–2004. The results indicated that an increasing trend in the number of category 4 and 5 hurricanes was directly linked to a trend in sea surface temperatures. Knutson et al. (2008) used a climate model to examine the influence of warming ocean temperatures on Atlantic hurricane activity from 1980 to 2006. The results indicated that the frequency of hurricanes and tropical storms in the Atlantic Ocean could be reduced and near-storm rainfall

rates could increase substantially under future greenhouse-gas-induced warming. With respect to the potential adaptation strategies for the impact of climate change on the transportation system, the Transportation Research Board (TRB) (2008) proposed projected climate extremes such as more extreme temperatures, more intense precipitation, and more intense storms would likely have a considerable impact on the transportation infrastructure, which could cause environmental conditions beyond those for which the system was designed. In order to accommodate uncertainties about the nature and timing of expected climate changes, the TRB suggested that transportation decision-makers should adopt a more probabilistic risk management approach to infrastructure planning, design, and operations. Regarding the implications of climate change for both short-term and long-term infrastructure design, Meyer (2008) proposed an assessment of the climate-induced changes including temperature change, precipitation and water levels, wind loads, storm surges, and wave heights. Risk-oriented, probabilistic design approaches should be developed for design standards to accommodate the potential impact of climate change on the transportation system. Schmidt and Meyer (2009) further developed a conceptual framework for transportation planning to illustrate how some agencies incorporated climate change in the planning process which included the three additionally important steps of project prioritization, project development, and system monitoring. Recommendations were made to integrate greenhouse gas emission mitigation and climate change adaptation strategies into the planning process at the metropolitan and local level. Machado-Filho (2009) analyzed two transport policies with climate co-benefits for intra-city and inter-city transport in Brazil. The author proposed transport policies to encourage the freight modal shift from trucks to less energy-intensive rails and shipping which would provide the climate co-benefits of reduced energy costs, fewer accidents, and reduced local congestion and pollution. Financing issues for the investment in transport logistics infrastructure at the national level and the city level were also presented. Meyer and Weigel (2011) suggested an approach using an adaptive system management to identify vulnerabilities in the transportation system and assess different strategies for mitigating potential impact. Regarding the economic effects on freight transportation, the association between economic impacts (e.g., economic growth, oil prices) and freight movement have been investigated by many studies, such as Shan et al. (2014), Chao and Hsu (2014), Sorrell et al. (2012), Bröcker et al. (2011), Kasarda and Green (2005).

3 Data

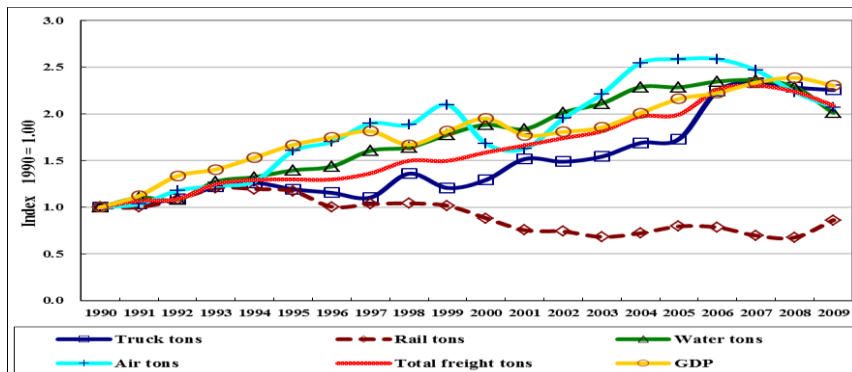
This paper explored the relationship between climate change (e.g., the increase in frequency and intensity of typhoons and precipitation) and freight movement. The measurements of freight movements are limited to the movement of cargo carried by truck, rail, water, and air, while passenger freight is excluded.

In order to identify the trend of climate variability and its impact on freight movement, twenty-year monthly meteorological data and associated freight data from 1990 to 2009 were collected from the Central Weather Bureau and the Institute of Transportation in Taiwan. Climate parameters contained the frequency and intensity of typhoons and precipitation. The data collected included three classes of typhoons with different intensities including weak typhoons (maximum sustained wind speed ranging from 17.2 to 32.6 m/sec), medium-strength typhoons (maximum sustained wind speed ranging from 32.7 to 50.9 m/sec), and severe typhoons (maximum sustained wind speed greater than 51.0 m/sec). Also, five classifications of precipitation intensity including light rain (less than 50 mm/24Hr), heavy rain (50-130 mm/24Hr), extremely heavy rain (130-200 mm/24Hr), torrential rain (200-350 mm/24Hr), and extremely torrential rain (greater than 350 mm/24Hr) were collected from sixteen land-based weather stations with complete precipitation records.

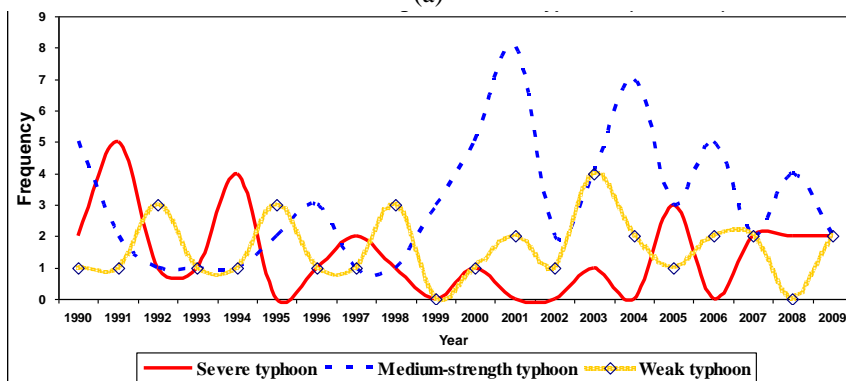
From 1990 to 2009, domestic freight movements (tons) carried by truck, water, and air increased by 125.5%, 101.3%, and 107.0%, respectively; however, rail tons declined by 13.8%. The truck-rail modal splits of freight shipment on land routes were competitive between parallel highways and railroads particularly for long-haul shipments. However, due to a lower shipping price and the ability to provide more flexibility and reliability such as door-to-door and just-in-time service, truck freight movement has become the dominant mode of inland transport since 1998. Due to the fact that the average domestic freight movements by truck, water, rail, and air accounted for 42.20%, 56.06%, 1.60%, and 0.14% respectively during the 1990-2009 period, this study focused on water and truck transportation, the major modes of freight transport, as well as the modal split of freight transported by rail to examine the effect of extreme weather on these three freight movements.

The changes in the frequency and intensity of extreme weather events are apparent as shown in Figure 1. Compared to the decade from 1990 to 1999, the frequency of weak, medium-strength, and severe typhoons in the 2000-2009 decade showed the changes of 14.3%, 47.4%, and -33.3%, respectively. The frequency of medium-strength typhoons increased more than weak typhoons; while severe typhoons declined. Meanwhile, the frequency of light rain, heavy rain, extremely heavy rain, torrential rain, and extremely torrential rain in the 2000-2009 decade showed the changes of -4.4%, 12.0%, 2.7%, -15.9%, and 10.8%, respectively as compared with the 1990-1999 decade. Light rain has become less frequent, but extremely torrential rain has become more frequent and intense since 2000.

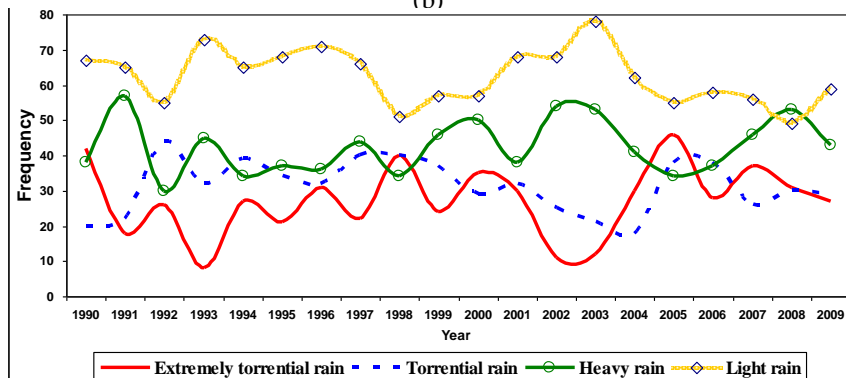
In addition to the adverse impact of climate change, freight movements were also significantly affected by specific events over the past 20 years such as economic crises (1997-1998 Asian financial crisis, 2008-2009 global financial crisis) and 1995-1996 Taiwan Strait missile crisis. For example, the impact of the 2008-2009 global financial crisis led to a decline in the total freight movements in tons in Taiwan by 6% as compared to 2007.



(a)



(b)



(c)

Figure 1: Trends of (a) freight movements and GDP, (b) typhoons, (c) rainfalls.

4 Methodology

To examine the impact of extreme weather on freight movement, time series data were utilized to develop forecasting models. The models take into account explanatory variables of different intensities of typhoons and precipitation. Economic effects of the gross domestic product (GDP) and changes in oil prices on freight were also examined in the models. In addition, the regional impact of the Taiwan Strait missile crisis and the Asian financial crisis as well as the global impact of the financial and economic crisis on freight were incorporated into the models. Two methods including a generalized additive model and a neural network model were applied to develop truck/water/rail freight prediction models.

4.1 Generalized Additive Model

In order to identify the variability of extreme weather affecting freight movements, this study developed a generalized additive model based on monthly time series data during the rainy and typhoon seasons between 1990 and 2009. To incorporate seasonal variation in adverse weather patterns, three classifications of typhoon intensity from weak typhoons to severe typhoons with extremely torrential rains were selected as explanatory variables. In addition, the GDP as a reflection of economic activity and oil prices associated with freight transport costs were selected. Moreover, the events of the 1995-1996 Taiwan Strait crisis and economic crisis (e.g., 1997-1998 Asian financial crisis, 2008-2009 global financial crisis) were selected as explanatory variables as well.

The generalized additive model (GAM) is a non-parametric regression model that incorporates nonlinear forms of the predictors through an appropriate link function (Hastie and Tibshirani, 1990; Pearce et al., 2011). The GAM can be described by the following equation:

$$\text{Log}(Y_i) = \beta_0 + \sum_{j=1}^n f_j X_{ij} + \varepsilon_i \quad (1)$$

where Y_i is the response (or dependent) variable, β_0 is the overall mean of the response, f_j is the unspecified (non-parametric) smooth functions of the explanatory (or independent) variable X_{ij} , n is the number of observations, and ε_i is the i th residual (error).

The formula of the GAM model and variables used are presented in the Appendix A.

4.2 Neural Network Model

The back propagation neural network (BPN), as one of the most representative algorithms of the artificial neural networks (ANN) model, has the ability to capture the nonlinearity in the data and provide accurate predictions (Fausett 1994; Bishop 1995). The BPN is a multilayer (input layer, hidden layer, and output layer) feed-forward and supervised learning neural network, which utilizes the steepest

descent method to minimize the error function and then adjusts the interconnection weights between neurons. The sigmoid function is usually used as the nonlinear transfer function in the hidden layer.

Excluding the data in 2009 for model validation, the seasonal data sets from 1990 to 2008 were randomly split into two subsets of an 80% training set and a 20% testing set. Based on the measure of accuracy of the minimum root mean square error (RMSE), a three-layer BPN model that consists of one input layer with five variables, one hidden layer, and one output layer with the variable of each freight mode was developed.

The RMSE equation is defined as below.

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_i^n (\hat{y}_i - y_i)^2} \quad (2)$$

where,

y_i = the i actual value

\hat{y}_i = the i forecast value

n = the number of observations

5 Main Results

5.1 Empirical Results of Generalized Additive Model

Statistical results for influential variables associated with freight movements identified in the generalized additive models are presented in Table 1. The results indicate that severe typhoons with extremely torrential rains had a significant influence on the decrease of both truck and water freight movements over the 20-year modeling period. Meanwhile, medium-strength typhoons with extremely torrential rains also caused a statistically significant decrease in rail freight movement.

In addition, the economic indicator GDP is statistically significant and positively related to truck and water freight movements but it shows the opposite effect on rail freight movement. Also, the effects of the financial and economic crises, the Taiwan Strait missile crisis, and the percentage change in oil prices from the previous year on truck and water movements are negative and statistically significant. Nevertheless, variables of the Taiwan Strait and economic crises also show an opposite effect on rail freight transport. This may be due to the fact that when compared to trucks, rails provide a safer, lower line-haul cost, and more

reliable freight transport under extreme weather conditions or during adverse economic/political-military events thus cause a significant modal shift of freight shipments from truck to rail mode. This also indicates that the domestic demand for freight transport is usually strongly affected by factors of global and regional impact that can significantly affect international trade and economic growth.

Table 1: Generalized additive models for different freight modes.

Explanatory variables	<u>Truck freight movement (1,000 tons)</u>		<u>Water freight movement (1,000 tons)</u>		<u>Rail freight movement (1,000 tons)</u>	
	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value
Constant	9.227**	<0.001	9.522**	<0.001	7.733**	<0.001
Frequency of extreme weather						
Severely typhoon with extremely torrential rain	-0.044*	0.098	-0.114**	0.005		
Medium-strength typhoon with extremely torrential rain					-0.126**	0.004
Weak typhoon with extremely torrential rain						
GDP (million US\$)	0.000048**	<0.001	0.000048**	<0.001	-0.000025**	<0.001
Percentage change in oil prices from the previous year	-0.137*	0.003	-0.026*	0.091		
Occurrence of financial and economic crises	-0.119*	0.004	-0.086**	0.011	0.119**	0.004
Occurrence of Taiwan Strait missile crisis	-0.187*	0.008	-0.122**	0.033	0.239**	0.004
Adjusted R ²	76.8%		83.6%		50.8%	

** Statistically significant at the 5% level. * Statistically significant at the 10% level.

5.2 Model Validation and the Best-Forecasting Model

To determine the best freight forecasting models, the time series data was used in the generalized additive model and the BPN model; while the latest 6-month data was used to validate forecasting accuracy. The formulas of three accuracy measures including the mean absolute percentage error (MAPE), the mean absolute deviation (MAD), and the mean squared deviation (MSD) are defined as

below.

$$\text{MAPE} = \frac{\sum_{t=1}^n |(\hat{y}_t - y_t) / y_t|}{n} \times 100 \quad (3)$$

$$\text{MAD} = \frac{\sum_{t=1}^n |\hat{y}_t - y_t|}{n} \quad (4)$$

$$\text{MSD} = \frac{\sum_{t=1}^n |\hat{y}_t - y_t|^2}{n} \quad (5)$$

where,

y_t = the actual value

\hat{y}_t = the forecast value

t = the time period

n = the number of observations

The validation results from the most recent 6-month data show that the BPN model provides more accurate forecasts than the generalized additive model, as shown in Table 2 and Figure 2. For the truck freight model, the BPN shows a very small MAPE value (1.2%) which represents a very good accurate prediction. The generalized additive model also produces a good accurate prediction (10.3%). For the water freight model, the BPN shows a very small MAPE value (2.4%) which represents a very good accurate prediction; while the generalized additive model produces a good accurate prediction (11.5%). For the rail freight model, both the BPN (9.3%) and the generalized additive model (9.4%) show a small MAPE value which represents a very good accurate prediction. In addition to the MAPE, the other two accuracy measures MAD and MSD also show consistent smaller values with the MAPE in the three freight models.

Overall, the BPN model outperforms the generalized additive model in forecasting the time series for truck/water/rail freight movements. This can be attributed to the fact that the BPN model can accurately capture the nonlinear relationships between these freight movements and their influential explanatory variables.

Table 2: Validation results of forecast accuracy for (a) truck, (b) water, and (c) rail freight.

(a) Truck freight movements (thousand tons)

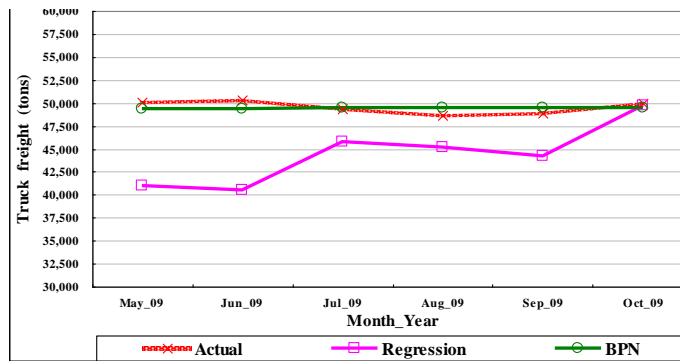
	Generalized additive model			BPN model	
<u>Time</u>	<u>Actual</u>	<u>Forecast</u>	<u>% error</u>	<u>Forecast</u>	<u>% error</u>
May2009	50,025	40,954	-18.1%	49,417	-1.2%
Jun.2009	50,337	40,478	-19.6%	49,415	-1.8%
Jul.2009	49,333	45,757	-7.2%	49,434	0.2%
Aug2009	48,693	45,177	-7.2%	49,431	1.5%
Sep.2009	48,839	44,276	-9.3%	49,427	1.2%
Oct.2009	49,967	49,764	-0.4%	49,441	-1.1%
Average	49,729	44,401	-10.3%	49,428	-0.2%
MAPE		10.32%		1.17%	
MAD		5,131		580	
MSD		37,580,205		399,323	
Accuracy		Good		Very Good	

(b) Water freight movements (thousand tons)

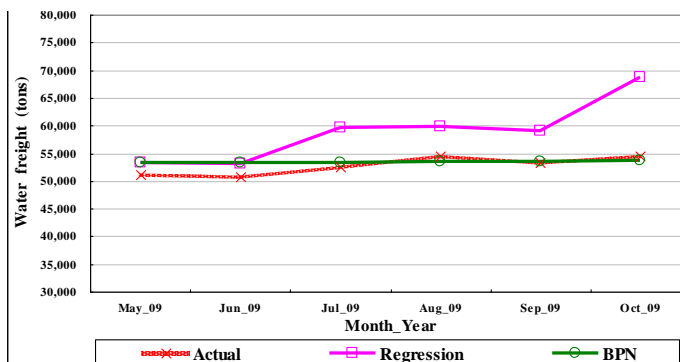
	Generalized additive model			BPN model	
<u>Time</u>	<u>Actual</u>	<u>Forecast</u>	<u>% error</u>	<u>Forecast</u>	<u>% error</u>
May2009	51,167	53,407	4.4%	53,256	4.1%
Jun.2009	50,785	53,071	4.5%	53,280	4.9%
Jul.2009	52,593	59,710	13.5%	53,350	1.4%
Aug2009	54,461	59,803	9.8%	53,425	-1.9%
Sep.2009	53,240	58,977	10.8%	53,446	0.4%
Oct.2009	54,492	68,671	26.0%	53,695	-1.5%
Average	50,479	58,940	11.5%	53,409	1.2%
MAPE		11.50%		2.36%	
MAD		6,150		1,230	
MSD		53,901,447		2,152,225	
Accuracy		Good		Very Good	

(c) Rail freight movements (thousand tons)

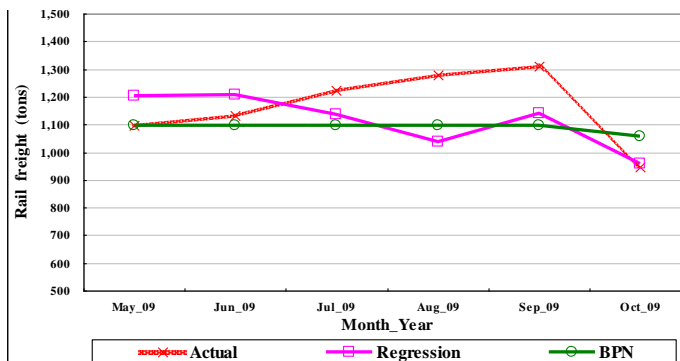
<u>Time</u>	<u>Generalized additive model</u>			<u>BPN model</u>	
	<u>Actual</u>	<u>Forecast</u>	<u>% error</u>	<u>Forecast</u>	<u>% error</u>
May2009	1,098	1,205	9.7%	1,096	-0.2%
Jun.2009	1,134	1,208	6.5%	1,097	-3.3%
Jul.2009	1,223	1,136	-7.1%	1,096	-10.4%
Aug2009	1,277	1,038	-18.7%	1,098	-14.0%
Sep.2009	1,311	1,140	-13.0%	1,097	-16.3%
Oct.2009	948	960	1.3%	1,058	11.6%
Average	1,165	1,115	-3.6%	1,090	-5.4%
MAPE		9.40%		9.30%	
MAD		115		112	
MSD		18,480		17,914	
Accuracy		Very Good		Very Good	



(a) Truck freight movement



(b) Water freight movement



(c) Rail freight movement

Figure 2: Validation of actual and predicted freight data: (a) truck (b) water (c) rail.

6 Conclusion

This paper focused on the analysis of extreme weather conditions and economic factors that affected the operation of freight transportation at the national level in Taiwan. The empirical results indicated that the BPN model supports the statistically significant relationships between freight movement and important variables identified in the generalized additive model. The results also showed that in addition to the significant impacts of economic factors (e.g., the GDP, financial and economic crises, oil prices), extreme weather conditions also significantly affected freight transportation. It should be noted that the freight models need to

take into account the recovery time of the normal operations of freight transportation affected by the extreme weather. Once the recovery from the disaster extends for a long period of time, the impact on the monthly volume of freight may show in the next month or continue for months until transportation facilities can be normally operated.

Recommendations for practice and policy-making to reduce the vulnerability of Taiwan' freight sector to the impact of climate change are presented: (1) reducing the impact of typhoons with extremely torrential rain on freight transportation, it is vital to enhance the vulnerability assessment and disaster management for the transportation infrastructure and high-risk areas vulnerable to floods, landslides, and mudslides which are induced by strong winds and torrential rains. Also, plans for action pertaining to disaster preparedness and recovery should be developed to ensure the minimum damage to the operation of freight movement. (2) examining the current design for vulnerable infrastructure weaknesses (e.g., road drainage system and bridges) and upgrade the existing 50-year flood design standard to a 100-year or 200-year flood level to withstand extreme climate change; (3) developing a multimodal freight transport system to reduce the disruptive effects of extreme weather events on a single transportation mode and also reduce CO₂ emissions, for example, facilitating a modal shift from truck to lower-carbon rail freight movement by expanding the capacity of the freight railroads to replace some truck freight routes; and (4) incorporating vulnerability assessments and climate change adaptation into a long-term transportation planning process, e.g., higher design standards for seaport infrastructure and coastal defenses.

Appendix A. Variables in the Generalized Additive Model

The formulation of the generalized additive model that uses a linear logarithmic regression for freight movement can be expressed as follows.

$$\ln Y_{Fim} = \beta_0 + \beta_{1im} \times \ln X_{1im} + \beta_{2im} \times \ln X_{2im} + \beta_{3im} \times \ln X_{3im} + \beta_{4im} \times X_{4im} + \beta_{5im} \times X_{5im} + \beta_{6im} \times X_{6im} + \beta_{7im} \times X_{7im} + \varepsilon_{im} \quad (1)$$

where,

Y_{Fim} = Freight movement (thousand tons)

X_{1im} = Frequency of severe typhoon/ extremely torrential rain

X_{2im} = Frequency of medium-strength typhoon/ extremely torrential rain

X_{3im} = Frequency of weak typhoon / extremely torrential rain

X_{4im} = Occurrence of economic crises

X_{5im} = Occurrence of Taiwan Strait missile crisis

X_{6im} = GDP (million US\$)

X_{7im} = Percentage change in oil prices from the previous year

β_{kim} = Coefficient of explanatory variable k

ε_{im} = Error term

i = Year i

m = Month m

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