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Urban Traffic Flow Predictions with Impacts of Weather and Holidays

Jenitta PRAGALATHAN [a,1] and Dieter SCHRAMM [a]
[a] *Chair of Mechatronics, University of Duisburg-Essen, Duisburg, Germany*

Abstract. Urban road traffic is influenced by many exogenous factors. Many research works have been carried out to analyze the impact of exogenous factors over traffic flow parameters. Among many other factors, holidays and weather influence urban road traffic to a major extent. Because of such exogenous factors, the traffic flow will be varied from usual traffic conditions due to drivers' decisions in choosing the mode of transport and time of travel. Hence a significant switch will be found in urban scenarios due to switching from public to private transportation modes during rainy or snowy days. This research work aimed to analyze the effects of weather (rainfall) and holidays on the forecasting of traffic volume within an urban area. One of the state-of-the-art time series prediction models is the Neural Prophet (NP) model (2020). Being quite new in the area of traffic engineering and having more benefits with decomposable additive model, NP model was chosen for forecasting the urban traffic with effect of exogenous variables. Traffic data from a busy urban area in Duisburg city, Germany was used for training and testing the model. The results from this research work showed the efficiency of traffic estimation with incorporation of weather and holiday data. Such prediction processes can be used in driving simulators for analysis of vehicle dynamics according to different road surfaces condition (wet/dry) due to rainy/snowy weather. Such predictions can also be used in real time traffic management systems for simulating urban traffic with the effect of holidays or special events, for reducing congestion.

Keywords. Urban traffic flow, predictions with exogenous factors, impact of rainfall on urban traffic, atypical predictions of traffic flow

1. Introduction

Traffic Engineering is becoming more meaningful with the availability of huge traffic data. Traffic flow predictions is one of the basic and necessary operations done for developing smart traffic infrastructure and vehicles. Especially in the future era of smart vehicles, real time and near future traffic predictions will play a major role in supporting the advanced technologies for building connected traffic and infrastructure. It is very much important to notice that the real-world traffic data depends on huge number of other external factors. The estimation of future traffic flow not only depends on the accuracy of the data used for model fitting and forecasting, but also on the external factors like peak/off-peak hour, day of the week, working day/holiday, seasons, effect of weather. Many research works have proved that there is a significant effect on traffic

[1] Corresponding author, Jenitta Pragalathan, Chair of Mechatronics, University of Duisburg-Essen, Duisburg, Germany; E-mail: jenitta.pragalathan@uni-due.de

flow due to weather conditions and holidays. In this article, the effect of holidays and precipitation over urban traffic flow was included and future predictions were carried out.

A number of external factors influence urban road traffic. Among them, weather is a very predominant and significant factor which impacts both capacity and demand of road traffic and hence also influences the level of service. The research work [1] confirmed that weather should be taken into account while considering demand of traffic for implementation of traffic management systems. An in-depth data analysis was done to quantify the effects of rain, snow, temperature and wind on road capacity and traffic demand. The effect of rain caused a reduction in both capacity and demand on relevant days, whereas the effect of snowfall was inconclusive because of limited observations. The impact of rainfall over various traffic parameters like flow, speed and density was measured by finding the deviation in MFD for rainy & non-rainy days [2]. Rainfall reduces operating efficiency and level of service of the road network. The effect of rainy conditions over traffic parameters were confirmed, especially during evening peak hour.

A similar study [3] was carried out with 3 classes of rainfall (light, moderate and heavy) and the reduction of maximum flow rate and free flow speed were analysed. Two regime speed density distribution traffic flow model was used to find the impact of rainfall on a freeway traffic. Weather Influence Coefficient was determined through regression analysis for evaluation of rainfall impacts. It was found that the adverse weather (rainfall) influenced greater on free flow speed and maximum flow rate when its rainfall intensity increased and also the results proved that traffic flow had more impact than speed. In the previous research [3], the maximum flow rate during moderate rainfall (5-10 mm/hr) and heavy rainfall (>10 mm/hr) was found decreased even up to 19% and 33% respectively when comparing to normal weather. The previous similar analyses parameters [1], [2], [4] were carried out to find the impact of weather on traffic flow and revealed the importance of weather while considering traffic.

The impact of weather on traffic flow of an urban freeway was studied by establishing relationship between speed and volume as a function of weather conditions – clear, rain, fog/mist & snow and with surface condition-dry, wet & icy [4]. It was found that rain reduced the capacity by 7-8% and light snow impacted demand leading to a significant reduction in traffic volume. Rainfall reduces traffic volume and hence traffic demand is also influenced, because of the user's decision to postpone or cancel the trip due to rain. Demand was also increased occasionally because of switch from public transport or non-motorised travellers to private modes of travel. Adverse weather can also shift peak hour if the drivers chose to leave early or later due to weather conditions. Even though weather influenced the urban traffic flow significantly, very few research works considered it as an exogenous factor for predictions [5].

Inclusion of exogenous variables in traffic forecasting models would improve the performance of the traffic predictions. Calendar information was highly focused on most of the prediction models, neglecting the impact of weather [6] [7]. Information like day of the week, holidays, month data were included for urban road traffic predictions for better accuracy [8]. However, very few works have focused on inclusion of weather data especially rainfall data into prediction models [9]. Traffic flow forecasting with both holidays and weather factors were scantly done in very few research works [10]. Hybrid spatio-temporal models were introduced and utilised for traffic flow and speed forecasting. The results showed significant improvements in the models' performances with inclusion of heavy rain and strong wind. Various models like LSTM, GRU, Stacked LSTM and CNN-LSTM were used to estimate the traffic flow with impact of weather data and confirmed the percentage reduction of error values in forecasting [11].

In the beginning, parametric methods were used in conventional traffic flow prediction models. SARIMA is one among such models which specifically gave high accuracy when compared to other statistical methods. Since the traffic data is complex with influence of external factors like weather and holidays and so on, eventually machine learning techniques overtook the traffic flow predictions considering external dependencies. For achieving more accuracy and incorporating exogenous variables, the complexity of the model also increases. Even though SARIMA is a proven classical method in statistics to predict the values in future by reading and analysing the past historical data over a period of time, it has its own drawbacks, especially the requirement of human intervention of model parameter definitions [12].

2. Model Description- Neural Prophet Model

Neural Prophet (2020) is a very recently developed time series prediction model which takes the advantage of both statistical and deep learning model, with expandable forecasting at scale technique [13]. NP is named as the successor of Fb-Prophet model [14] since it includes the modular decomposability nature of Fb-Prophet model and contains some more components for better performance [15]. The basic equation behind the Neural Prophet model is given in the following equation.

$$y(t) = T(t) + S(t) + E(t) + F(t) + A(t) + L(t) \quad (1)$$

Where each term represents specific model at time ‘t’
T(t): trend function - piecewise linear regression
S(t): seasonal effects (additive or multiplicative) - Fourier terms
E(t): the influence of events and holidays - with various user defined formats
F(t): regression for future-known exogenous variables - real valued regressor
A(t): auto-regression based on previous values - AR-Net
L(t): regression for lagged observation of exogenous variables - auto lags

The Neural Prophet model bridges the conventional models and neural network techniques (AR-Nets) [16] as shown in Figure 1 and develop a more accurate prediction technique with decomposable modular regression model.

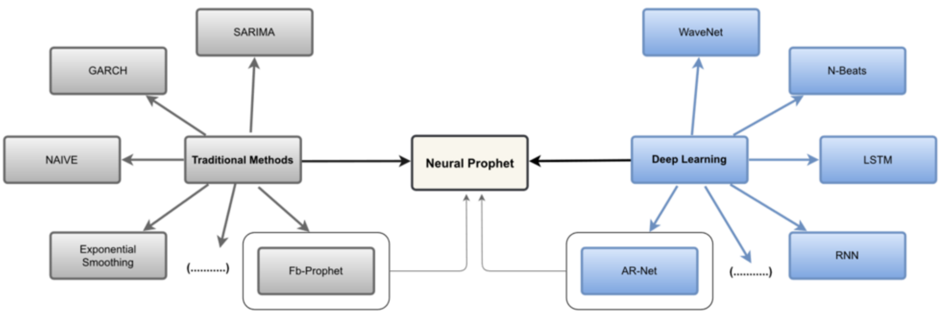

Figure 1 Neural Prophet model bridging traditional and deep learning methods

Table 1 List of Holidays in North Rhine-Westphalia, Germany

Holidays	Dates		
New Year's Day	01/01/2017	01/01/2018	01/01/2019
Good Friday	14/04/2017	30/03/2018	19/04/2019
Easter Monday	17/04/2017	02/04/2018	22/04/2019
May Day	01/05/2017	01/05/2018	01/05/2019
Ascension Day	25/05/2017	10/05/2018	30/05/2019
Whit Monday	05/06/2017	21/05/2018	10/06/2019
Day of German Unity	03/10/2017	03/10/2018	03/10/2019
Christmas Day	25/12/2017	25/12/2018	25/12/2019
St.Stephan's Day	26/12/2017	26/12/2018	26/12/2019

With numerous advantages over other prediction models, it is dominating in many other fields like financing, weather forecasting, marketing and so on. Being quite new in the traffic flow prediction industry, the performance of the model for a highway traffic was studied in the paper [17]. Traffic flow prediction is one of the important aspects of current advanced traffic management and control systems, Intelligent Transportation Systems and future vehicles. Most of the research works studies the impacts of rainfall on the operation point of view, like capacity, operating speed and level of service etc. It is very much important to consider weather into traffic prediction models. The predictions of hourly traffic counts in Germany were improved with inclusion of meteorological variables [18]. The analysis was done for different vehicle types and the mean squared error was reduced up to 60% with weather data like precipitation, temperature, cloud cover and wind speed data. Knowing the necessity of traffic predictions with inclusion of external data, this current research work focused on analysing the performance of Neural Prophet model for urban traffic predictions considering holidays and precipitation data. Thus, the fluctuations in the traffic flow pattern with the effect of holidays and weather (precipitation) will be analysed in this paper.

3. Traffic Flow Predictions with Neural Prophet Model

The availability of accurate historical traffic data plays a major role in traffic predictions. Traffic data were collected from inductive loop detectors at a busy urban intersection in the city of Duisburg, Germany during the period of 2017 to 2019 and were used for training the prediction models. Traffic predictions are also possible for limited historical data collected few days [12], [17]. Nevertheless, in this research work to incorporate the effect of weather and holidays, huge database was used. Simultaneously the data for local/regional holidays were also obtained [19] and tabulated in the Table 1. Climate data was collected by Climate Data Center (CDC) of the Deutscher Wetterdienst (DWD) at 400 climate stations and provided free access to historical meteorological data [20]. Several parameters like humidity, temperature, precipitation, wind speed and so on were collected and given at different time intervals (10-minute, hourly, daily and monthly).

For the current work, both traffic data and weather data (precipitation) were considered at hourly interval for prediction modelling. The hourly precipitation with maximum severity (greater than 5mm) were considered for modelling and the dates are listed in the Table 2.

Table 2 List of Day with heavy rainfall

List of days with severe precipitation (>5mm/hr)		
22/02/2017 19:00	05/08/2017 08:00	08/05/2019 17:00
16/04/2017 12:00	18/08/2017 20:00	10/06/2019 16:00
12/05/2017 21:00	30/09/2017 02:00	11/07/2019 15:00
15/06/2017 15:00	30/09/2017 11:00	20/07/2019 21:00
15/06/2017 16:00	16/05/2018 15:00	27/07/2019 16:00
28/06/2017 13:00	29/08/2018 22:00	02/08/2019 19:00
12/07/2017 12:00	29/08/2018 23:00	29/08/2019 04:00
14/07/2017 16:00	30/10/2018 03:00	29/09/2019 19:00
20/07/2017 05:00	08/12/2018 21:00	01/10/2019 08:00
23/07/2017 00:00	02/05/2019 16:00	

NP model can capture the effect of holidays or events or exogenous factors while forecasting the time series even with higher sub-daily frequency. Model components include Auto regression, trend, Seasonality, lagged regression, future regression and events. Being open source, the model allows to define a list of days to include the holidays/events in a specific country or a region. Traffic data from inductive loop detectors were split into training and testing datasets and were used for model fitting and forecasting. Being automatic, lesser human intervention was needed for model parameter definitions [21]. After calibration, the model was able to capture the repetitive pattern of everyday traffic flow at morning and evening peak hours as shown in Figure 2 and also the pattern repeated over a week as shown in Figure 3.

The Figure 4 reveals how the impact of holidays are repeated with both positive and negative coefficients over every year. The impacts are significantly noticed by comparing the list of holidays (Table 1)and rainfall (Table 2)and the plot Figure 4 at corresponding dates. Additionally, it can be seen that the plot depicts the negative impact of hourly precipitation over traffic flows which confirms the previous research works. Thus, the estimation of future 24 hours (01/10/2019) traffic data was carried out by using Neural Prophet model with the incorporation of weather and holiday data. The model was also be able to capture the effect of holiday or weather over the previous time span, which increased the accuracy of overall predictions.

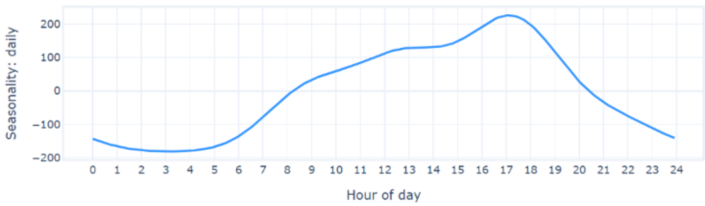

Figure 2 Daily Seasonality captured by Neural Prophet model

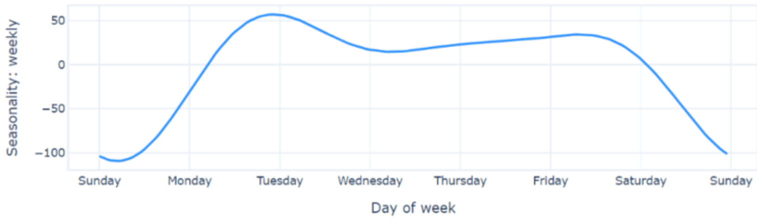

Figure 3 Weekly Seasonality captured by Neural Prophet model

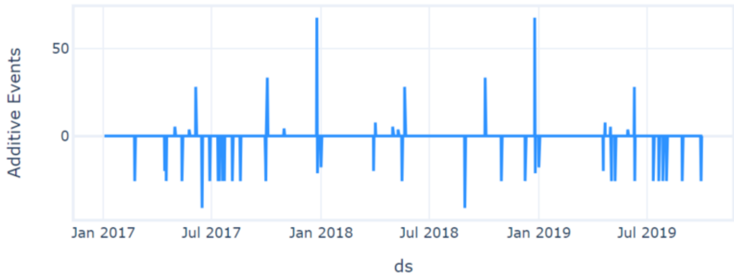

Figure 4 Effect of Holidays and Rainfall captured by Neural Prophet model

4. Results and discussions

Traffic flow prediction models provided the traffic volume or flow (number of vehicles per unit duration) for the following 24 hours. The Table 3 shows error values calculated from the actual traffic and the predicted values with external factors (holidays/weather). The evaluation metrics MAPE, MAE and RMSE values were also tabulated for analysing the efficiency of the model. Thus, the results and the interpretation in the table proves that the model performed more efficiently with incorporation of the effect of external factors. All the error values were reduced and the accuracy was increased with incorporation of weather and holidays.

Table 3 Evaluation Metrics

Metrics	Error Values (%)	Interpretations
MAPE	13.94	10%-20%
MAE	19.73	< 10% of 288 veh/hr(average flow)
RMSE	27.49	Rooted RMSE = 0.04, very much nearby 0

5. Conclusion

Traffic Simulations plays a major role for analysis of alternate smart solutions to reduce congestion and travel time. Instead of random day traffic flow as demand input for simulations, the traffic flow predictions can be used for simulations with the effect of exogenous variables. Most of the time, the impacts of external dynamic factors were neglected while establishing traffic flow prediction models. Weather has impact on various traffic flow parameters like speed, density and volume and other network operations and traffic managements. The effect of weather especially precipitation (rainfall) on urban traffic flow was incorporated into traffic flow prediction model successfully. This paper hence proved the efficiency of Neural Prophet model for prediction of any special events or any atypical conditions like severe weather. With availability of historical external data, it is possible to incorporate the exogenous variables into the model and predict the atypical or adverse conditions. In future work, the prediction results will be used for simulation of urban traffic at severe weather conditions and can be used in driving simulators for analysis of vehicle dynamics at different weather conditions.

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