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An Application of Dynamical System in Forecasting Motorway Traffic flow

Anamarija L. Mrgole*

University of Maribor, Faculty of Civil Engineering, Transportation Engineering and Architecture, Smetanova ulica 17, 2000 Maribor, Slovenia

Email: anamarija.mrgole@um.si

Abstract

Circumstance is essentially too surely understood to every one of us. You're on your route, when out of nowhere you're stuck in traffic. It isn't an average "rush hour" time and ordinarily you do not worry about traffic jam. There must be a mishap or some kind of genuine accident up ahead. You slowly advance your way, heavily congested, always endeavoring to discover the blazing lights of ambulances and squad cars. At that point quickly, activity begins to move ordinarily once more. There's no sign of a mishap, episode, or whatever other reason for the slowing down in traffic. So what happened? Traffic Flow system is a human-joined, variable, open and cacheable framework. It is very nonlinear and uncertain. Under certain circumstance, disorder shows up in it. The overview of publish studies implicates the importance of finding and detecting disorders in traffic. Furthermore, the outline of procedures to recognize chaotic features - disorders in traffic flow and to forecast them demonstrates the requirement on current techniques and angle of study.

Keywords: Traffic Flow; Forecasting; Dynamical System Network; Neural Network.

1. Introduction

One probable scenario goes as it follows'- the streets contain no apparent hazards that will create problems with traffic flow. Traffic concerning this particular highway is rather thick, but it is flowing easily and continuously. A man inside a yellow vehicle, decides that people in his lane are moving far too slow for his taste. It quickly changes lanes so that they can reach a quicker moving lane.

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* Corresponding author.

He doesn't correctly check his mirrors and reduces another driver within the lane beside him. This forces that driver to use his brakes in order to avoid getting clipped from the large yellow vehicle. There's no impact, and also the guy at a yellow vehicle proceeds. The motive force that had been expected to use their brakes has slowed up a little, leading to the motive force in it to use their brakes too. Consequently, the person in it must hit their brakes too. Human reaction moment what it's, each following time that somebody needs to hit their brakes, it might be progressively more sudden eventually leading motorists farther in the future having to slam on their own brakes and are available to some complete pause and avoid rear ending the individual before them. As a result of the dead stop at that lane, motorists start to change lanes to change position to among the other lanes which are moving correctly. Because this happens, another similar lane starts to slow as individuals are merging over. Exactly the same process repeats itself inside the other lanes before the entire highway has slowed down to some crawl and finally an entire stop. An event similar to this may be known by many people to become a probable theory along with a probable reason for most of the traffic jams we all experience events like every day. The predicament is inside a theory of Chaos and Non Linear Dynamics [1]. It is simply like the principles from the “domino effect” as well as the “butterfly effect”. The “butterfly effect” results in a conclusion when a butterfly flaps its wings, that small disruption within the chaotic motion from the atmosphere could create a chain reaction enhancing the result to what large atmospheric motion able to changing the elements in another place in the world. The “butterfly effect” shows the impracticality of creating forecasts for complex systems. This sensitive attachment to initial conditions could be the essence from the Chaos Theory [2]. Our situation may be loosely referred to when it comes to a “domino effect”, however the “domino effect” uses linear number of identical occasions. The “butterfly effect”, however, seems to suit our circumstances better because it demands the effect increases the problem upon each iteration. Within our demonstration of the traffic jam, the result was increased each time as motorists were forced to use breaks, more abrupt action creating a slowdown and eventual dead stop. Vehicle accidents might have been induced by all this action and response, resulting in more traffic and events as emergency automobiles are rerouted towards the arena from the accident. Some motorists may take another exit than usual to avoid the traffic, resulting in elevated traffic and occurrences on side roads distributing the problem past the confines from the original highway. This could begin affecting traffic and people’s lives all around the city weight loss actions and responses derive from the first traffic jam. Each reaction brought to another reaction creating a finish result that has been impossible to calculate. It’s feasible for both ideas involve some devote explaining a predicament for example ours. It is also probable that neither can precisely describe the succession of occasions. Most of the events might have happened without worrying about our “man in a yellow car”. It is also entirely possible that if traffic hadn’t been subsequent so carefully

2. Previous literature

Traffic procedures on roadways might be improved by field study and field experiments of real-life traffic flow [3]. However, in addition to the scientific problem of recreating such experiments, costs and safety be a factor of dominant importance as well. Because of the complexity of the traffic flow system, analytical methods may not provide the preferred results [4]. Consequently, traffic flow (simulation-) models designed to characterize the actions of the complex traffic flow system have become an essential tool in traffic flow investigation and experimentation. With respect to the type of model, the application area of these traffic flow models is extremely broad, e.g. [5]:

- Evaluation of alternative treatments in (dynamic) traffic management.
- Design and testing of new transportation facilities (geometric designs).
- Operational flow models serving as a sub-module in other tools (model based traffic control and optimization, and dynamic traffic assignment).
- Training of traffic managers.

The description of discovered phenomena in traffic flow is nevertheless not self-evident. Common mathematical models aimed at describing this behavior using mathematical equations [6].

Kotsialos and Papageorgiou [7] convincingly claimed that it is improbable that traffic flow theory will achieve the descriptive precision achieved in other areas of science. The sole correct physical law in traffic flow theory may be the preservation of vehicles equation; all other model structures reveal either counter-intuitive idealizations or coarse approximations of empirical findings [8]. Therefore, the challenge of traffic flow researchers is to search for useful theories of traffic flow which may have sufficient illustrative power, where sufficiency depends on the application purpose of their concepts [9]. Concerning the relationship between microscopic and macroscopic traffic flow models, the work of Franklin [10] and Del Castillo [11] also needs to be pointed out. Franklin [10] has evolved a microscopic model that catches macroscopic highlights of traffic flow, such as shockwaves, using a stimulus reaction car following model. In the same vein, Del Castillo[11] suggests a car-following model, the three parameters of which can be determined directly from speed-density data. This car- following model displays comparable shockwave distribution behavior as the model of Franklin [10]. Time series analysis of nonlinear dynamic system is a macroscopic traffic flow model, in order to recognize the importance of chaos theory in modeling traffic one needs to explore all of the aspects of traffic flow theory [12].

3. Use of Chaotic Feature as Forecast for Dynamical System

We take $-x^3+x^5$ as equation for Duffing oscillator [13] restoring force item:

$$x+kx-x3+x5=\gamma cos(\omega t) \qquad (1)$$

Adjusting the range value of the driving force, which makes the system alternate between chaotic state and periodic state, we can use four step Runge-Kutta [14] calculation method to derive new equation. On a derived x(t), we should apply Wigner transform, which is written as W(t, ω). Its amplitude frequency is shown in figure 1 [15].

In figure 1, horizontal coordinate represents frequency and vertical one represents the width. It clearly shows differences between chaotic state and periodic state. Its Wigner distribution domain is flat, but it still has certain regularity, and it is exactly that intrinsic regularity we have mentioned above when talking about chaotic nature. In periodic state, graph of Wigner distribution clearly shows wave peaks [16], while other parts are flat. This explains that at that moment Duffing system has been entering from one into another periodic state. Still, these frequency spectrograms cannot describe or identify these two types of states. This requires usage of Lebesgue measure in order to further explore the system [10].

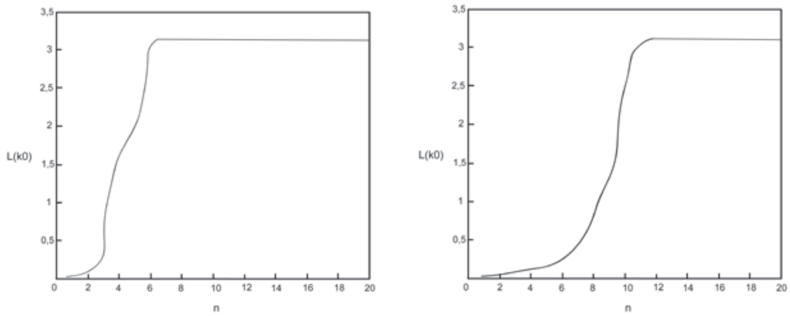

Figure 1: (I) Chaotic state vs (II) Periodic state

$$L(k0) = (\omega \text{ of Lebesgue measure } \|W(t,w)\| \geq k0) \quad (2)$$

According to [17] about Lebesgue measure and additivity of union of all non-overlapping countable interval lengths, we must point out Lebesgue measure as:

$$L(k0)=L0+L1+L2 \quad (3)$$

There are many methods to select k0, but whether the selection of k0 is suitable immediately decides the accuracy of chaotic pattern identification. We use golden section point, that is [18]:

$$k0 = \max \|W(t,w)\| \times 0.61^n \quad (4)$$

In this way, thanks to the change of selected value observe situation with Lebesgue measure L(k0) when there is a change in size of chaotic and periodic states.

Table 1: N value Chaotic State L(k0) Large period L(k0)

N value	Chaotic state L(k0)	Large period L(k0)
5.2	0.8752	0.1598
5.3	0.8851	0.3130
…		
7.3	1.7717	0.9980
…		
12.2	1.7517	1.3308
…		
12.7	1.7707	1.7707
12.8	1.7707	1.7707

Based on Figure 1 and Table 1 we can conclude:

(1) Different states of system. System is in chaotic and periodic state, while ω of Lebesgue measure rises along with the rise of n value.

(2) Despite L(k0)'s n-value increase follows the increase of n, their curves are still different. Rise of the curve of periodic state is smooth, stable, and that is because of the shape of spectrogram after curve goes through Wigner transform. In chaotic state, its shape is not smooth and stable, it shows irregular ups and downs, and the curve's speed of descending is faster than the one in periodic state.

(3) When n value is the same, L(k0) value in the large periodic state has to be lower than the same values in chaotic state. Using the above simulation experiments and conclusions, we can see that the method of chaotic pattern identification which is based on Wigner transform and Lebesgue measure is actually based on assessing trends of speed changes in L(k0) value when it follows the changes of n value in order to observe chaotic state. At the same time, we have used Duffing system to prove this method's effectiveness. Of Lebesgue measure following change in n.

3.1. Chaotic Pattern Identification in Traffic Flow-time sequence

As we mentioned above, traffic flow system is a non-linear system with chaotic features. Traffic flow system appears to be irregular, but it still has inherent certainty. For example, at a certain period of time and at a certain part of the road, when quantity of cars reaches its overcapacity limit, the movement behavior of a single car might occur as a random and irregular one. But, driver's destination and time of arrival are clearly certain. It is exactly because of this, that chaotic phenomena appear and that some of the chaotic features can be predicted. Backpropagation - BP neural network because of its learning and training characteristics, always needs large amounts of samples, and in reality, it is hard to get by so much material. So, we will use chaotic features of traffic flow and by joining time-sequence, previously phase space reconstructed with neural network, make forecasting of traffic flow. This method of identification of chaotic patterns in traffic flow combines processing of time-sequence, theory of phase space reconstruction and neural network predictions in order to predict traffic flow within a period of time. The main idea is to: first, determine chaotic features in time-sequence, then use theory of phase space reconstruction to reconstruct phase space and finally after reconstruction, enter gathered data into BP neural network as to do exercises and consequently make predictions.

Main steps of this method are as follows:

Step 1: In order to make chaotic features found in observing traffic quantity in time sequence more clear and more suitable for neural network, we need to make preprocessing of traffic quantity time-sequence, and this pre-processing should contain smoothing and differential method.

Step 2: As for pre-processed time-sequences, if chaotic neural network model is used for the first time to make predictions, you must do chaotic pattern identification on processed time-sequence to see if chaos theory can be applied.

Step 3: Phase space reconstruction must be done on traffic flow time-sequence, which corresponds to chaotic features in order to restore its attractor features. After reconstruction, this sequence will transform from a vector into m dimensional matrix.

Step 4: This step is crucial for combination of chaos theory and neural network. Because of phase space reconstruction, vectors cannot be immediately entered into neural network for exercises and predictions, but instead they have to be split and then entered. For short introduction on main idea in data splitting, please refer to the following section.

Step 5: Exercise vectors which we acquired by splitting data in a way, which is described in step four enter into network in order to make exercises. After you find optimal approximation of F, and use this F to enter prediction vector to get prediction value.

Step 6: Do reverse calculations on the data gathered in step 5 and retrieve real predictive value of original time sequence.

3.2. The Results of Forecasting Traffic Flow by Chaotic Neural Network

Firstly, we need to identify chaotic patterns in data, we have already processed this time-sequence for chaotic pattern recognition and have established that this sequence has chaotic features. Step two requires phase space reconstruction before step 3 requires data splitting. BP neural network is a mentoring exercise network, so you cannot immediately enter vector collection gathered from sequence reconstruction. Thus, you have to split the data from the period of traffic flow in order to make them more suitable for neural network exercises and predictions. Main idea in splitting data is: Consider a time sequence ｛xn｝ where we set this time sequence as suitable for phase space reconstruction, that is sequence has chaotic features. Select embedded dimension as m and delay time as t. But in neural network, due to added prediction value Ωn+1, original time sequence should be reconstructed according to m+1 dimension, which will give us following matrix: Matrixes should be divided into exercise sample vectors collection and prediction vectors. Exercise sample vectors are gathered as vector collection. Prediction vector is the last series of vectors in matrix, but the last element necessary for prediction is not known, so prediction value will be a vector. When selecting exercise samples, one should take vector collections, which are relatively close to prediction vector. In this prediction, operation goes as follows:

1. Based on m+1 number of embedded dimensions and delay τ exercise phase space reconstruction on time-sequence to get the exercise vectors.

2. Start taking data from original time-sequence by taking numerical values starting from first n+1-mτ and then at each delay all the way to the first n+1-mτ and regard them as prediction vectors.

In step 4 we start exercising and predicting the structure of neural network First initialize neural network. Most important is to set numbers present in exercise vectors and parameters of exercise frequency. Then set recording mark for initialization of sample exercise frequency of exercise vectors as 1, while weight matrix is created automatically by simulation software. Note that exercise numbers are parameter numbers taken in end-beginning direction. Frequency of exercises should be set up according to one's own experience, hence it should be set at 150. After completing the exercise frequency, which was set up earlier, prediction vector should be entered by nodal points and neural network will based on already exercised various layers of weight make a prediction. But, this time, all prediction result will not be in original time-sequence. Values of prediction need to be restored at data for original time-sequence.

Step 5 When we restored prediction values to original time-sequence, we already did pre-processing by smoothing and differential method, so all we have to do now is restore differential processing, because when we were smoothing data, we only used the last data value xn, and we did not use smoothing method data. That way there are no smoothed data and there is no need to do restoring of differential data.

$\{xi\}$: $\Omega n+1$ *represents the last prediction value.* (5)

Base on retrieved embedded dimension m=4, we can take entry nodal point as 6 and then take output nodal point. This way we get the total number of samples equal to 600. First take 510 samples for network exercises and the next 90 for prediction. Select three BP network layers: input layer, hidden layer and output layer and then do one step prediction. We use chaotic neural network and BP neural network to make predictions on traffic flow time-sequence. Their results and real results are compared below.

Table 2: Comparison of BP neural network and Chaos BP neural network prediction methods

	Operation time	EpocH	Average deviation	Parity coefficient
BP neural network prediction	8.97245	1777	0.0098547	0.6309
Chaos theory neural network prediction	6.13523	790	0.0000536	0.98792

Table 2 shows us that prediction method based on chaos theory and BP neural network is slightly more precise, its simulation features are relatively better, calculation time is also relatively shorter, which makes it more apt for real-time control and guidance of traffic flow.

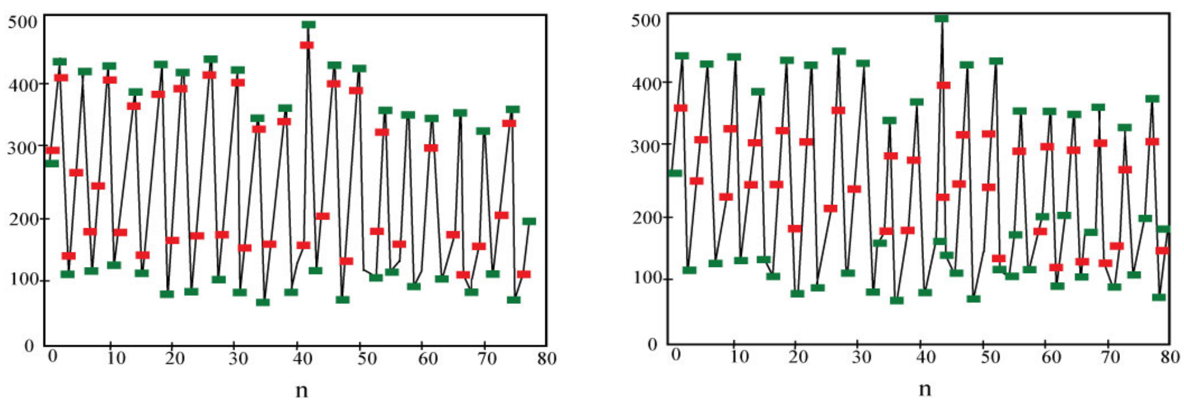

Figure 2: Comparison of (I)prediction result (red) with real values (green) in neural network based on chaotic theory and in (II) conventional neural network

4. Conclusion

The study shows importance of chaotic pattern recognition in traffic flow forecasting. The figures and numbers in tables presents new possible model for traffic flow prediction. Lebesgue measure and Wigner-Ville distribution presented as unusual but accurate methods for calculating neural network in search of traffic flow patterns.

From the study, it can be concluded while the system is in chaotic and periodic state, ω of Lebesgue measure ascents along with the ascents of n value; despite L (k0)'s n-value progress follows the progress of n, their curves are still different; while n value is the same, L (k0) value in the large periodic state has to decrease as the same values in chaotic state. Results show feasible model with the use of Duffing system in Chaotic neural network. Characteristic with chaotic state in time sequence of traffic flow presented accurate and satisfactory results. Further research successfully incorporated presented model in new model of chaotic neural network. It can be assumed the model is better and reliable than usual use of neural network.

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