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Using information collected by weigh in motion for modeling traffic structure of vehicles

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ABSTRACT

The article presents an example of a dynamic traffic flow modeling using as a data source information the measurement system weight Preselection Implemented in Gdynia. The measuring point is located on the road leading to the Gdynia container terminals and to Gdynia Kwiatkowski, which is Directly connected with the Tri-City Bypass. One of the goals of the system is collect data which can be used for operational purposes and statistics. Measurement period allowed the appointment of a mathematical model which describes the dynamic variation of the structure of the stream. In Addition, an analysis of the variability of the traffic flow in both the daily and weekly basis is presented. This give possibility to determine the effect of time of day and day of the week on the parameters of a dynamic model describing the structure of a generic stream. The resulting model allows the study of the impact of the share of heavy vehicles on ride comfort of passenger cars.

KEYWORDS: Intelligent Transportation System, Weight in Motion, Transport Modeling, Dynamic model, traffic structure

1. Introduction

In view of the increasing number of vehicles on the road network in the city especially trucks. In order to improve control over the movement of heavy in Gdynia, it was used a pilot system - "prescreened by weight", as an additional element of integrated motion control solutions using transport telematics. The system was created as part of Civitas Dynamo, financed from EU funds. The CSO data shows that in 2015 passenger cars were registered in Poland 20,723,423 namely about 719,560 more as compared with 2014 lorries registered in Poland in 2015 was 32958, about 26397 more than in 2014 [2].

Vehicles that exceed the allowable weight are a great danger on the road. The road infrastructure on which they move is extensively degraded resulting an increased financial commitment to infrastructure repairs. Despite the introduction of restrictive restrictions on the total weight of the vehicles still there are situations where willingness to carry more (limit of the total weight: for modular vehicle composed of three-axle motor vehicle and triaxial trailers carrying 40-foot ISO container - 44 tons for vehicle modular or an assembly of a vehicle motor and trailer on the number of axles not more than four - 32 tons, for a vehicle with a larger number of axes than four - 40 tons. [1]) of cargo vehicles during a single trip wins with the application of to the rules or not widely exposed road users at risk. In answer to insubordination of some drivers / carriers around the world are created Intelligent Systems - weight in motion. These systems are designed to enable the departments responsible for compliance with the load of vehicles (Road Transport Inspection) selection of vehicles provided for a thorough inspection. Using data from Gdynia System prescreened weight developed a stochastic model describing the share of trucks in designated section of road.

2. Weight – in – motion (WIM) System

In January 2016, the City of Gdynia was implemented a pilot program of System Weight in motion - weight preselection, organized within the framework of the EU project CIVITAS DYN @ MO. Weight preselection system is designed as a dynamic weigh a vehicle, in terms of the total weight as well as by specifying the pressure on the single axis of the vehicle. In Gdynia, automatic detection of the weight of the vehicle is located on Wisniewskiego Street in the district of Obłuże. The measuring length has not been chosen at random, the main reason to choose the location is close proximity the container terminals as well as direct connection to the wharf Kwiatkowskiego and farther from the Tri-City Ring Road or the main street of transit Hutnicza Street. In the publication [4] on the already implemented system in Lodz, was described the guidelines for the section in which the measurement can be performed: "At least 100 m stretch of road in front of the measuring station and 30 m downstream of the station with the following parameters: - Rectilinear with a radius greater than 1.5 km. - Flat with fixed longitudinal and transverse inclination of less than 2% - Correctly made and the good technical condition of the road surface (no visible cracks and damage, with possible ruts with a depth of less than 5 mm) - Preferably concrete surface with a minimum thickness of 10 cm or made from plates, 2) at least 100 meters from the catenary, 3) away from the factors changing the structure of the surface (e.g. culverts, bridges, canals, subways, changes in surface material) [4]. Figure 1 shows the location of the point of measurement (red) and shows the strategic destination points for vehicles (container terminals, flyovers Kwiatkowskiego, Hutnicza Street, etc.).

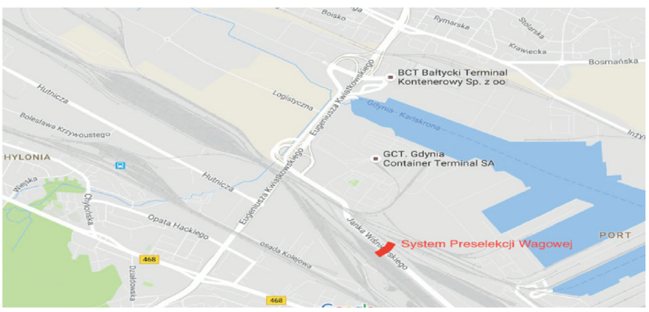


Fig. 1. Location of the weight in motion system in Gdynia [own study]

The main components of WIM System are:

- 2 induction loops 2x2
- 2 weigh stations
- 4 strain gauges
- 3 ANPR cameras
- 3 infrared illuminators
- 1 Technical rack
- 1 video rack
- The necessary wiring
- tele-technical infrastructure (Tele-technical-well)

Figure 2 shows the real picture taken in the field, the view of WIM System

Fig. 2. WIM System on Wiśniewskiego Street [own study]

2.1. The Subsystems of WIM System

Induction loops are most commonly used solution for achieve detection of presence of the vehicle in the measurement point. The system can be extended with sensors operating on the basis of mechanical treatment of the wheels of the vehicle and the sensor located in the road surface. This solution has allowed to detection of axis of the vehicle. Induction loop has a simple structure formed of several turns of copper wire disposed in the gap, a saw cut in the surface and secured suitable material. [3]

Camera ANPR - cameras installed above the main road surface mainly directed to the lane in order to form a detection area.

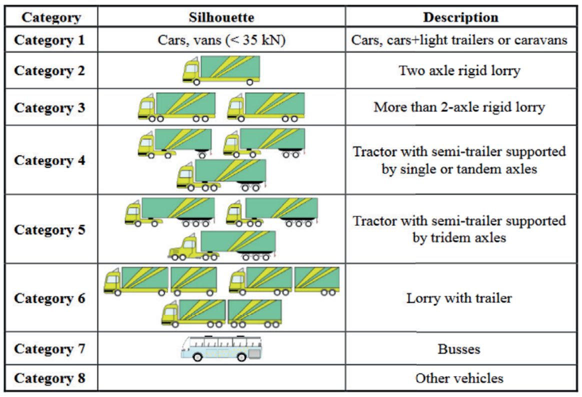
The camera ANPR (Automatic Number Plate Recognition) is designed to automatically detect the number plate of the vehicle and to identify number that appears on it. Currently used systems ANPR features enhanced database (the ratio of length to width) of a vehicle to enable identification of the type, make, model of the vehicle, as well as its color.

The infrared illuminators are used in conjunction with ANPR cameras to drivers passing by after dark were not blinded by white light (used e.g. A speed camera). Infrared illuminators allow you to take pictures in dark conditions, while maintaining a satisfactory quality for the automatic reading of a registration number.

The most important element of the system is the strain gauge weight preselection panel, which allows the measurement of weight, measurement of total weight, the distinction pressure on the single axis of the vehicle.

2.2. Data from WIM System

Data from the system weight preselection are sent to the database, which allows managing the system have access to the time, date, registration number, the total mass of the vehicle, the speed at which the moving vehicle, pressure on individual axles, as well as a picture taken at the moment of automatic measurement . These data after processing the mathematical could serve as a prediction of the intensity with the generic structure for the intersection Wiśniewskiego street - Kwiatkowskiego flyover. Knowledge of the structure of the traffic light controller is useful information due to the fact that heavy goods vehicles, buses, etc. Need more time to execute maneuvers as the steering or the start from space in case of a change of red light. There are a lot of vehicle classifications which is used in Europe, the most important one is COST 323 classification. This one is mainly based on the silhouette of vehicles, and on their mechanical dynamic behaviour while travelling at speed. COST 323 is used in Gdynia's WIM System, there are eight categories. Category 1 contains: cars and vans under 35 kN. Category 2 contains vehicles with two axles rigid lorry. Category 3 contains vehicles with more than two axles rigid lorry. Category 4 contains tractor with semi-trailer supported by single or tandem axles. Category 5 contains tractor with semi-trailer supported by triple axles. Category 6 contains lorry with trailer. Category 7 contains busses. Category 8 is other vehicles. [5] Figure 3 shows COST 323 vehicle classification.



Category	Silhouette	Description
Category 1	Cars, vans (< 35 kN)	Cars, cars+light trailers or caravans
Category 2		Two axle rigid lorry
Category 3		More than 2-axle rigid lorry
Category 4		Tractor with semi-trailer supported by single or tandem axles
Category 5		Tractor with semi-trailer supported by tridem axles
Category 6		Lorry with trailer
Category 7		Busses
Category 8		Other vehicles

Fig. 3. COST 323 Vehicle classification [5]

3. Traffic Data Statistical Analysis

The traffic flow data is important for the road networks subsequent maintenance. Traffic flow pattern appears to be random in distribution, as it reflects people's motivation in terms of different composition of vehicles on roads under varying environmental conditions.

Pavement-based traffic detection will be met with competition from detectors that are liberated from the road surface. A variety of traffic sensors are used to count, weigh and classify vehicles while in motion, and these are collectively known as Weigh in Motion (WIM) sensor systems. Traffic Data Collection and projections there of traffic volumes are basic requirements for road management schemes. Traffic Data forms an integral part in drawing up a rational transport policy for movement of passengers and goods [6].

3.1. Summery statistics

At first, we summarize a single sample of data, Table 1, Fig4, Fig.5. Data are taken at July and consist of hours' number of HGV vehicles registered by WIM system. We used program Statgraphics Centurion for the statistical analysis.

Table 1. Summary Statistics for HGV [own study]

Average	79,2385
Median	46,5
Geometric mean	
Variance	7030,29
Standard deviation	83,8468
Coeff. of variation	105,816%
Standard error	3,17821
MAD	41,5
Sbi	74,7071
Range	444,0
Lower quartile	13,0
Upper quartile	130,5
Interquartile range	117,5
Skewness	1,42783
Stnd. skewness	15,3782
Kurtosis	2,21178
Stnd. kurtosis	11,9108

The Table 1, shows summary statistics for HGV. It includes measures of central tendency, measures of variability, and measures of shape. The standardized skewness value is not within the range expected for data from a normal distribution, because it is outside the range of -2 to +2.

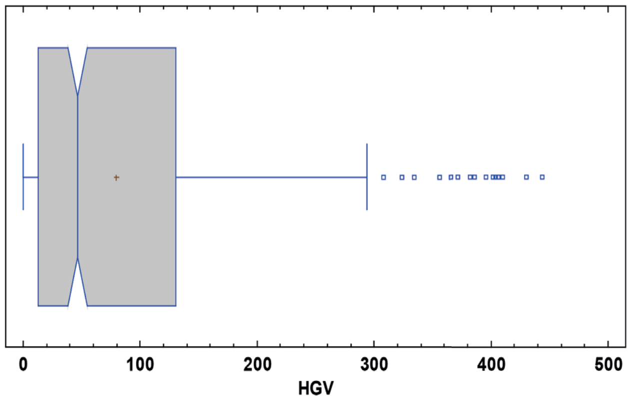


Fig. 4. Box and Whisker plot [own study]

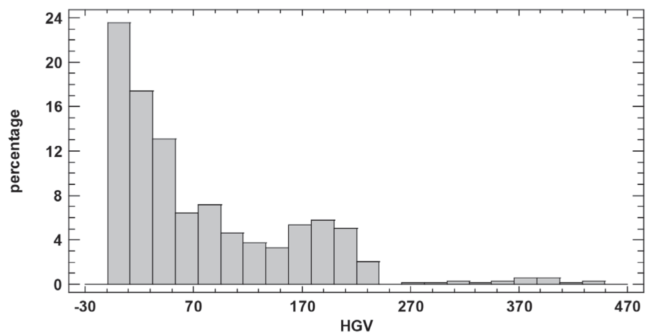


Fig. 5. Histogram [own study]

3.2. Time series analysis

The Seasonal Decomposition procedure divides a time series into three components: trend-cycle, seasonality, irregular, Fig.7, Fig.8, Fig.9.

Each component may be separately plotted or saved. In addition, the decomposition can be used to create a seasonally adjusted version of the original time series, Fig.6. Seasonal subseries and annual subseries plot may also be created, [7].

Seasonality: the length of seasonality s, or number of observations in a full cycle of the seasonal pattern. Hourly data that repeat every day have a seasonality of s = 24.

To get an idea about the variable that we wished to forecast let's start with a graphical plot of historic data, ordered by time points.

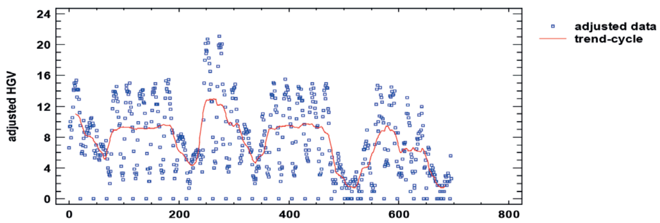


Fig. 6. Trend Cycle component plot for adjusted HGV data [own study]

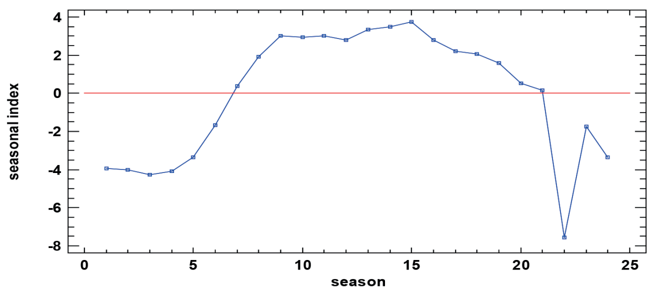


Fig. 7. Seasonal index plot for adjusted HGV data [own study]

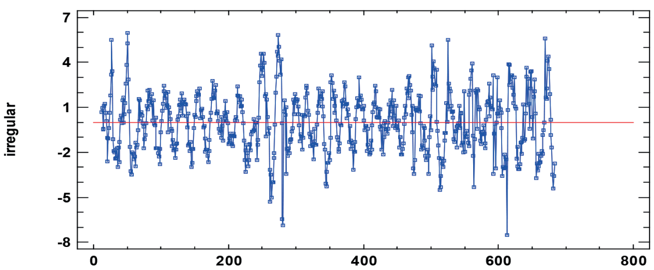


Fig. 8. Irregular component plot for adjusted HGV data [own study]

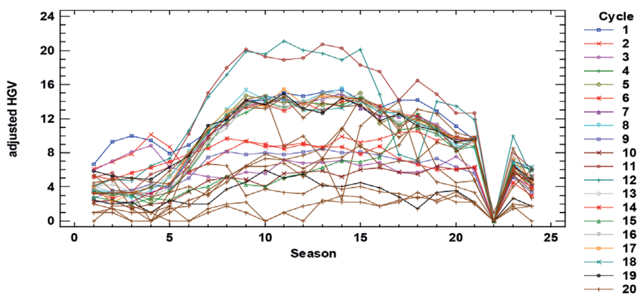


Fig. 9. Annual subseries plot for adjusted HGV data [own study]

Traffic flow time series analysis are necessary at management of road transport. In particular, it is important to anticipate changes in traffic. The impact of the heavy vehicles traffic on transport in the city is specifically important. The aim of forecasting is to predict a future value of a variable such as percent of HGV at traffic flow. A typical forecasting process consists of four steps:

1. construct a parametric model of the data process, Table 2, Table 3, Table 4,
2. estimate the unknown parameters in the model using historic data,
3. compute the forecasted values,
4. check the obtain forecast by experts, other data and adjust if necessary, Fig.10., Fig.11.

3.3. Forecasting

An autoregressive integrated moving average (ARIMA) model has been selected. This model assumes that the best forecast for future data is given by a parametric model relating the most recent data value to previous data values and previous noise. A multiplicative seasonal adjustment was applied.

Table 2. Model Comparison, Estimation Period [own study]

Model	RMSE	RUNS	RUNM	AUTO	MEAN	VAR	Models
(A)	37,377	**	***	***	OK	***	(A) Random walk
(B)	37,3981	**	***		OK	***	(B) Random walk with drift = -0,248291
(C)	68,9096	***	***		***	***	(C) Constant mean = 76,9541
(D)	64,7062	***	***		OK	***	(D) Linear trend = 112,602 + -0,102584 t
(E)	63,9475	***	***		OK	**	(E) Quadratic trend = 106,826 + -0,0526445 t + -0,0000718554 t^2
(F)	30,8155	***	*		OK	***	(F) Simple moving average of 2 terms
(G)	34,494	***	***		OK	***	(G) Simple exponential smoothing with alpha = 0,3129
(H)	39,0259	***	***		OK	***	(H) Brown's linear exp. smoothing with alpha = 0,1683
(I)	34,4593	***	***		OK	***	(I) Holt's linear exp. smoothing with alpha = 0,3115 and beta = 0,0042
(J)	43,041	***	***		OK	***	(J) Brown's quadratic exp. smoothing with alpha = 0,1042

(K)	3165,87	OK	***	***	OK	***	(K) Winter's exp. smoothing with alpha = 0,2043, beta = 0,2034, gamma = 0,2068
(L)	27,0375	*	OK	***	OK	OK	(L) ARIMA(1,0,0) x(2,1,1)24
(M)	26,9701	OK	OK	***	OK	OK	(M) ARIMA(2,0,1) x(2,1,1)24
(N)	27,0359	OK	OK	***	OK	OK	(N) ARIMA(2,0,0) x(2,1,1)24
(O)	26,9987	OK	OK	***	OK	OK	(O) ARIMA(1,0,2) x(2,1,1)24
(P)	27,0383	OK	OK	***	OK	OK	(P) ARIMA(1,0,1) x(2,1,1)24

Model	RMSE	MAE	MAPE	ME	MPE	AIC	HQC	SBIC
(A)	37,377	16,0726		-0,230716		7,3082	7,36628	7,45841
(B)	37,3981	16,0735		0,0178526		7,31221	7,37281	7,46894
(C)	68,9096	47,5393		2,28445		8,53456	8,59516	8,69129
(D)	64,7062	43,3809		2,38491		8,41155	8,47468	8,57482
(E)	63,9475	42,8327		2,38327		8,39084	8,45649	8,56064
(F)	30,8155	16,1261		-0,846273		6,925	6,98561	7,08174
(G)	34,494	20,0375		-1,35077		7,15054	7,21114	7,30727
(H)	39,0259	22,8936		-1,4002		7,39742	7,45802	7,55415
(I)	34,4593	20,2834		2,38565		7,1514	7,21453	7,31467
(J)	43,041	25,8653		-1,4545		7,59327	7,65387	7,75001
(K)	3165,87	713,649		102,655		16,129	16,1366	16,1486
(L)	27,0375	17,8047		-0,328537		6,60595	6,61605	6,63207
(M)	26,9701	17,8258		-0,325844		6,6067	6,62185	6,64588
(N)	27,0359	17,7786		-0,342154		6,6087	6,62133	6,64135
(O)	26,9987	17,6985		-0,305419		6,60882	6,62397	6,648
(P)	27,0383	17,7773		-0,309415		6,60888	6,6215	6,64153

Key: RMSE = Root Mean Squared Error
RUNS = Test for excessive runs up and down
RUNM = Test for excessive runs above and below median
AUTO = Box-Pierce test for excessive autocorrelation
MEAN = Test for difference in mean 1st half to 2nd half
VAR = Test for difference in variance 1st half to 2nd half
OK = not significant (p >= 0,05)
* = marginally significant (0,01 < p <= 0,05)
** = significant (0,001 < p <= 0,01)
*** = highly significant (p <= 0,001)

The table summarizes the results of five tests run on the residuals to determine whether each model is adequate for the data. An OK means that the model passes the test. One * means that it fails at the 95% confidence level. Two *'s means that it fails at the 99% confidence level. Three *'s means that it fails at the 99,9% confidence level. The model with the lowest value of the Akaike Information Criterion (AIC) is model N, which has been used to generate the forecasts.

Table 3. ARIMA Model Summary [own study]

Parameter	Estimate	Stnd. Error	t	P-value
AR(1)	0,913706	0,0157659	57,9544	0,000000
SAR(1)	0,0687103	0,0391744	1,75396	0,079437
SAR(2)	-0,110813	0,0395223	-2,80382	0,005050
SMA(1)	0,946153	0,00673518	140,479	0,000000

Backforecasting: yes

Estimated white noise variance = 745,842 with 668 degrees of freedom

Estimated white noise standard deviation = 27,3101

Number of iterations: 7

Table 4. Statistical significance of the terms in the forecasting model [own study]

Statistic	Estimation Period	Validation Period
RMSE	27,0375	
MAE	17,8047	
MAPE		
ME	-0,328537	
MPE		

The table summarizes the performance of the currently selected model in fitting the historical data. It displays:
(1) the root mean squared error (RMSE)
(2) the mean absolute error (MAE)
(3) the mean absolute percentage error (MAPE)
(4) the mean error (ME)
(5) the mean percentage error (MPE)

The output summarizes the statistical significance of the terms in the forecasting model. Terms with P-values less than 0,05 are statistically significantly different from zero at the 95,0% confidence level, Table 3l. The P-value for the AR (1) term is less than 0,05, so it is significantly different from 0. The P-value for the SAR (2) term is less than 0,05, so it is significantly different from 0. The P-value for the SMA (1) term is less than 0,05, so it is significantly different from 0. The estimated standard deviation of the input white noise equals 27,3101.

Each of the statistics is based on the one-ahead forecast errors, which are the differences between the data value at time t and the forecast of that value made at time t-1, Table 4. The first three statistics measure the magnitude of the errors. A better model will give a smaller value. The last two statistics measure bias. A better model will give a value close to 0. NOTE: the MAPE and MPE were not calculated because the smallest data value was less than or equal to 0.

The lag k partial autocorrelation coefficient measures the correlation between the residuals at time t and time t+k having accounted for the correlations at all lower lags. It can be used to judge the order of autoregressive model needed to fit the data. Also shown are 95,0% probability limits around 0. If the probability limits at a particular lag do not contain the estimated coefficient, there is a statistically significant correlation at that lag at the 95,0% confidence level. In this case, 5 of the 24 partial autocorrelation coefficients are statistically significant at the 95,0% confidence level.

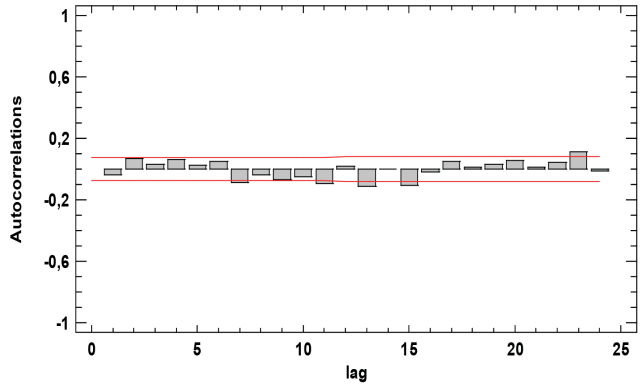


Fig. 10. Residual autocorrelations for adjusted HGV data [own study]

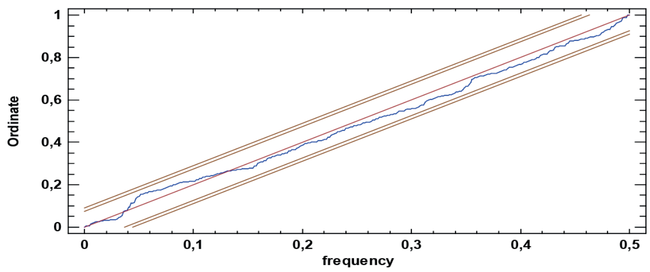


Fig. 11. Periodogram for residuals [own study]

The periodogram is constructed by fitting a series of sine functions at each of 337 frequencies, Fig.11. The ordinates are equal to the squared amplitudes of the sine functions. The periodogram can be thought of as an analysis of variance by frequency, since the sum of the ordinates equals the total corrected sum of squares in an ANOVA table. During the period where actual data is available, Fig. also displays the predicted values from the fitted model and the residuals (data-forecast). For time periods beyond the end of the series, it shows 95,0% prediction limits for the forecasts. These limits show where the true data value at a selected future time is likely to be with 95,0% confidence, assuming the fitted model is appropriate for the data.

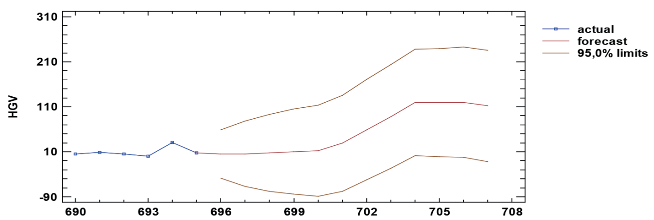


Fig. 12. Forecast plot for HGV data [own study]

As with regression models, forecasting models, Fig.12, Fig.13., involve unknown parameters *p* that are usually determined so that the model fits the data reasonably well, Table 4., [8].

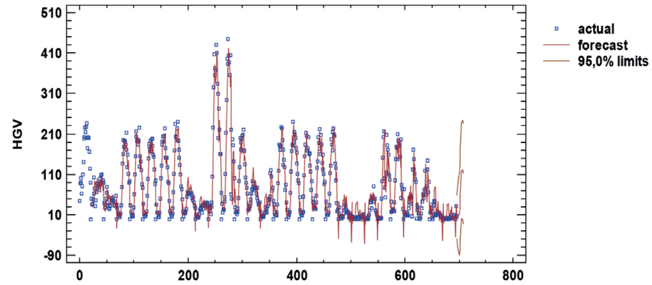


Fig. 13. Time sequence plot for HGV data [own study]

4. Conclusion

Research indicates that the use of data from the WIM at a very high level of accuracy can be used to supplement the traffic control. Locating weight in a long distance between the two intersections can be a prediction system for drivers, traffic light for the use of intelligent traffic control. Transport Telematics allows for more efficient use of existing road infrastructure. The use of weight in motion allows you to supervise the weight of vehicles. The combination of different elements using new technologies in traffic management and control is the basis of effective traffic in the city.

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