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AUTOMATIC INCIDENT DETECTION AND SHORT TERM PREDICTION OF TRAFFIC FLOW

DIPLOMA THESIS

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Contents

INTRODUCTION

Congestion in urban areas has now become a major cause for concern for drivers and traffic authorities. It affects the quality of life of virtually every citizen, and has severe implications for business. There are high hopes that measures like urban traffic control with coordinated signals and current traffic states recording will bring relief to our cities in future. Also development of electronic systems such as route guidance by variable message sings and by incur equipment as well as road pricing will perhaps bring additional relief.

This thesis addresses the problem of forecasting the urban situations. Specifically, it concerns the short time (20 minutes prognosis horizon) prediction of the urban traffic volume on signalized streets. Eleven forecasting models have been tested and assessed in order to find a reliable solution. The final target is to make a combination of an incident detection algorithm and the forecast model. The incident detection algorithm that has been used is the Automatic Incident Detection Algorithm (AIDA) which is the first algorithm that has been used for incident detection on streets with signal controlled intersections. This also means that the combination of incident detection and forecast of traffic situations on signalized streets is an approach that has been never applied. Thus, the results of the following investigation can be considered as very important and interesting. The data that have been elaborated have been taken from a German field trial. It concerns the Ingolstädter Straße between Neuerbergstraße and Middle Ring Road in Munich. On the same field the AIDA has been already successfully applied since 1996. In the coming up chapters one can find a complete study of urban traffic situations prediction. Particularly, chapter one deals with the general theory of incident detection. Definitions, several methods, the target and applications are the main subjects. In chapter 2 a description of the Automatic Incident Detection Algorithm (AIDA) is presented where the different steps of the algorithm, the form of the data input or output, and the test site are treated. In the next chapter (chapter 3) a general description of tested or existing similar methods of forecast and several prediction model types are given. The main work of this thesis is described in chapter 4. It deals with the data elaboration, the data categorization, the form of the data implemented on the prognosis models, the error definition and finally the prognosis models implementation. Several time series diagrams, lists of error indications and other kind of figures are displayed in order to gain a visual image of the models performance. In chapter 5 an assessment of the results and suggestions are given based on specified criteria. The models performances are described for each model separately by giving the advantages and the disadvantages of each one. Finally, in chapter 6 the initial target of the thesis is taken up. A proposal combination of prognosis and Automatic Incident Detection Algorithm is described. The benefits that are gained from this combination are also mentioned in order to give a feeling of the impacts in citizen’s life.

From the above description can be easily understood that this thesis concerns an investigation in the area of traffic engineering science. This thesis could be the starting point of a further examination and applications as far as the prognosis of signalized streets traffic situations concerns.

CHAPTER 1

THEORY OF INCIDENT DETECTION

1.1 Definition of incident detection terms

A usage of the terms “incident” within the different definitions in the international specialist literature is not standardized.

- Incident/Disturbance: Event, which has negative effects on traffic flow. An incident often is defined as a generic term for different types of extraordinary events in traffic flow. Compulsory stopping of a vehicle on the carriageway, connected with a reduction of in-road capacity, which lasts until the removal of the vehicle. In an extensive sense every derivation of one or more roads users from the momentary driving intention has to be defined as a disturbance [12]. Incidents can be defined also as any event which causes a reduction in capacity [14].
- Disturbance value: Magnitude, which can lead to a short term change in influence on traffic flow. Thereby the following important types of disturbance values have to be distinguished :
    1. drivers constitution,
    2. disturbances caused by the vehicle,
    3. disturbances caused by traffic,
    4. disturbances caused by weather as well as
    5. disturbances caused by malfunction.

Disturbance values can occur alone or in combination with others [12].

- Incident detection: Measure or process for temporal and spatial identification of incidents. Incident detection is a special task of traffic flow analysis, which represents the basis for the assessment and influence of traffic flow. The automatic incident detection (AID), which tries to identify the incident by online analysis of data, measured directly on the road and non automatic incident detection (NAID), which includes the sector of human observation and messages, e.g. incident localization by police, emergency call systems, CB-broadcasts, TV-observation, etc., have to be distinguished [12].

1.2 Methods for automatic incident detection

For the automatic incident detection there are mainly two model approaches, the cross-section process at measuring site level and the process at segment-level.

a. The <u>processes at cross section level</u> operate with local measurements and draw conclusions on the traffic conditions along the road. The local, smoothed traffic parameters are used directly or subsequent to a temporal prognosis for decision making , e.g. by comparing them with given threshold values or bringing them into a goal function. The extrapolation of local measurement results on a stretch is useful in case of short stretches and a homogenous stretch geography.

b. The <u>process at segment (link)-level</u> is suitable for longer section with larger distances between the measurement-sites, because of its assessment of measurements of at least two neighboring measuring sites.

1.3 Target of automatic incident detection

In Northern America the original sense of automatic incident detection is to give the possibility of a quick reaction on accidents and vehicle breakdowns on motorways. This is connected with three decidable advantages:

1. Because of a fast removal of the disturbance, which causes a reduction of competitiveness, the loss of time for the remaining traffic will be minimized.
2. Reduction of the risk of secondary accidents of vehicles, which run into the end of the queue.
3. The possibility of faster help for the driver of the conked out vehicle.

In Germany however the main sense of incident detection is warning in case of congestion, that means a congestion, whatever type it is, has to be identified, for warning the driver timely. For this reason the techniques used in Germany should rather be called congestion detection than incident detection of ecological damages, fuel consumption and journey times have to be defined as aims. Automatic incident detection processes should work so that the identification is as quickly as possible and the localization as precise as possible [12].

1.4 Processes and approaches

Over the years many processes have been developed to detect incidents. Nearly all processes are dealing with incidents of regional areas. So far no algorithm is known, which was used for incident detection on signalized streets with signal controlled junctions. In the following some processes of the regional incident detection on motorways and federal roads are shown briefly:

1. California Algorithm: Some parameters of neighboring measuring sites, which were derived from the occupancy[3], are being compared. The occupancy is being determined as an average 20 seconds values between the upstream and downstream measuring sites. The following parameters are being compared with alarm thresholds:
    a. occupancy difference both measuring sites
    b. relative occupancy difference
    c. relative (temporal) change of occupation on the first measuring sites
2. Temporal prognosis: Knowing the temporal development of an examination value until the actual point of time, a prognosis is being drawn up for the next (or further next) time interval. This prognosis is being compared with the real values. The most often used prediction method is the double exponential smoothing. This process of a temporal prognosis can be used as a measuring site process as well as a link process.
3. Spatial prognosis: Using the values from the upstream and downstream located measuring sites, a prognosis is drawn up for the downstream located measuring site and is compared with the real value. Condition for a successful incident detection is the knowledge of the vehicle speeds with a remarkable changing on the downstream measuring

site as well as a reduction of the traffic volume[1] downstream. The spatial prognosis is a link related method .

4. Filter techniques : The distance between two measuring sites is seen as a real system, for which a model system is defined. The measurements of both measuring sites are used as input/output values. With the (filtered) input values the system output is estimated and compared with the real output values.
5. Feature correlation: Using the pattern of detector output signals, a classification of the single vehicle is carried out so that single vehicles or vehicle collectives can be identified via an auto correlation formulation at the next measuring site. By this, a direct determination of traffic times between the measuring sites is possible as well as a determination of traverse speeds as the characteristic of traffic flow. The prerequisite of such a pattern recognition is the application of particular detectors, which are providing an analog output signal. The detectors have to be suited to produce precise and comparable processes of detector signals, even if the conditions of the less favorable [12].
6. Cluster analysis: Using off line analysis an algorithm for incident detection is defined in that way that vectors of traffic parameters are collected for different traffic situations. These vectors are transformed on line, so that the groups, which are created with the Cluster process, can be clearly assigned to traffic conditions.

1.5 Applications and experiences

The beginning of the automatic incident detection are going back to the sixties in the USA. The so far gained experiences with AID systems are based mainly on municipal high speed roads with short sections and a high density of measuring sites. The biggest part of the known AID systems is working with sections between 400m and 800m. The most experiences have been gained on American urban freeways. As examples, the following systems for incident detection can be nominated:

- The “Freeway Surveillance and Control Systems” in Chicago (since 1961). The data collection takes place on single cross sections (Distances between the measuring sites is approx. 800m, collection of the number of vehicles) as well as on complete cross section with distances of 5km with an additional recording of speeds. The AID covers cross section and section processes and was continuously enlarged and corrected.

- Since 1971 a huge network of high speed roads in the high density area Los Angeles is controlled semi automatically. A maximum distance of 1,5km between the measuring sites should not be exceeded, the data collection takes place on the approach road and exit road in between.
- The demonstration system "Queen Elizabeth Way" near Toronto works since 1977. Every 800m data are recorded with the aim to reduce traffic jams caused by frequent overloads and accidents. They are also using the California Algorithm with TV control. The distance of the detectors are 500m.
- Since 1978 Algorithms, developed by TRRL, are used and tested on a test section on the M1 north of London with an additional TV monitoring. The distances of the measuring sites are in between 400m and 600m.
- The traffic control system A13/A20 in the Netherlands, which is working since the end of 1981,controllsnearly 50km motorway between The Hagne and Rotterdam. The capturing on the complete cross section takes place at distances of 500m.
- On the "Neue Weinsteige" in Stuttgart five video cameras are installed on a section of 2 km. Four of them are out bound and one is bound. The evaluation takes place with automatic image processing. The traffic parameters are taken within intervals of one minute and aggregated to 5 minute values [12].

CHAPTER 2

AUTOMATIC INCIDENT DETECTION ALGORITHM (AIDA)

2.1 Methodical approach

After the overview and the attempts for automatic incident detection that have been done in the previous chapter, the AIDA program is represented now. As it mentioned before, so far no algorithm is known, which was used for incident detection on signalized streets with signal controlled junction. As far as urban applications concerns, AIDA is the first applied algorithm. The AIDA program for incident detection consists of the following modules[12]:

a. <u>Plausibility examination</u>

Examination of the data input with regard to plausibility, removing/(replacing) of invalid data out of the further calculation.

b. <u>Algorithm for incident detection / traffic situation analysis</u>

- Incident detection, step 1: early diagnosis of disturbances via a link process
- Incident detection, step 2: incident detection during several measurement periods via a process at measuring site level.
- Traffic situation analysis, step 3: analysis of the current traffic situation in the fundamental diagram and congestion detection.
- analysis of capacity utilization, step 4: analysis of the current capacity utilization at the junctions, determination of the actual reserve of capacity with regard to currently applied signal plans.

2.2 Data input, data output

The data, which were collected by the detectors, are edited and cycle actuated aggregated at the face. The data format for the AIDA research computer includes the following information:

a. measurement sites values

- date
- time stamp (‘real time’ in seconds ,derived by radio clock)
- number of measurement site
- error identification 0 or 1
- cycle time (in case of break down 120 sec.)
- number of lanes

b. detector values (lane actuated)

- green period (end and duration of green period of the observed direction)
- total number of vehicles
- total number of heavy goods vehicles (HGV)
- harmonized average[7] speeds of all passengers cars
- harmonized average speeds of all heavy goods vehicles (HGV)
- time of occupancy.

The data flow terms are described in the **Annex**.

2.3 Algorithms

2.3.1 *Examination of plausibility*

The following examinations of plausibility are carried out per traffic inductive loop:

- Br, i, Qr, i and Vr, i ≥ 0
- Br, i, ≤ Bmax, i
- Qr, i ≤ Qmax, i
- Vr, i ≤ Vmax

where Br is the occupancy,
Qr is the traffic volume,
Vr is the speed,

i	is the detector of measuring site,
r	is the number of the measurement.

2.3.2 *Incident detection, step 1*

In assumption that a big part of accidents occur in a junction area, an approach, which uses detectors located downstream the junctions, is tested. This link process uses the cut off at the measuring site downstream as a criterion: there is more traffic flowing in at the upstream measuring site than flowing out at the downstream measuring site. This situation is the so called incident detection. Step 1. The situation changes as soon as the consequences affect the neighboring measuring sites. Therefor step 1 of the incident detection serves the early diagnosis of incidents.

The process considers the turning streams Qa and Qz at the observed junctions. An incident is defined by the following condition:

$$\boxed{(Q_1(t) + Q_1(t-1))/2 > Q_2(t) + Qz - Qa + Qs}$$

where Q_1 is the traffic volume upstream,
Q_2 is the traffic volume downstream,
Q_z is the traffic flow in,
Q_a is the traffic flow out,
Q_s is the threshold for the traffic volume.

The traffic volume at the measuring site downstream is compared with the mean traffic volume of the current and previous signal plan cycle. The correction value Qa considers the parts of the stream Q_1, which turn before measuring site Q_2 and do not pass it for this reason. The correction value Qz considers in the streams, which flow in addition to Q_1 from the neighboring junction arms in the measuring site Q_2. Qz and Qa are determined, based on existing historical time series for traffic volume, for each junction. The value Qs describes the tolerance area, within which the traffic volume downstream can vary without leading to an alarm. It is given exogenously as a relative value part of Q_2: $Qs = a*Q_2$. The value "a" will be calculated empirically during the trial and can be adjusted in the computer program.

2.3.3 *Incident detection, step 2*

Two Algorithms for an urban incident detection have been developed. Both operate at measuring site level and use as criteria typical changes in the measurement data caused by an incident:

- higher occupancy and lower traffic volume at the measuring site upstream
- lower occupancy and lower traffic volume at the measuring site downstream.

The AIDA module is described in the **Annex**.

If the congestion affects the measuring site upstream the incident, the values of traffic volume and occupancy do no longer change significantly during the incident, so that this Algorithm does no longer lead to an alarm. At this moment the third part of Algorithm, the congestion detection, intervenes. However, the congestion detection can already appear during the alarm of step 2.

2.3.4 *Congestion detection, traffic situation analysis, step3*

In the framework of the traffic situation analysis, the actual traffic situation is the help of fundamental diagrams. The fundamental diagrams are determined empirically for each observation point as Q/V diagrams and are divided in Level-of-Service-areas (LOS). Thereby the traffic volume is given in passenger car units. The **Figure 2.1** describes an exemplary fundamental diagram. Thereby the LOS area 1 and 2 can be seen as unstable traffic situations (congestion), while the LOS areas 3 up to 5 are describing the dependence between traffic volume and speed during a stabile traffic flow.

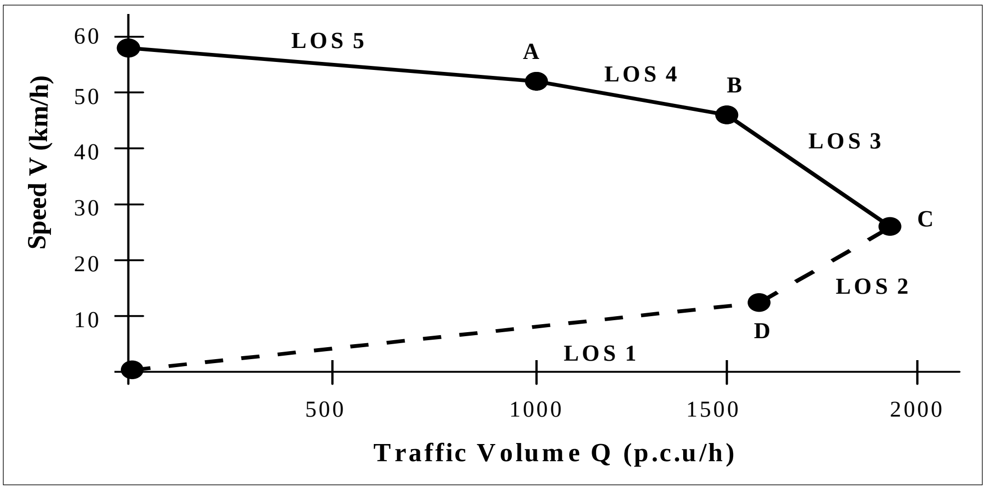


Figure 2.1 - Fundamental diagram

2.3.5 *Capacity utilization analysis, step 4*

For the decision algorithm of the dynamic re-routing, the incident detection as well as the question "if and if yes, how much additional traffic can be led into the street because of the actual traffic situation", are of substantial importance. Within the urban area, the road network capacity is determined mainly by the capacities of the intersections. The theoretical capacity is calculated by using the maximum capacity utilization and green period at the traffic light for the observed travel direction at the cycle time of the current signal program. As an additional criterion for the control logic the capacity utilization is determined out of actual measurements. The capacity reserves at the intersections result from the difference of the maximum capacity and the real traffic volume. Therefore, the traffic volume, which is counted for each cycle per measuring site, is used as data input. This traffic volume is assigned to each upstream intersection with consideration of historical flow-ins.

2.6 Alarm definition

Alarm are set off if an incidents identified by the following conditions: An incident is identified either by step 1 or 2 of the Algorithm or if the speed falls below the defined congestion speed of V=35 km/h within of more than five successive detection intervals (step 3). The condition for switching on and for the duration of the alarm are as follows:

- Alarm on, if an incident is detected by step 1 and/or 2 of the Algorithm and/or if the condition for congestion is performed
- Alarm off, if 15 minutes passed after setting the alarm due to Algorithm steps 1 or 2 V_{stau} did not appear during this period and/or if there is no more congestion.

The flow chart in **Figure 2.2** describes the general function of the above steps.

2.7 Test site

The automatic incident detection algorithm (AIDA) has been designed on the basis of satisfying the requirements of every urban road. The first adjacent area of the AIDA covers the Ingolstädter Straße between Neuerbergstraße and Middle Ring Road in Munich, Germany. The adjacent area consists of residential buildings mixed with buildings for commercial purposes.

The traffic load on the Ingolstädter Straße, with at least two lanes per direction, is about 17,000 up to 20,500 vehicles per day and travel direction and can be classified as high. Thereby, the big part of HGV (between 5.4% and 10.8%) is remarkable. The **Figure 2.3** shows the test site with the location of measurement sites and detectors. The detectors are inductive loops and to distinguish the kind of vehicles (passenger car and HGV) or to get the speeds, double inductive loops have been installed [12]. The detectors are located downstream, and the exact location in the test field is described in the list of **Figure 2.4**. The prognosis has been done by using the data of the 2nd detector.

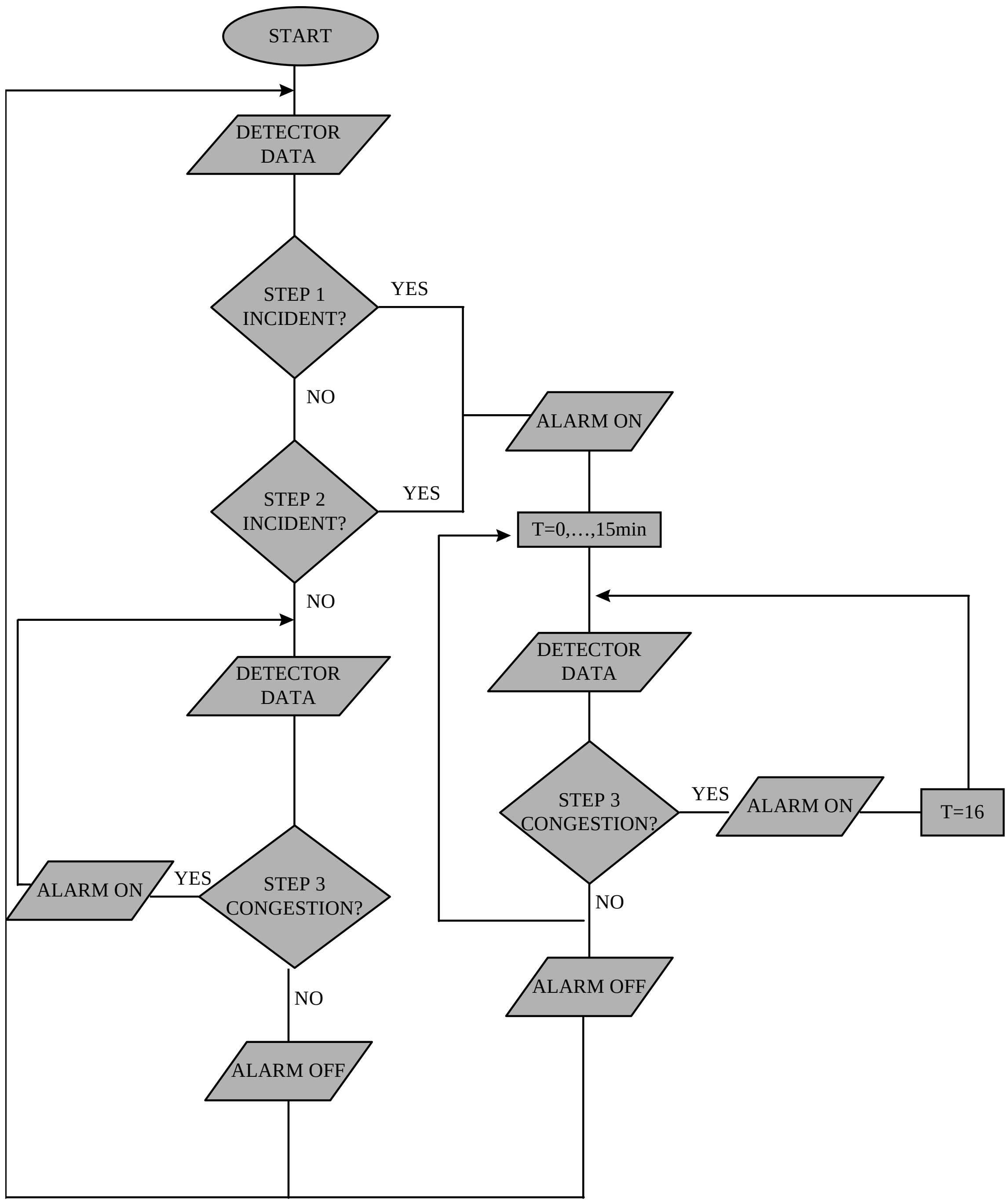


Figure 2.2 - General description of A.I.D.A. algorithm.

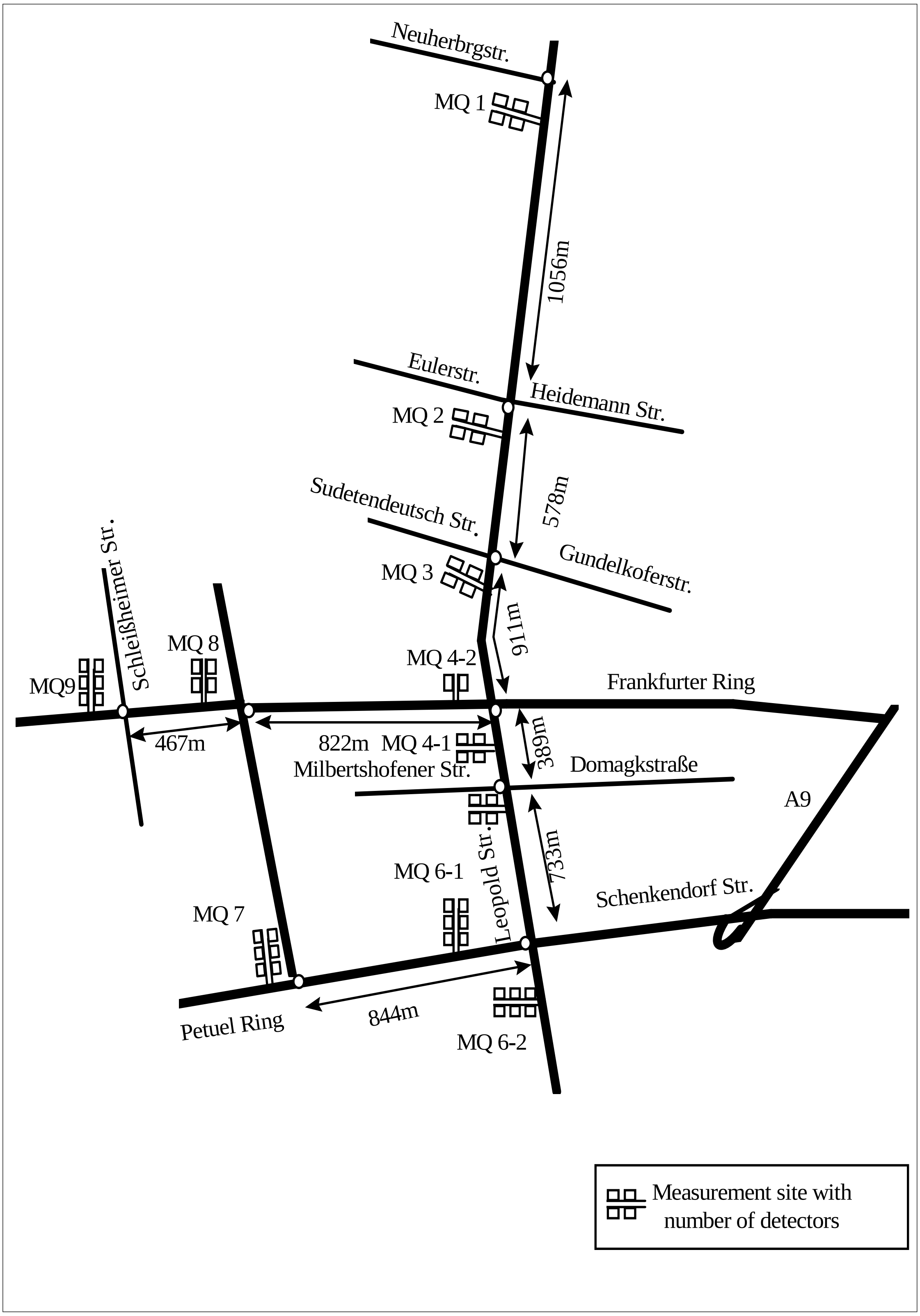


Figure 2.3 - Test site.

Measuring site	Amount of detectors
1 Inglstädter Straße / Neuherbergstraße	2
2 Inglstädter Straße / Heidemannstraße	2
3 Inglstädter Straße / Sudetendeutsche Str.	2
4-1 Inglstädter Straße / Frankfurter Ring	2
4-2 Frankfurter Ring / Inglstädter Straße	1
5 Inglstädter Straße / Domagkstraße	2
6-1 Petuelring / Leopoldstraße	3
6-2 Leopoldstraße / Petuelring	3
7 Petuelring / Knorrstraße	3
8 Frankfurter Ring / Knorrstraße	2
9 Moosacher Straße / Schleißheimer Straße	3
Σ	**25**

Figure 2.4 - Detectors location list.

CHAPTER 3

TRAFFIC SITUATION PROGNOSIS - EXISTING METHODS

3.1 General

In traffic control systems used for the regulation of urban networks, there is always a certain delay between the computation of traffic signal settings and their actual implementation on the network. Therefore, such systems can be appreciably improved by using predictive models.

Three specific types of prediction can be distinguished, depending on time scale:

- Long term prediction (a few months or a year). This is mentioned only in passing. It is not actually used in control systems but can be used to forecast the required capacity of facilities such as freeways or tunnels, or to compute fixed time coordination plans which are to be implemented over a long period.
- Medium term prediction (a few days). Is similar to the following short term prediction. It has been used in combination with the short term prediction in order to gain information useful for various applications within the area of traffic management [9].
- Short term prediction (a few minutes or hours). This is used in adaptive regulation systems including usually a package of coordination plans, from which a decision algorithm chooses, every 5-min. or more so, the one to be implemented. Hence, the traffic variations have to be estimated a few minutes ahead.

- Very short term prediction (a few seconds to a minute). This is used by real time regulation algorithms which are highly responsive to traffic variations.

In all cases, the parameter to be predicted are mostly traffic volumes, either through a road section or in a network. For the prediction of traffic situations there are mainly two model approaches.

1. Prediction at cross section level. It operates with local measurements and makes a forecast for the traffic conditions along the road.
2. Prediction at segment level. It assess measurements of at least two neighboring measuring sites. It is suitable for longer section with larger distances between the measurement sites.

Various inputs and model structures are used, depending on which type of prediction is considered. The type of prediction that this thesis concerns is a short term cross section level prediction. At the following section a general description of short term models that have been tested is given.

3.2 Existing models for short term traffic flow prediction

Several kinds of predictive model based on techniques of time series analysis are used for short term prediction. Some models rely on the periodicity of traffic volumes from one day or one week to another, and use historical data as inputs. Others rely on the stability of traffic volumes over a short period and use current day measurements as inputs, while yet others use a combination of both kinds of input. All models are endogenous. That is , all inputs are previous values of the parameter to be predicted. In the following a description of some of the tested models is given.

3.2.1 *Linear models using smoothed information*

Linear models using smoothed information are classified in accordance to the prediction models developed in the USA for the second and third generations of urban traffic control systems (UTCS-2 and UTCS-3). The second generation models such as UTCS-2 or ASCOT use both historical information and current day measurements as inputs. The time unit of prediction is 5-15-min.. For example, considering $f(t-1)$ the measuring volume at time interval $t-1$, $m(t)$ the smoothed historical volume for time interval $t-1$ and $r(t) = ar(t-1)+(1-a)[f(t-1)-m(t-1)]$ the exponentially smoothed difference between measured and historical volumes, the UTCS-2 model will give the predicted volume at time interval *t* by

$$V(t) = m(t) + r(t) + d(t)$$

where $d(t) = b[f(t-1) - m(t-1) - r(t-1)]$ is the difference between the real and smoothed values of *f-m* with a coefficient *b* computed by identification. The smoothed historical volume is obtained by fitting the Fourier series.

$$m(t) = A_0 + \sum_{i=1}^{6} [A_i \cos(2\pi.it/k) + B_i \sin(2\pi.it/k)]$$

to a representative volume data set.

The main shortcoming of this kind of model is its poor responsiveness to abrupt changes in the traffic, related to the importance of historical information in the model. To avoid this disadvantage, the third generation models such as UTCS-3 or similar algorithms rely on current day measurements. The time unit of prediction is from one to a few traffic signal cycles, and the prediction is a two step one. The UTCS-3 model is as follows. Considering *f(t)* the exponentially smoothed volume and *d(t)=f(t)-x(t)* the difference between the real and smoothed values, the predicted volume *q(t)* is given by

$$q(t) = x(t-2) + bd(t-2)$$

where

$$b = \frac{(N-1)\sum_{t=1}^{N-2} d(t)d(t=2)}{(N-3)\sum_{N-1}^{N} d(t)^2}$$

The constant *b* is computed from a representative data set, and *N* is the number of data points user for this determination. This kind of model responds well to traffic changes, but always presents a certain inherent time lag.

Comparisons between the two generations of models show that, generally speaking, the second generation models are better than the third generation ones, because of the use of historical data. On the other hand, third generation models do not need historical data and are more responsive to nonperiodic phenomena such as accidents and the weather [7].

3.2.2 *Short term prognosis used on a German freeways tested in the Rhein-Main field trial.*

Short term prognosis models applied on German freeways forecasts the traffic density[2] k and by using an initial diagram calculates the speed (mean instant speed) and the traffic volume on a cross section level. The measurements of the analysis area[8] from $t=-T_a$ to $t=0$ produce a regression line of the form:

$$\boxed{k(t) = k_e + \frac{k_e - k_a}{T_a} t}$$

where $k_a = k(-T_a)$,

$k_e = k(0)$.

The above line is extrapolated to the prognosis area[9] by applying a function which is composed by three terms:

$$\boxed{k(t) = k_1(t) + k_2(t) + k_3(t)}$$

where $k_1(t) = (k_a - k_e)\, e^{-t/Ta}$,

$k_2(t) = k_e - (k_a - k_e) = 2k_e - k_a$,

$k_3(t) = (k_E + k_a - 2k_e)(1 - e^{-\lambda t^2})$,

$0 \leq t \leq T_p$,

k_E is the long term estimated value for the traffic density,

λ is the convergence parameter.

The k_1 follows the linear trend of the analysis horizon, the k_2 limits this linear trend by taking under consideration a limit value and the k_3 takes under consideration long term estimated value that is produced by previous time series. The convergence parameter shows how fast the prognosis function approaches the estimated value. This combination of the three terms gives a reliable and accurate forecast. The first two give to the model the flexibility to traffic changes during the day. The third makes the model to take under consideration the reality by adding older days values [3]. A latest research project based on the above model has been carried out. The objective of this project was to develop a process for large area prognoses of traffic demand for prognosis horizon of up to 4 hours (short term prediction) and up to 2 days (medium term prediction). The prognosis results are of use in particular for large area journey information and destination guidance systems. The calibration and evaluation of the model was based on measured data obtained from the autobahn network between Frankfurt and Stuttgart [9].

CHAPTER 4

FORECAST CALCULATION

4.1 Data elaboration

To apply a prognosis model first an elaboration of the data must be done. In the following sections, the procedure of this elaboration is described. The data have been taken from the detector MQ2 at the measuring site Ingolstädter Sraße/Heidemannstraße (**Figure 2.3**). The dates which traffic data were available are listed in **Figure 4.1**. They are 49 dates and they belong to the year 1996. There is a big variety of days that have a particular time series (Sundays, holidays etc.) and they have to be under consideration.

4.1.1 *Detector data*.

The data that are transmitted from a detector have a special form. The form of the data transmitted from the detectors in Ingolstädter Straße is as it is shown in **Figure 4.2**. Specifically, these magnitudes are:

I. date
II. time stamp (“real time” in sec., derived by the radio clock)
III. number of lane
IV. cycle time (in case of break down 120 sec.)
V. specific error code
VI. gross time gap
VII. net time gap
VIII. total number of vehicles
IX. total number of heavy good vehicles (HGV)
X. harmonized average speeds of all passenger cars

XI. harmonized averaged speeds of all HGV

XII. time of occupancy.

The values of V, VI, VII are not taken into consideration as far as the data elaboration is concerned. In addition, because of making prognosis of the future traffic volume, the X, XI, XII, values have not been processed.

4.1.2 *Data processing*

As mentioned before, the first thing that must be done is the data elaboration. The data, which are collected by the detectors, are classified per lane. Thus, first the data have been transformed into road data. For this purpose the calculations that have been done are:

- addition of the total number of vehicles of the lanes
- addition of the total number of HGV of the lanes.

In the next step the total traffic volume of the road has been calculated. The total number of vehicles and the total number of HGV have been used for this calculation. HGV have been converted into passenger car estimated by a factor of 1.75 in order to have a common vehicle basis. The function that estimates the total traffic volume of the road is:

$$\boxed{Q_{ct} = X + 1.75\ Y}$$

where Q_{ct} is the total road traffic volume (number of vehicle per cycle time),

X is defined as the difference between the total number of vehicles and the total number of HGV,

Y is the total number of HGV.

The values that are estimated by this function have the form number of vehicles per cycle time. Thus, the next step was to transform these values into vehicles per hour. This was done by the following calculation:

$$\boxed{Q_h = Q_{ct}\ \frac{3600}{cycle}}$$

January 2, 1996	April 12, 1996	June 25, 1996
January 3, 1996	April 13, 1996	August 2, 1996
January 4, 1996	April 14, 1996	August 3, 1996
January 5, 1996	April 15, 1996	August 4, 1996
January 6, 1996	April 16, 1996	August 5, 1996
January 7, 1996	April 17, 1996	August 6, 1996
April 1, 1996	April 18, 1996	August 7, 1996
April 2, 1996	April 30, 1996	August 8, 1996
April 3, 1996	May 1, 1996	August 15, 1996
April 4, 1996	May 15, 1996	August 16, 1996
April 5, 1996	May 16, 1996	August 17, 1996
April 6, 1996	May 24, 1996	August 18, 1996
April 7, 1996	May 25, 1996	August 19, 1996
April 8, 1996	May 26, 1996	September 10, 1996
April 9, 1996	May 27, 1996	September 11, 1996
April 10, 1996	May 28, 1996	September 12, 1996
April 11, 1996		

Figure 4.1 -Dates for which traffic data were available.

YEAR	MOUNTH	DAY	HOUR	MINUTE	SECOND	LANE	CYCLE TIME	SPECIFIC ERROR CODE	GROSS TIME GAP	NET TIME GAP	T.N.OF VEHICLES	T.N.OF HGV	H.A.SPEED OF VIHICLES	H.A.SPEED OF HGV	TIME OF OCCUPANCY
96	4	16	0	0	0	1	52	1	0	0	3	0	61	0	1
96	4	16	0	0	0	2	52	1	0	0	1	0	65	0	0.5
96	4	16	0	0	52	1	52	1	0	0	1	0	46	0	0.5
96	4	16	0	0	52	2	52	1	0	0	0	0	0	0	0
96	4	16	0	1	44	1	52	1	0	0	3	0	49	0	1
96	4	16	0	1	44	2	52	1	0	0	0	0	0	0	0
96	4	16	0	2	36	1	52	1	0	0	3	1	58	43	1.5
96	4	16	0	2	36	2	52	1	0	0	0	0	0	0	0
96	4	16	0	3	28	1	52	1	0	0	1	0	55	0	0.5
96	4	16	0	3	28	2	52	1	0	0	3	0	56	0	1
96	4	16	0	4	20	1	52	1	0	0	2	1	77	37	1.5
96	4	16	0	4	20	2	52	1	0	0	0	0	0	0	0
96	4	16	0	5	12	1	52	1	0	0	2	0	63	0	0.5
96	4	16	0	5	12	2	52	1	0	0	0	0	0	0	0

Figure 4.2 - Excerpt of the output.

where 3600 is one hour in seconds and

cycle is the cycle time for each Q_{ct} value.

Diagrams have been drawn of the volume as a function of time. Some examples of these diagrams (time series) are shown in **Figure 4.3** where one can see that the characteristics differ.

As can been seen from the diagrams presented in **Figure 4.3** rapid changes occur between the values. This can cause a failure in the following estimations. Because of this fact, an implementation of a smoothing model is obligatory. Thus, the exponential smoothing has been chosen as a model with good performance in smoothing down these changes. The function that has been used is:

$$\boxed{Q_{sm}(t) = a\, Q_h(t) + (1-a)\, Q_{sm}(t-1)}$$

where $Q_{sm}(t)$ is the smoothed volume in time t,

$Q_h(t)$ is the real volume in time t,

$Q_{sm}(t-1)$ is the smoothed volume in time t-1,

a is the smoothing parameter and it has been chosen to be 0.1 .

Some examples of smoothed time series can be seen in **Figure 4.4**. The time has been transformed in seconds according to the function:

$$\boxed{t = h\, 3600 + m\, 60 + s}$$

where t is the time in seconds,

h is the hour,

m is the minute,

s is the second.

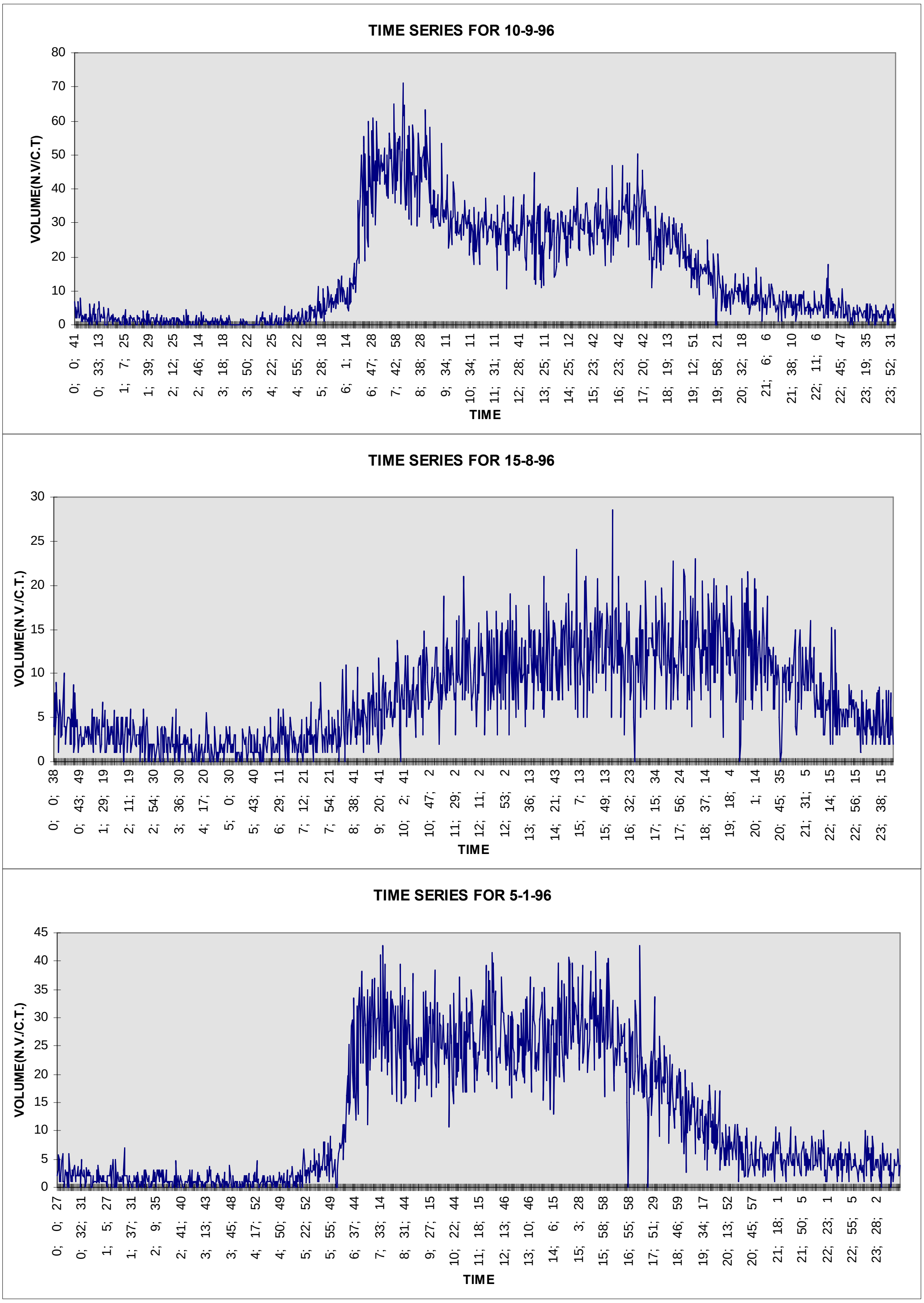


Figure 4.3 - Examples of Time Series.

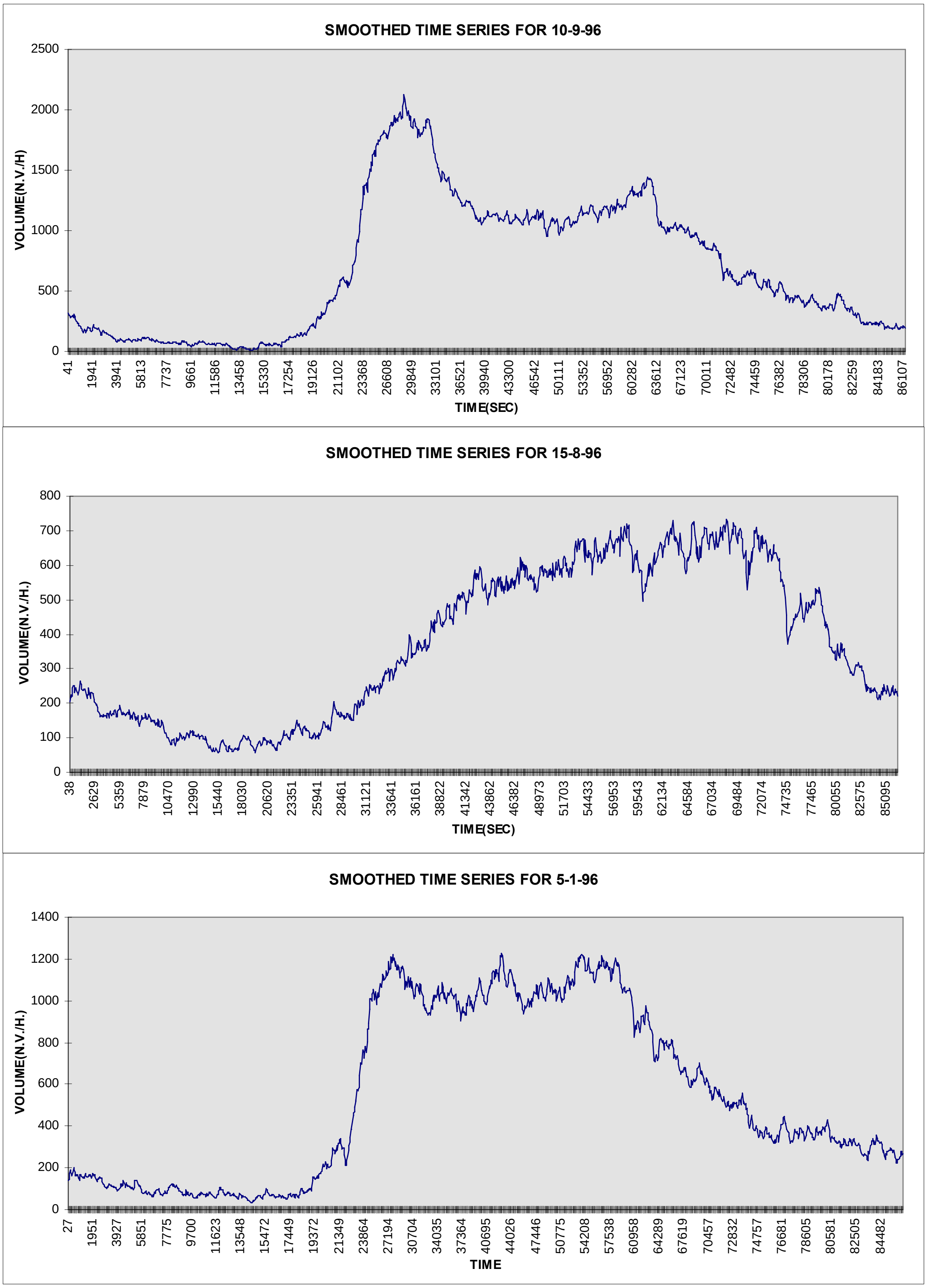


Figure 4.4 - Examples of Smoothed Time Series.

All the calculations found in the remaining part of the report concern the smoothed values that have been produced before.

4.2 Data categorization

As mentioned before, depending on the day, different volume standards can occur. Because of this fact, an attempt to categorize the data has been made and is shown in the following paragraphs.

First of all, measurements have been collected in a time period of 1000 seconds. This has been done because the data cycle time differ on the analogy of the traffic volume. The cycle times that mainly appear are 52, 70, 90, 102, 120 seconds. In **Figure 4.5** an example of the produced time series are shown.

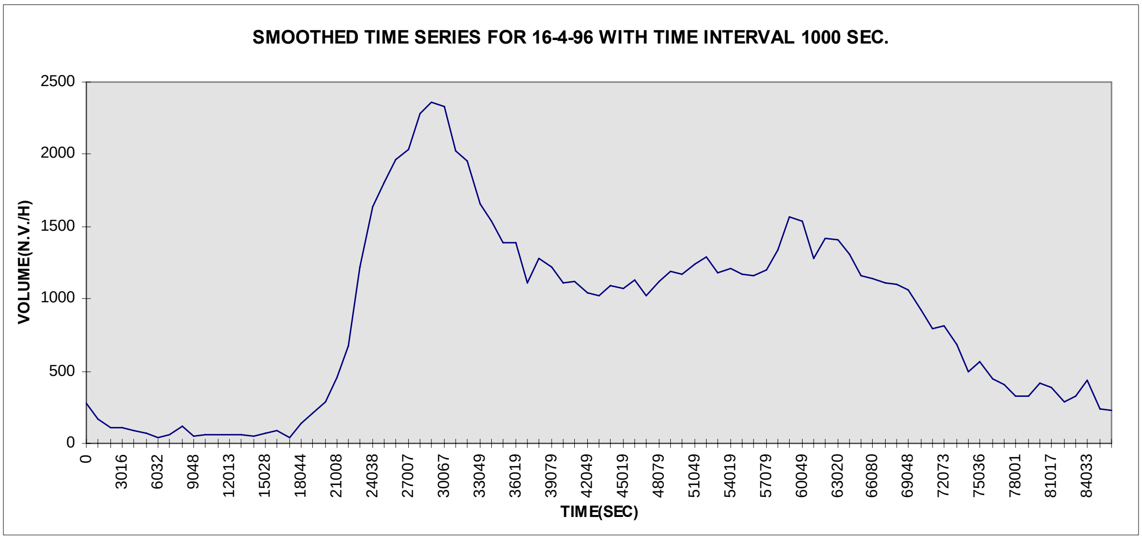


Figure 4.5 - Example of Time Series with 1000 sec time interval.

To make data grouping a reference time series has been created. This time series consists of the average values of four days. The days used for the generation of the reference time series have been characterized as usual days. That means that they are normal work days and their time series feature is as shown in **Figure 4.5**. Specifically, they show a morning peak hour (between 7 and 9 o'clock) and an afternoon peak hour (between 16 and 18 o'clock). These days are Tuesdays and their dates are: 10/9/96, 16/4/96, 6/8/96, 30/4/96. The new time series that arises can be seen in **Figure 4.6**.

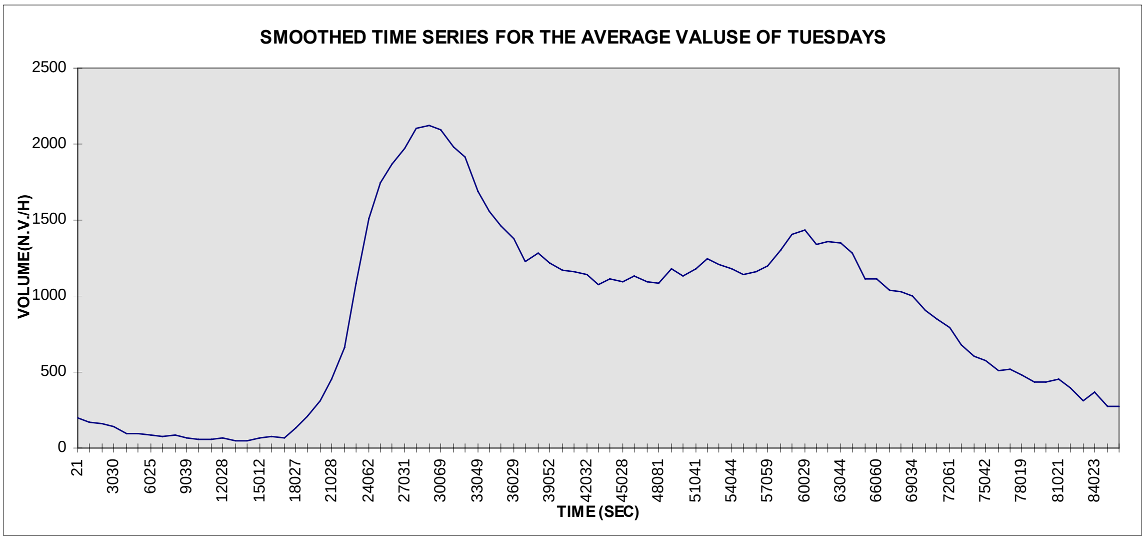


Figure 4.6 - The Reference Time Series (the average of four Tuesdays).

The next step is to calculate the differences between the average values and the values of the rest of the days. The form that has been used for this calculation is:

$$\boxed{\Delta Q = \frac{\sum (x_i - a_i)^2}{n}}$$

where x_i is the average values,

α_i is the current values,

n is the number of values.

In the above form square differences have used in order to stress larger differences more. In this way, a significative grouping can be gained. After the above estimations, comparison diagrams have been plotted to show visually the differences. Three of them are shown in **Figure 4.7**. The estimated differences were listed in ascending order (**Figure 4.8**) and finally thresholds have been chosen to categorize the data. As it can be easily noticed, sharp differences exist between the values of:

- the 10^{th} of April (52510.26) and the 4^{th} of January (109713.44)
- the 3^{rd} of January (148585.64) and the 3^{rd} of August (312104.73)
- the 17^{th} of August (377513.21) and the 1^{st} of May (515182.81)

Thus, the thresholds that have been chosen are:

1. $\Delta Q = 100{,}000$
2. $\Delta Q = 300{,}000$
3. $\Delta Q = 500{,}000$

The above thresholds separate the value horizon in to four groups. Each group has its special characteristics.

- ♦ Group 1: Contains the work days from Monday to Friday. The main characteristic is that they present a morning (between 7 and 9 o'clock) and an afternoon (between 4 and 6 o'clock) peak hour.
- ♦ Group 2: Contains days that don't present a morning and afternoon peak hour
- ♦ Group 3: Contains Saturdays or other days with similar traffic situations. They present a peak hour between 10^{30} and 12^{30} but the traffic volume is not very high (compared to Group 1).
- ♦ Group 4: Contains Sundays and holidays. The traffic volume during the day is at a low level.

Representatives of these groups are displayed in **Figure 4.9**.

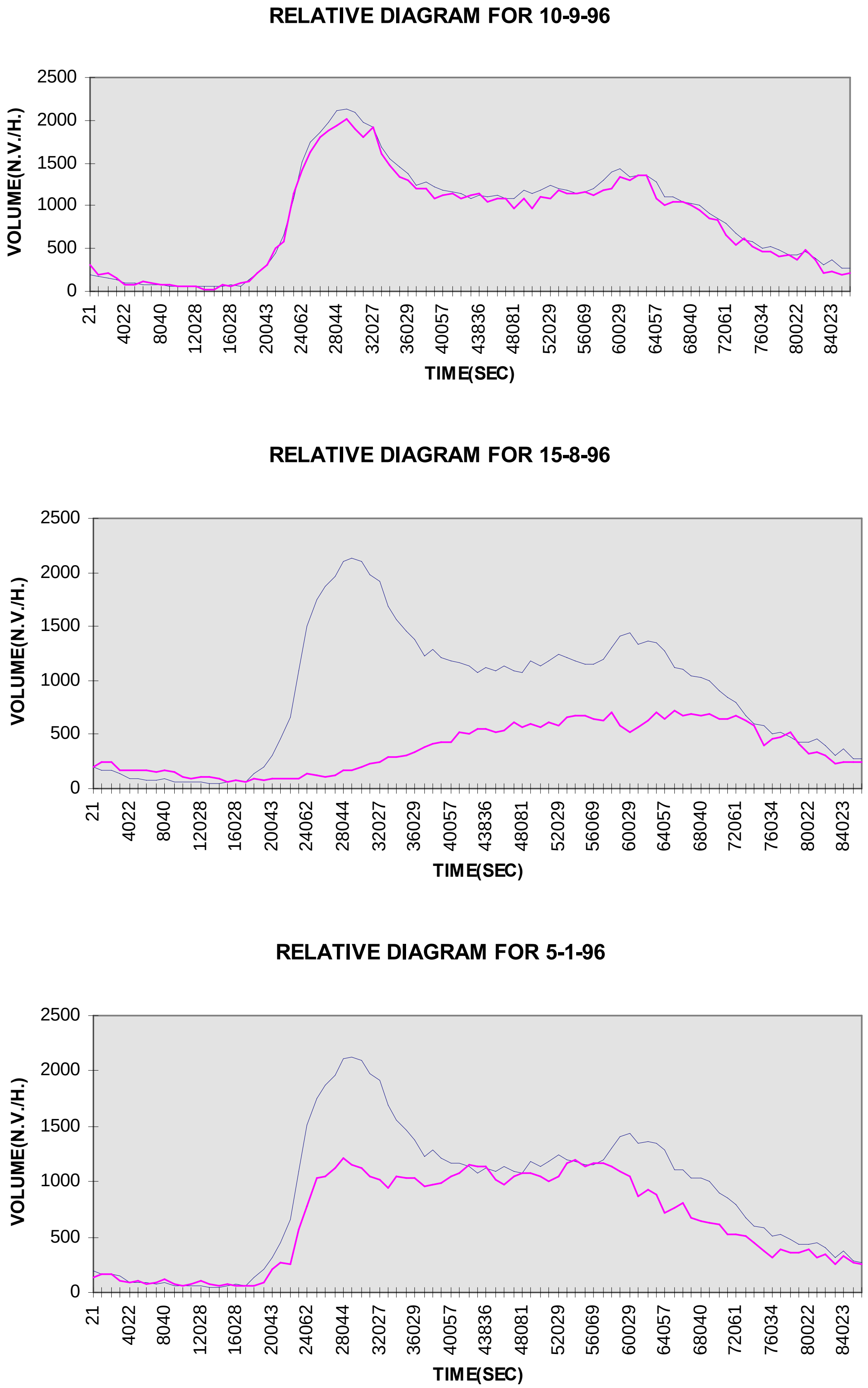


Figure 4.7 - Relation between Basic Time Series and the rest of the Time Series **(— current**, — reference).

DATE	DIFFERENCE
April 16, 1996	4858.83
April 3, 1996	6154.86
September 11, 1996	6300.91
August 6, 1996	6531.85
September 10, 1996	6732.68
April 17, 1996	7134.49
April 15, 1996	7835.56
April 1, 1996	8049.60
September 12, 1996	9198.22
August 7, 1996	9314.84
May 15, 1996	10709.94
August 8, 1996	12341.16
April 18, 1996	12701.02
August 5, 1996	12800.03
April 30, 1996	13579.39
April 11, 1996	13596.26
April 9, 1996	15423.11
August 19, 1996	23294.27
April 2, 1996	28970.76
August 2, 1996	29608.67
April 12, 1996	32146.22
April 4, 1996	42239.40
April 10, 1996	52510.26
January 4, 1996	109713.44
January 5, 1996	127829.61
January 2, 1996	134805.85
August 16, 1996	147205.42
January 3, 1996	148585.64
August 3, 1996	312104.73
April 13, 1996	341158.13
May 24, 1996	349744.35
April 6, 1996	358299.17
August 17, 1996	377513.21
May 1, 1996	515182.81
May 16, 1996	515998.97
August 18, 1996	521708.50
April 14, 1996	523215.09
August 4, 1996	524280.17
May 25, 1996	549741.01
August 15, 1996	555030.38
May 26, 1996	557092.00
April 8, 1996	560670.96
April 7, 1996	585036.82
April 5, 1996	599231.74
January 6, 1996	611469.73
January 7, 1996	617011.28

Figure 4.8 - Differences between the basic time series values and values of the rest of the time series.

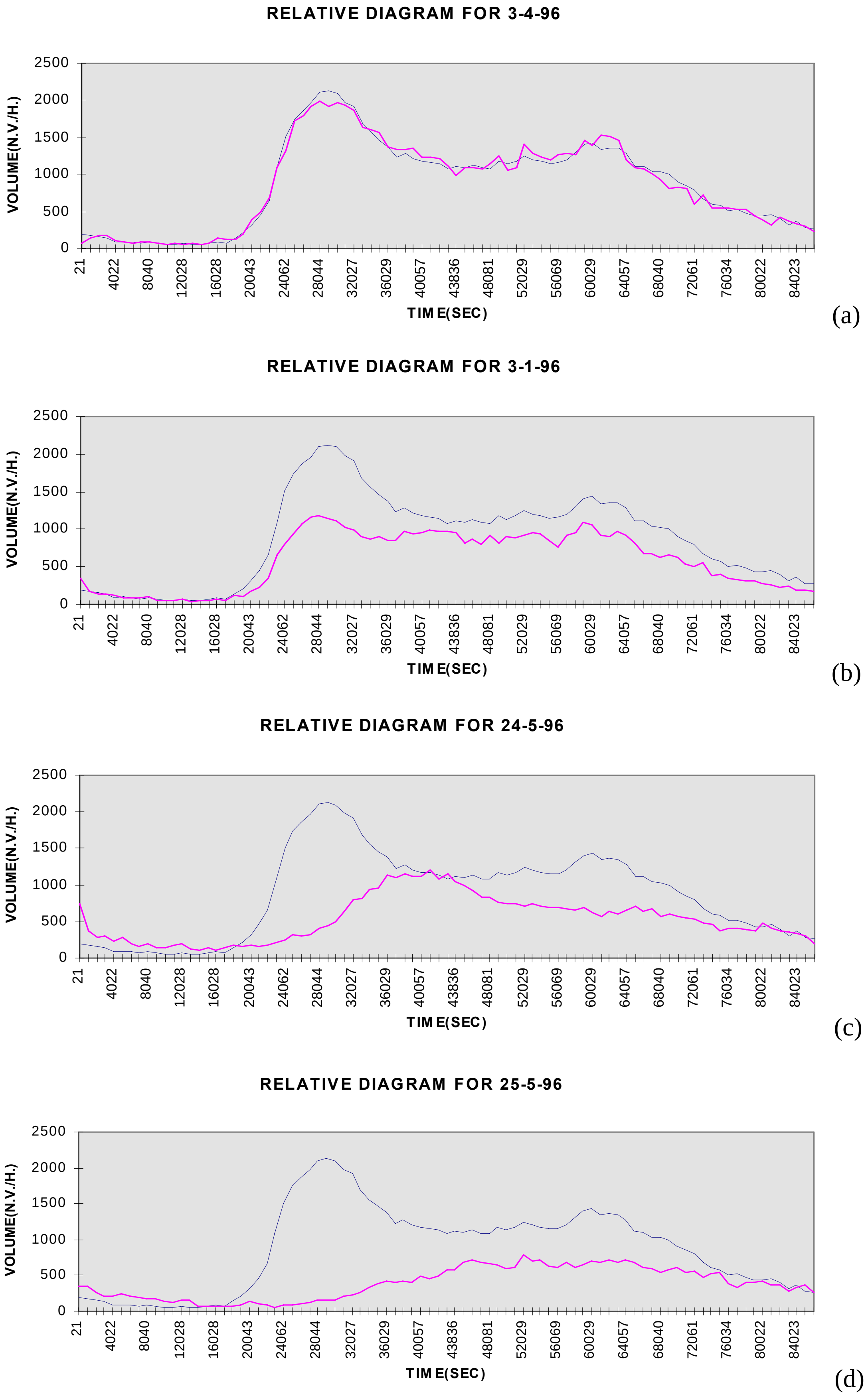


Figure 4.9 - Group Representatives. (a) Group 1, (b) Group 2, (b) Group 3, (d) Group 4 (— **current**, — reference).

4.3 Implemented data on the prognosis models

4.3.1 *Data presentation.*

In the previous section a categorization was made. Observations of this categorization have concluded that the most difficult situation in implementing forecasting models is the data group 1. This can be easily substantiated by comparing the time series with these of the rest of the data groups. In group 1 the time series with two peak hours during the day are included and these have the highest level of traffic volume. They are characterized by sharp changes. Specifically, the values during the day can vary approximately from 100n.v./h to 2300n.v./h during the morning hours and from 1500n.v./h to 500n.v./h (during the afternoon). Because of this fact, the following research has been applied only on the data of group 1. It is certain that the model which can best forecast the future traffic situations of the group 1 can also successfully forecast the traffic situations of the rest of the groups.

In order to have objective results, real data have been chosen from one representative day. This day is the 16th of April 1996. The smoothed time series for this date is displayed in **Figure 4.10**. It has all the elements that characterize the group1 (sharp changes, big traffic volumes, etc.). Thus, it is a very good sample of group 1. The way of processing the data is described in the following section.

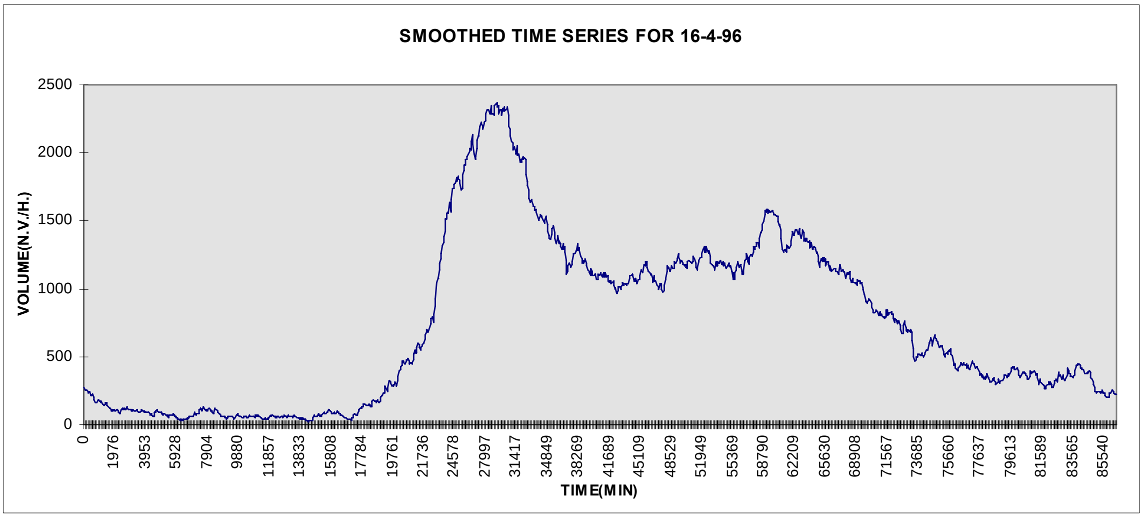


Figure 4.10 - Smoothed Time Series for 16th of April 1996. Group 1 representative day.

4.3.2 *Data processing*

Before a prognosis was done, a further data process should have been done. This arose from the fact that 20- and a 5-minute time intervals were required. Values have been taken at both 1200- and 300-second intervals. As mentioned before, the recorded data do not have a constant cycle time. On the other hand, there is no multiple that can produce the above intervals, so an accurate segmentation is not possible. To obtain the missing values a linear interpolation has been used. It was implemented between two values that include the missing value which is needed to complete an accurate segmentation. Example of these segmentation are displayed in **Figure 4.11**. Also the new time series are shown in **Figure 4.12**. The linear interpolation form that was used is:

$$\boxed{Q = \frac{t(Q_1 - Q_2) + t_1 Q_2 - t_2 Q_1}{(t_1 - t_2)}}$$

where Q is the missing traffic volume

t is the time which is determined by the segmentation

t_1 is the lower time

t_2 is the higher time

Q_1 is the traffic volume of t_1

Q_2 is the traffic volume of t_2

After all these calculations, the data are ready to be applied to the forecasting models. In the following section the error estimations and the model applications are described.

RECORDED	INTERPOLATED	RECORDED	INTERPOLATED

VALUES		VALUES		VALUES		VALUES	
0	276.9	0	276.9	0	276.9	0	276.9
1248	144.4	1200	152.1	312	237.2	300	239.7
2445	118.2	2400	109.6	624	204.5	600	211.5
3640	100.1	3600	96.9	936	178.3	900	181.3
4836	92.8	4800	94.6	1248	144.4	1200	152.1
6032	42.9	6000	45.8	1508	144.4	1500	146.8
7228	80.5	7200	79.6	1820	99.9	1800	101.3
8424	113.2	8400	112.4	2132	115.3	2100	113.7
9620	45.43	9600	46.7	2445	118.2	2400	109.6
10817	57.8	10800	57.7	2705	115.7	2700	115.5
12013	59.6	12000	59.7	3016	111.2	3000	110.3
13209	63.3	13200	63.3	3328	104.5	3300	102.4
14405	29.7	14400	29.8	3640	100.1	3600	96.9
15600	89.6	15600	89.6	3901	99.1	3900	98.9
16848	42.04	16800	41.7	4212	78.6	4200	80.7
18044	140.4	18000	139.5	4524	91.7	4500	78.6
19241	229.2	19200	226.1	4836	92.8	4800	94.6
20437	464.7	20400	459.9	5148	77.3	5100	78.2

Figure 4.11 - Example of the segmentation. Recorded and interpolated values.

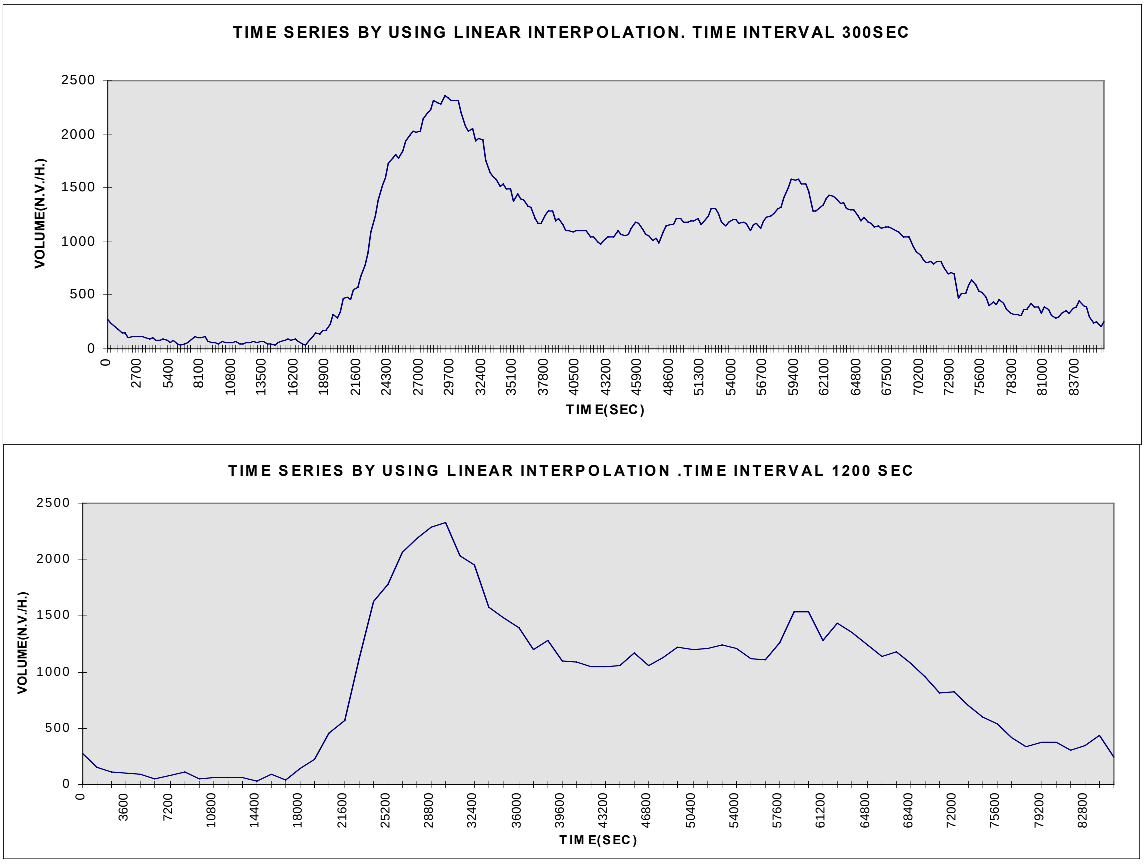


Figure 4.12 - Time series created by interpolated values.

4.4 Prognosis

4.4.1 *Error definition*

In forecasting generally and time series forecasting in particular, a number of alternative indicators are commonly used. They are designed to indicate in a general way how good the forecasting model is [5]. Two of them are the mean absolute error and the mean absolute percentage error. They are described by the following forms.

Mean absolute error:

$$\boxed{MAE = \frac{\left[\sum |x_i - f_i|\right]}{n}}$$

where x_i is the actual value,

f_i is the forecast,

n is the number of values.

Mean absolute percentage error:

$$\boxed{MAPE = 100\frac{\left[\sum \frac{|x_i - f_i|}{x_i}\right]}{n}}$$

where x_i is the actual value,

f_i is the forecast,

n is the number of values.

MAE treats all differences equally. That means that the differences are calculated regardless of the traffic volume level and then the mean value is estimated. On the other hand, MAPE gives equal weight to equal percentage differences large values of which may arise both due to large absolute differences and also small actual values. Thus, the mean value that is estimated, is depended on the current traffic volume level. Both of the error estimations have been done for all the models. However, the assessment is based on the MAPE. Since MAPE takes under consideration the traffic volume level, can give a better sense of the model's performance. Low and high levels are treated differently so a homogenous examination can be done. That means that the model that has low MAPE, performs well during all the time series length. Apart from that, graphical comparisons for all the models are displayed in the **Annex** so a visual estimation can be made. Below the models are tested and the MAPE criterion has been applied.

4.4.2 *Prognosis model application*

There is a big variety of models that can be used in order to make a forecast of a traffic situation. In this thesis eleven models have been tested. These are:

1. Linear Regression Model,
2. Bartlett Regression Model,
3. Improved Bartlett Regression Model,
4. Exponential Smoothing,
5. Exponential Smoothing with Differences,
6. Exponential Smoothing with Differences and two Coefficients,
7. Forecast by using an average time series and linear interpolation,
8. Forecast by using an average time series and exponential interpolation,
9. Forecast by combining Linear Regression and model 7,
10. Forecast by combining Linear Regression and model 8.
11. Forecast by combining Linear Regression and an average time series.

The models 1 to 6 are flexible to forecast non recurring congestion[11] since they do not depend on historical time series. They predict the coming up traffic situations by taking under consideration only the measurements of the current day. On the other hand, the models 7 and 8 are more accurate because they take into account the recurring congestion[10] and their forecasts depend on historical time series. Models 9, 10 and 11 are combinations of the two above types and they will be tested in a following section.

The prognosis horizon consists of one time interval (20-min.). Thus, a direct forecast has been made for the 20th min. and no smaller segmentation has been tested. This has been done in order to avoid an additional error that could have appeared. Older estimations have shown that a bigger segmentation can cause increase of the error.

In the following sections each of the models are described as well the results of the assessment are presented.

4.4.2.1 *Linear Regression Model*

Perhaps the oldest method of forecasting the future situations of an item is by way of the linear regression model [13]. The N most recent situations entries ($x_{T-n+1}, \ldots, x_{T-1}, x_T$) are used with equal weight to seek estimates of *a* and *b* of the interpolated line. This line equation that also estimates the forecast for the τ^{th} future periods is given by:

$$\boxed{x(\tau) = a + b\tau}$$

In this model the least squares method is used to seek the estimate of *a* and *b*. The forms that are used are:

$$\boxed{b = \frac{\frac{-(N-1)}{2}\sum x_{T-j} + \sum (j x_{T-j})}{\frac{N(N-1)^2}{4} - \frac{N(N-1)(2N-1)}{6}}} \qquad \text{for j = 0 to j = N-1}$$

$$\boxed{a = \text{aver}(x) + b\,\frac{N-1}{2}}$$

where N is the number of the most recent situation (traffic volume) entries and

T is the most current time period.

The time interval is 20-min. (or 1200-sec.). That means that the entries are taken once every 20-min.. Applying $\tau = 1$ (there is one period of 20-min.) the forecast is obtained from:

$$\boxed{x(1)=a + b}$$

The model has been tested for several number of entries N (N = 2, 3, 4, 5, 6, 7, 8, 9). For N = 5 an optimum MAPE (=18.67004) has been found. In **Figure 4.13** a list of MAPE is shown as a function of the number of entries (or number of time intervals). In the following figure (**Figure 4.14**) a graphical comparison of the forecast and the actual time series for N = 5 is displayed. The rest of the diagrams can be found in the **Annex**.

	N	M.A.P.E.
OPTIMUM	5	18.67004
2nd	6	20.36614
3rd	7	20.47971
4rh	8	20.69343
5th	4	22.03806
6th	9	23.58737
7th	3	25.25586
8th	2	29.68076

Figure 4.13 - Linear Regression Model. Mean Absolute Percentage Error function of the number of entries.

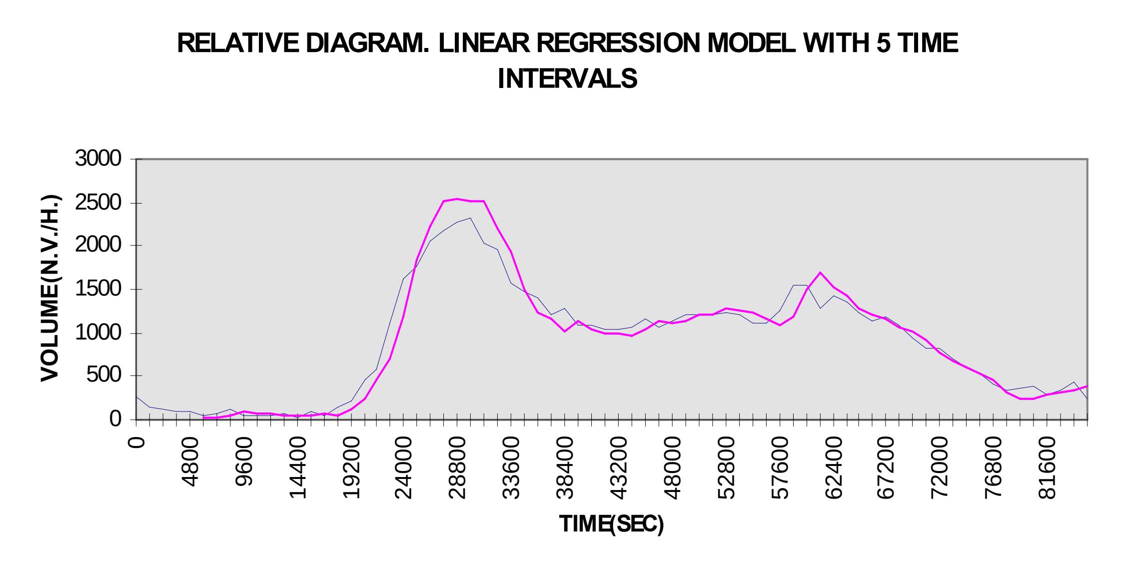


Figure 4.14 - Linear Regression Model. Graphical comparison of the forecast and the actual Time Series for N = 5 (— actual, **— forecast**).

4.4.2.2 *Bartlett Regression Model*

In a similar way to the previous model, this model calculates a line by using a number of entries and then extrapolates it in the prognosis area. According to this model, two mean values are calculated in the analysis area [15]. Using these values a slope is calculated which, by using a point of the analysis area, creates the demanded line. Thus, a 5-min. segmentation has been assigned and the analysis area consists of eight 5-min. intervals. The mean values of the first and the last four entries has been calculated. The first four entries are assigned the "previous 20-min. time interval" and the last four entries are assigned the "new 20-min. time interval". The line slope is estimated by using the form:

$$\boxed{s = \frac{\overline{q}_{-1} - \overline{q}_{-2}}{4\Delta t}}$$

where $\Delta t = 5$ min,

$\overline{q}_{-1} = \frac{1}{4}\sum_{j=1}^{4} q_{-j}$ is the average volume for the new 20-min.,

$\overline{q}_{-2} = \frac{1}{4}\sum_{j=5}^{8} q_{-j}$ is the average volume for the prev. 20-min.,

q_{-j} is the recorded value in time interval j (5-min.) of the analysis area.

The line start point is at the mean value of the new 20-min. time interval. The form that calculates the traffic volume forecast is:

$$\boxed{q(t) = \bar{q}_{-1} + as(t + 2\Delta t)}$$

where t = 20-min. or 1200-sec.,

$\bar{q}_{-1}$ is the average volume for the new 20-min. time interval,

a is the slope adjuster,

s is the line slope,

Δt = 5-min. or 300sec.

The final form that has been used is:

$$\boxed{q(20) = \bar{q}_{-1} + 30as}$$

where $\bar{q}_{-1}$ is the average volume for the new 20-min. time interval,

a is the slope adjuster,

s is the line slope.

The line slope can be changed by using different slope adjusters. For each adjuster value a different forecast can be obtained. Thus, the model has been tested for several slope adjusters (*a* = 0.1, 0.2, 0.26, 0.27, 0.28, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9) and an optimum MAPE (=21.34507) has been calculated for *a* = 0.27. In **Figure 4.15** and **4.16** a list of MAPE as a function of the slope adjuster and a graphical comparison (forecast - actual time series) for *a* = 0.27 are displayed respectively. Some typical graphical comparisons for the rest of the forecasts can be found in the **Annex**.

	a	M.A.P.E.
OPTIMUM	0.27	21.34507
2nd	0.26	21.34706
3rd	0.28	21.34729
4th	0.3	21.361
5th	0.2	21.46877
6th	0.4	21.61706
7th	0.1	21.93729
8th	0.5	22.02129
9th	0.6	22.73328
10th	0.7	23.66473
11th	0.8	24.75914
12th	0.9	25.92004

Figure 4.15 - Bartlett Regression Model. Mean Absolute Percentage Error function of the slope adjuster.

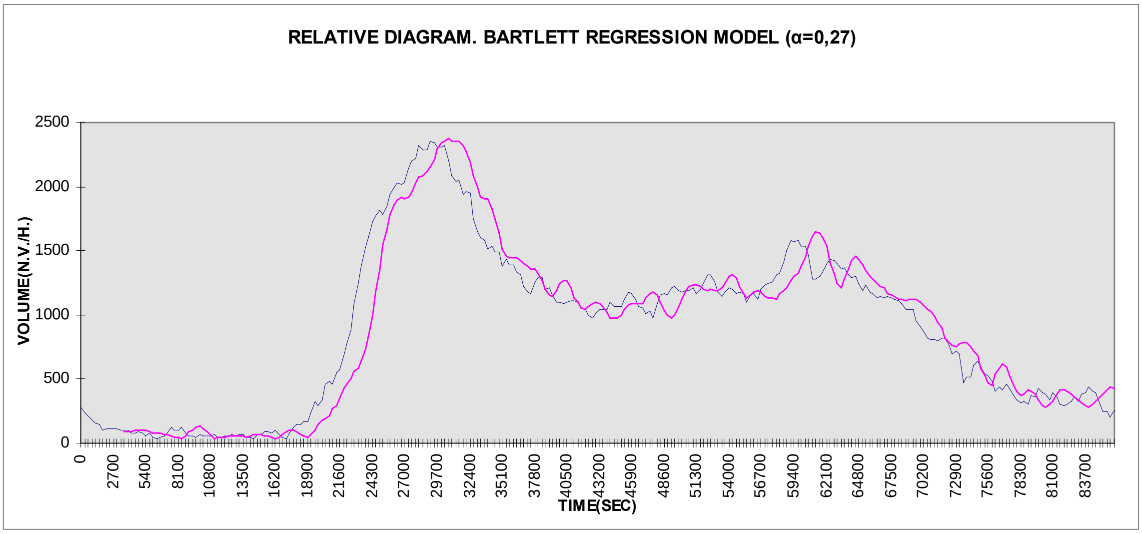


Figure 4.16 - Bartlett Regression Model. Graphical comparison of the forecast and the actual Time Series for *a* = 0.27 (— actual, **— forecast**).

4.4.2.3 *Improved Bartlett Regression Model*

This model has been created in order to eliminate the analysis area. In the previous model, the analysis area consisted of 40-min. intervals and 8 entries. Instead of taking two sequential segments of 20-min. interval, two segments of the same size (20-min.) have been taken but the start point of the first 20-min. interval differs from the start point of the second by only five minutes. In this way, the analysis area has come down from 40min to 25-min.. The forms that have been implemented are the same with the previous model. The implementation showed an improvement since a better MAPE was achieved. An optimum of 20.1561 MAPE have been obtained for *a* = 15.43. The *a* values which have been tested are: 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15.3, 15.42, 15.43, 15.44, 16. In **Figure 4.17** and **4.18** a list of MAPE as a function of the slope adjuster and a graphical comparison (forecast - actual time series) for *a* = 15.43 are displayed respectively. Some typical graphical comparisons for the rest of the forecasts can be found in the **Annex**.

	a	M.A.P.E.
OPTIMUM	15.43	20.1561
2nd	15.44	20.15614
3rd	15.42	20.15616
4th	15.5	20.15638
6th	15.3	20.1572
7th	16	20.15838
8th	14	20.17658
9th	13	20.20835
10th	12	20.26128
11th	11	20.3209
12th	10	20.38053
13th	9	20.44351
14th	8	20.51324
15th	7	20.58629
16th	6	20.66533
17th	5	20.75058

Figure 4.17 - Improved Bartlett Regression Model. Graphical comparison of the forecast and the actual Time Series for *a* = 15.43.

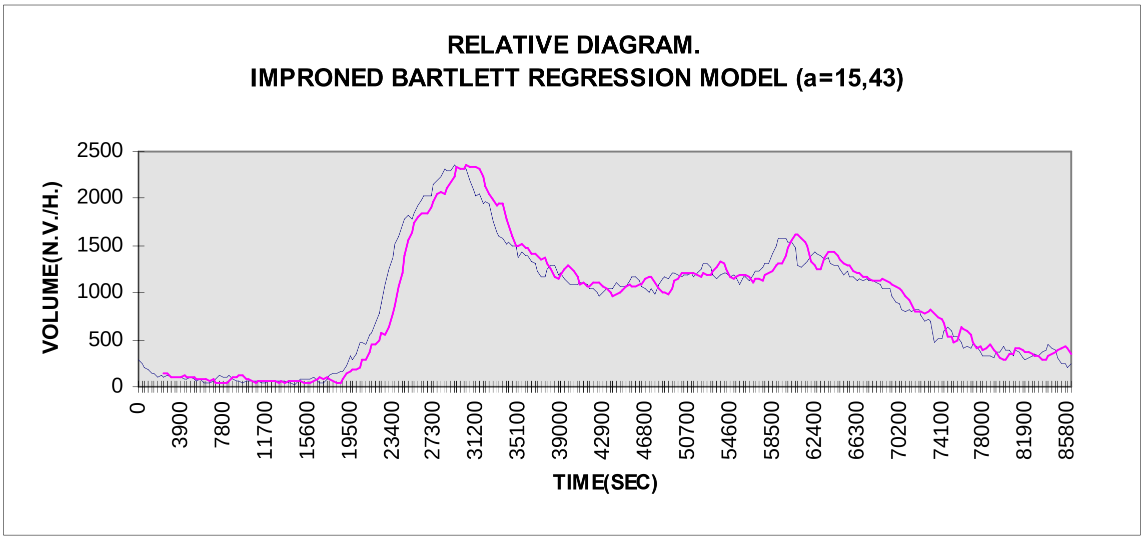


Figure 4.18 - Improved Bartlett Regression Model. Graphical comparison of the forecast and the actual Time Series (— actual, **— forecast**).

4.4.2.4 *Exponential Smoothing*

Perhaps the most common forecasting model in use today is exponential smoothing [13]. At each time period the forecasts are updated conveniently in a recursive manner using the most current situation entry. The model assigns more weight to the more current situations, and in this way the forecasts can react more quickly to potential shifts in the level of situation (traffic volume). Because little data storage is needed to carry out the calculations, the model is well suited to traffic situations where a large number of items are to be considered. To apply the exponential smoothing, a smoothing parameter *a* should be selected, which must lie between zero and one and expresses a value weight. The forecast for the next time period (the next 20-min.) is found using *a*, the current traffic volume q_{-1}, and the prior one period ahead forecast $\bar{q}_{old}$. The weight *a* corresponds to the current traffic volume and the weight 1- *a* corresponds to the one period ahead forecast. In a lot of literature, exponential smoothing is presented as a kind of average value [1]. The average value at t = 0 equals the forecast traffic volume at the 20thmin. Thus, this average is defined as:

$$\boxed{q_f = \bar{q}_0 = aq_{-1} + (1-a)\bar{q}_{old}}$$

where $\bar{q}_f$ is the forecast traffic volume,

$\bar{q}_0$ is the exponential smoothing average at t = 0,

a is the smoothing parameter,

q_{-1} is the current traffic volume,

$\bar{q}_{old}$ is the one period ahead forecast.

The model has been tested for several smoothing parameter *a* (*a* = 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 0.99, 1) and an optimum MAPE (= 22.49461) has been found for *a* = 1. In **Figure 4.19** a list of MAPE function of the smoothing parameter is shown. In the following figure (**Figure 4.20**) a graphical comparison of the forecast and the actual time series for *a* = 1 is displayed. Some typical diagrams of the rest forecasts can be found in the **Annex**.

	a	**M.A.P.E.**
OPTIMUM	1	22.49461
2nd	0.99	22.5005
3rd	0.9	22.65139
4th	0.8	23.0153
5th	0.7	23.85134
6th	0.6	25.34174
7th	0.5	27.63357
8th	0.4	31.6785
9th	0.3	38.0063
10th	0.2	49.53696
11th	0.1	71.15357

Figure 4.19 - Exponential Smoothing. Mean Absolute Percentage Error function of smoothing parameter.

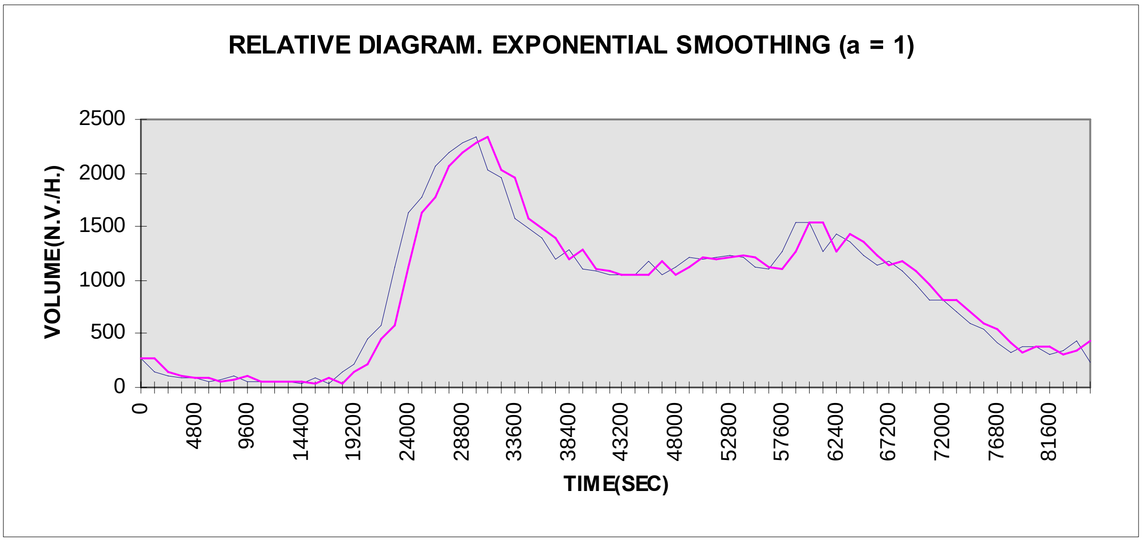


Figure 4.20 - Exponential Smoothing. Graphical comparison of the forecast and the actual Time Series (— actual, **— forecast**).

4.4.2.5 *Exponential Smoothing with Differences*

Exponential Smoothing with Differences is an extension of the exponential smoothing. A smoothing parameter is chosen and is used to assign weights to the situation entries of the past. As before, a higher weight is assigned to the more current traffic volumes. An advantage of Exponential Smoothing with Differences over the Exponential Smoothing is that it reaches the actual level of traffic volume faster. This is done by using a correction term named “sliding trend” [15]. It contains the difference between the current value and the previous average value (one period ahead forecast) and assigns a trend. This trend is transferred from the last average value to the prognosis area. The forecast traffic volume is calculated by adding the sliding trend to the exponential smoothing average at t = 0. The forms that have been used and express this model are:

$$\boxed{\bar{q}_0 = aq_{-1} + (1-a)\bar{q}_{old}}$$

$$\boxed{\overline{\Delta q}_0 = a(q_{-1} - \overline{q}_{old}) + (1-a)\overline{\Delta q}_{old}}$$

$$\boxed{q_f = \overline{q}_0 + \overline{\Delta q}_0}$$

where q_f is the forecast traffic volume,

$\overline{q}_0$ is the exponential smoothing average at t = 0,

a is the smoothing parameter,

q_{-1} is the current traffic volume,

$\overline{q}_{old}$ is the one period ahead forecast,

$\overline{\Delta q}_0$ is the exponential smoothing trend at t = 0,

$\overline{\Delta q}_{old}$ is the exponential smoothing trend at the previous calculation.

As in the previous models, this model has been tested for several smoothing parameters *a* (*a* = 0.1, 0.2, 0.3, 0.4, 0.44, 0.445, 0.449, 0.45, 0.451, 0.5, 0.6, 0.7, 0.8, 0.9) and an optimum MAPE (= 21.3954) has been found for *a* = 0.45. In **Figure 4.21** a list of MAPE function of the smoothing parameter is shown. In the following figure (**Figure 4.22**) a graphical comparison of the forecast and the actual time series for *a* = 0.45 is displayed. Some typical diagrams of the rest forecasts can be found in the **Annex**.

4.4.2.6 *Exponential Smoothing with Differences and two Coefficients*

So far two exponential smoothing models have been tested trying to take advantage of the requirement for far fewer data. However, the mean absolute percentage

	a	**M.A.P.E.**
OPTIMUM	0.45	21.3954

2nd	0.451	21.39619
3rd	0.449	21.39677
4th	0.445	21.41612
5th	0.44	21.44296
6th	0.5	21.68778
7th	0.4	21.91723
8th	0.6	22.63775
9th	0.7	24.10489
10th	0.3	24.2659
11th	0.8	26.07733
12th	0.9	27.92715
13th	0.2	30.26067
14th	0.1	47.22648

Figure 4.21 - Exponential Smoothing with Differences. Mean Absolute Percentage Error function of smoothing parameter.

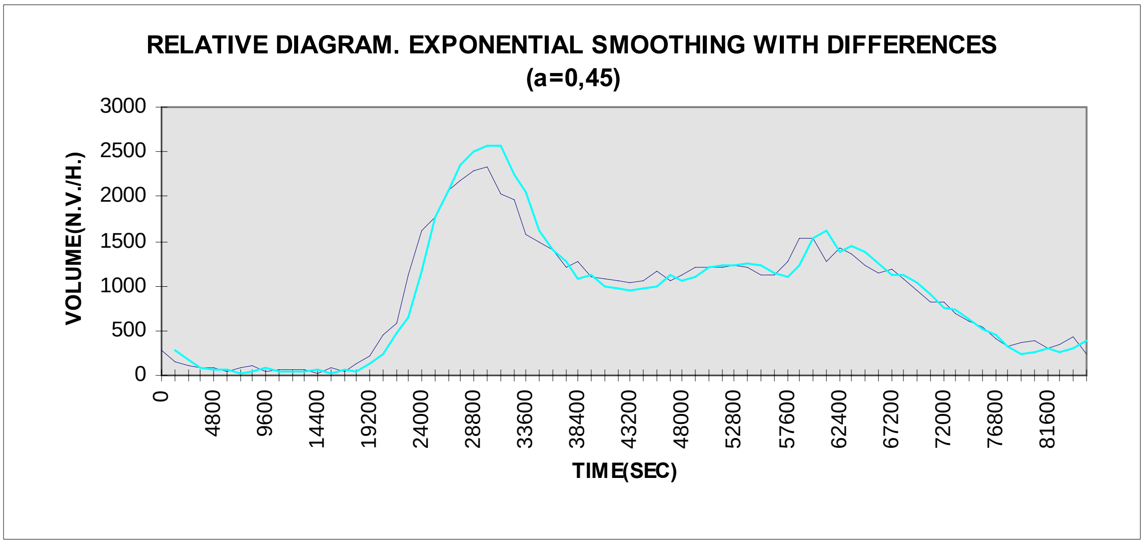


Figure 4.22 - Exponential Smoothing with Differences. Graphical comparison of the forecast and the actual Time Series (— actual, **— forecast**).

error is still high. Trying to reduce this error an improved exponential smoothing model was also implemented. This model is based on the previous Exponential Smoothing with Differences. It has been called Exponential Smoothing with Differences and two

Coefficients since two separate coefficients were applied instead of the one in the last model (a, exponential smoothing parameter). Thus, the forms have been changed in the following way:

$$\boxed{\bar{q}_0 = aq_{-1} + b\bar{q}_{old}}$$

$$\boxed{\overline{\Delta q}_0 = a(q_{-1} - \bar{q}_{old}) + b\overline{\Delta q}_{old}}$$

$$\boxed{q_f = q_0 + \overline{\Delta q}_0}$$

where q_f is the forecast traffic volume,

$\bar{q}_0$ is the exponential smoothing average at t = 0,

a is the smoothing parameter,

b is the smoothing parameter,

q_{-1} is the current traffic volume,

$\bar{q}_{old}$ is the one period ahead exponential smoothing average,

$\overline{\Delta q}_0$ is the exponential smoothing trend at t = 0,

$\overline{\Delta q}_{old}$ is the exponential smoothing trend at the previous calculation.

The a values are independent of b values. All of them lie between zero and one. For each smoothing parameter a different forecast can be obtained. Thus, the model has been tested for several smoothing parameters a and b and an optimum MAPE (=20.52421) has been calculated for a = 0.41 and b = 0.5. In **Figure 4.23** and **4.24** a graphical comparison (forecast - actual time series) for a = 0.41 and b = 0.5 and a list of MAPE as function of the smoothing parameters are displayed respectively. The graphical comparisons for some of the forecasts can be found in the **Annex**.

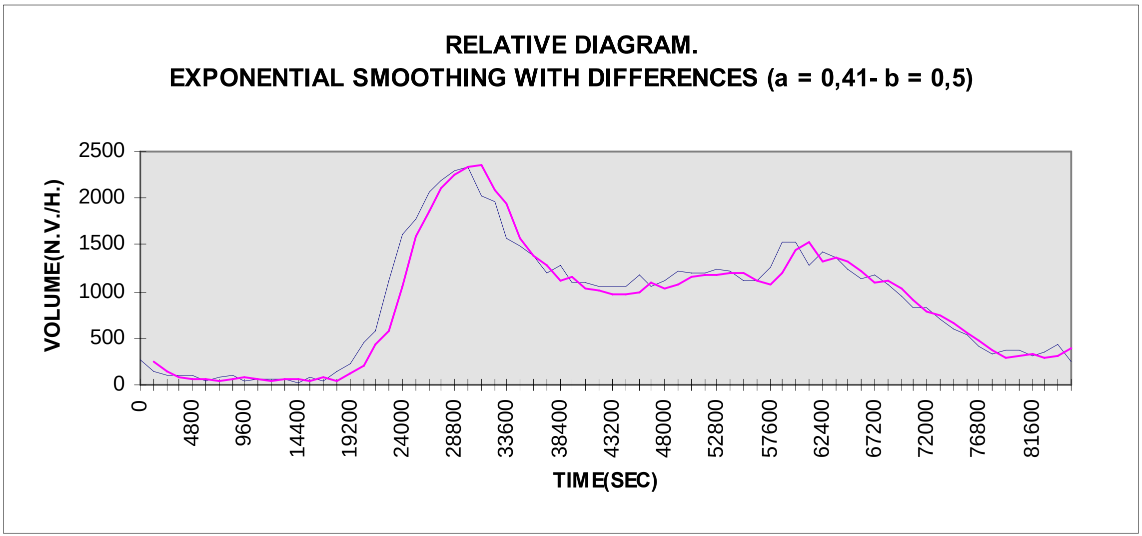


Figure 4.23 - Exponential Smoothing with Differences and two Coefficients. Graphical comparison of the forecast and the actual time series (— actual, **— forecast**).

4.4.2.7 *Forecast by using an average time series and linear interpolation*

So far the models that have been tested by using current day measurements as inputs. In this and in the following section two models are tested that use an average time series in order to achieve a better prediction of a recurrent congestion. This average time series is similar to the reference time series that had been produced at the categorization section (§ 4.2). The same days have been used but the measurements have been collected in a time period of 1200-sec. instead of 1000-sec.that previously had been taken. This change in the time period has been done because of the need of 20-min. forecast. In **Figure 4.25** the new average time series is shown. This time series is created to test the data from group 1. In the same way, average time series can be created for the rest of the groups. The prediction during a specific day depends on the group that this day belongs to. The following estimations concern the group 1.

a	b	M.A.P.E.	*a*	b	M.A.P.E.
0.41	**0.5**	**20.52421**	0.4	0.7	37.04527
0.4	0.51	20.52982	0.3	0.2	39.96382
0.4	0.5	20.53818	0.7	0.5	40.42258
0.41	0.49	20.53845	0.1	0.7	41.53154

0.42	0.5	20.54475	0.2	0.4	42.53358
0.41	0.51	20.55065	0.3	0.1	44.50724
0.4	0.49	20.56506	0.1	0.9	47.22648
0.5	0.4	20.76435	0.2	0.3	48.55215
0.3	0.6	21.39381	0.9	0.4	50.10467
0.5	0.3	21.66934	0.6	0.6	50.83386
0.5	0.5	21.68778	0.1	0.6	51.97273
0.4	0.4	21.72373	0.2	0.2	53.94401
0.6	0.3	21.82318	0.2	0.1	58.49037
0.4	0.6	21.91723	0.1	0.5	60.19228
0.6	0.2	22.46331	0.8	0.5	61.61328
0.6	0.4	22.63775	0.3	0.8	61.9277
0.3	0.5	23.17659	0.1	0.4	66.485
0.7	0.2	23.5622	0.1	0.3	71.27782
0.7	0.1	23.6499	0.1	0.2	74.92559
0.2	0.7	23.7119	0.1	0.1	77.79063
0.6	0.1	24.02752	0.5	0.7	82.07344
0.7	0.3	24.10489	0.7	0.6	88.75602
0.5	0.2	24.20836	0.9	0.5	91.89793
0.3	0.7	24.2659	0.2	0.9	123.5892
0.8	0.1	25.3693	0.8	0.6	141.9592
0.4	0.3	25.44573	0.6	0.7	151.9592
0.8	0.2	26.07733	0.4	0.8	155.2972
0.7	0.4	26.2116	0.9	0.6	209.1615
0.6	0.5	26.92458	0.7	0.7	247.0999
0.8	0.3	27.38846	0.5	0.8	305.7253
0.5	0.1	27.65925	0.8	0.7	367.6597
0.9	0.1	27.92715	0.3	0.9	410.1029
0.2	0.6	27.95417	0.6	0.8	511.6685
0.3	0.4	28.79423	0.9	0.7	513.0751
0.9	0.2	29.17232	0.7	0.8	774.2825
0.5	0.6	29.60164	0.4	0.9	889.9288
0.2	0.8	30.26067	0.8	0.8	1092.809
0.4	0.2	30.32941	0.9	0.8	1466.972
0.1	0.8	31.21358	0.5	0.9	1567.113
0.9	0.3	33.52624	0.6	0.9	2438.828
0.3	0.3	34.77668	0.7	0.9	3504.532
0.4	0.1	34.91187	0.8	0.9	4762.966
0.8	0.4	35.0795	0.9	0.9	6213.195
0.2	0.5	35.65852			

Figure 4.24 - Mean Absolute Percentage Error as a function of smoothing parameters using the Exponential Smoothing with Differences and two Coefficients model.

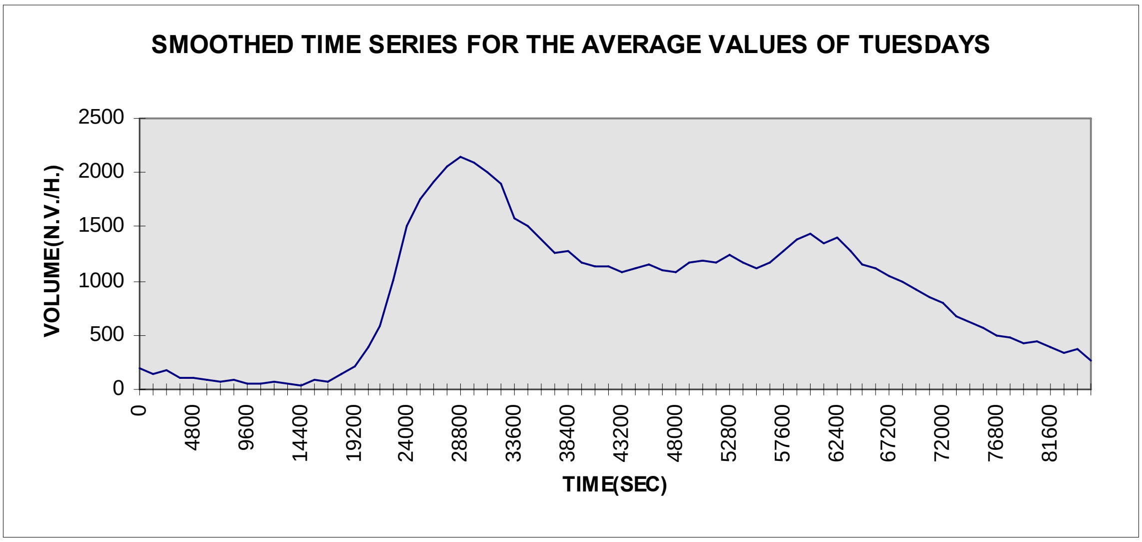


Figure 4.25 - The Average Time Series.

As it can be easily understood by reading the title of this model, linear interpolation has been used in order to make a forecast of the next 20-min. The current measurement and the value of the average time series after an hour are the inputs [6]. The traffic volume of the 20^{th} min. is estimated by using the interpolated line. The form that estimates the traffic volume after a time interval Δ*t* (0< Δ*t* <Δ*T*) is:

$$\boxed{q(t+\Delta t) = q(t) + [q_A(t+\Delta T) - q(t)]\frac{\Delta t}{\Delta T}}$$

where t is the current time,

ΔT is the biggest targeted time interval and the time interval where values from the average time series are taken (1 hour),

$q(t+\Delta t)$ is the forecast traffic volume,

$q(t)$ is the current traffic volume,

$q_A(t+\Delta T)$ is the volume from the average time series at the latest targeted time.

By substituting Δ*t*=1200 seconds (20 minutes) and Δ*T*=3600 seconds (1 hour) :

$$q(t+1200) = q(t) + [q_A(t+3600) - q(t)]\frac{1}{3}$$

The model indicated a very good error value (MAPE = 18.1206). It should be mentioned that this error value could be worse if the tested time series had more non recurrent congestion. The range of the error is analogous to the range of non recurrent congestion since the forecasts depend on the average time series. In **Figure 4.26** a graphical comparison between the forecast and the actual time series is displayed.

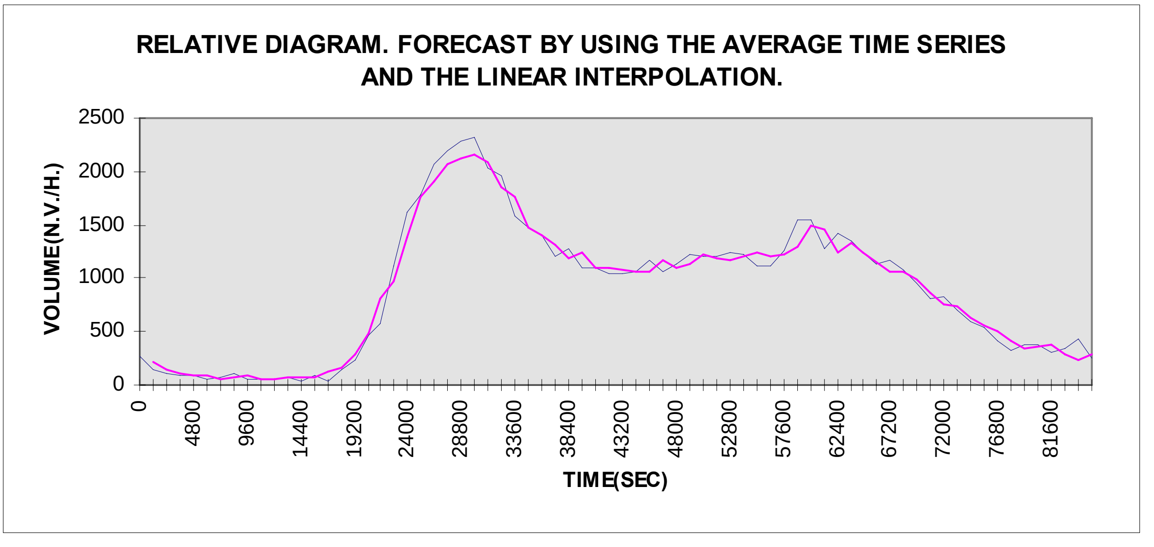


Figure 4.26 - Forecast by using an average time series and linear interpolation. Graphical comparison of the forecast and the actual Time Series (— actual, **— forecast**).

4.4.2.8 *Forecast by using an average time series and exponential interpolation*

This model is also a model that can predict the recurrent congestion. Is similar to the previous one. This model uses exponential interpolation instead of linear in order to predict the following traffic situations [6]. As before, the current measurement and the value of the average time series after an hour are the inputs. The form that estimates the traffic volume after a time interval Δ*t* (0< Δ*t* <Δ*T*) is:

$$q(t+\Delta t) = q(t) + [q_A(t+\Delta T) - q(t)](1 - e^{-a\frac{\Delta t}{\Delta T}})$$

where t is the current time,

ΔT is the time biggest targeted time interval and the time interval where values close to the average time series are taken (1hour),

$q(t+\Delta t)$ is the forecast traffic volume,

$q(t)$ is the current traffic volume,

$q_A(t+\Delta T)$ is the volume from the average time series at the latest targeted time.

a is the slope adjuster.

The factor *a* is an slope adjuster of the latest point of the exponential function. It adjusts how close is the latest value to the average time series value. The model has been tested for several *a* (= 0.9, 1, 1.1, …, 2) and an optimum MAPE (=17.98118) has been gained for *a* = 1. By substituting Δt = 1200 seconds (20 minutes), ΔT = 3600 seconds (1 hour) and *a* = 1:

$$q(t+1200) = q(t) + [q_A(t+3600) - q(t)](1 - e^{\frac{1}{3}})$$

This model indicated also a very good error value. In **Figure 4.27** and **4.28** a graphical comparison between the forecast and the actual time series and a list of MAPE function of *a* are respectively displayed. Also typical graphical comparisons for the rest forecast are displayed in the **Annex**. It should be mentioned again that the range of the error is analogous to the range of non recurrent congestion so, the error could be worse. This problem could be solved by combining models that predict the recurrent congestion with the models that predict the non recurrent congestion. This is the subject that the following section exams by testing two more models.

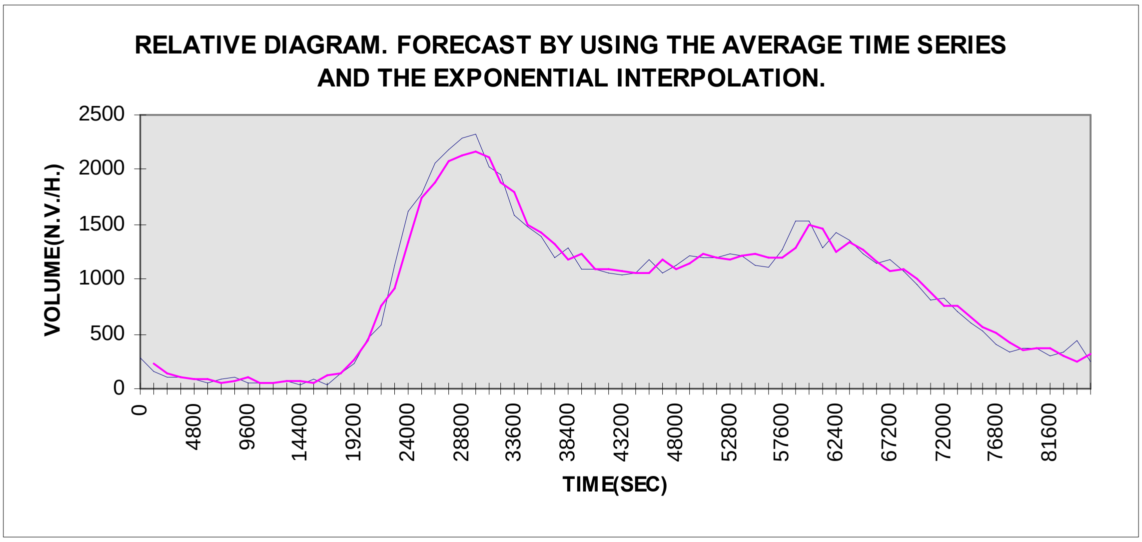


Figure 4.27 - Forecast by using an average time series and exponential interpolation. Graphical comparison of the forecast and the actual Time Series (— actual, **— forecast**).

	a	M.A.P.E.
OPTIMUM	1	17.98118
2nd	1.1	17.99515
3rd	1.2	18.10207
4th	0.9	18.15332
5th	1.3	18.21443
6th	1.4	18.33787
7th	1.5	18.47731
8th	1.6	18.63276
9th	1.7	18.7942
10th	1.8	19.00412
11th	1.9	19.28563
12th	2	19.60164

Figure 4.28 - Forecast by using an average time series and exponential interpolation. Mean Absolute Percentage Error function of the slope adjuster.

4.4.3 *Combined models*

So far two types of short term prognosis models have been tested. The first 6 concern the kind of models that indicate a sensitivity to the current day values changes. The advantage of these models is that they have the ability to forecast non recurrent congestion and generally they can follow any abnormal changes that can not be found in an average time series. On the other hand, the second type of short term prognosis models (concerns the models 7 and 8) have the ability to predict the different situations during a normal day (without abnormal changes) of a specific group with a very small error value. The general idea of the next three models is that if the advantage of following abnormal changes by the first type of models could be combined with the advantage of following normal changes of the second type models then a better error indication could be achieved. The models below use a weighing function in order to gain this combination. The linear regression model has been used in this combination since it has indicated the lowest error value.

4.4.3.1 *Forecast by combining Linear Regression and model 7*

This is the first combined model that has been tested. It contains the linear regression model and the model 7 that makes forecasts by using an average time series and linear interpolation. The model has the ability to forecast traffic situations up to 1 hour. The forecast after one hour is equal to the value that is taken from the average time series and the rest values are combined with a weight factor. The model at the beginning of the one hour time horizon assigns more weight to the linear regression. This weight decreases as the time in the forecast horizon increases and the model assigns more weight to the model 7. The form that forecasts the traffic volume after a time interval Δt ($0<\Delta t<\Delta T$) is:

$$\boxed{q(t+\Delta t) = (1-\frac{\Delta t}{\Delta T})q_{LR}(t+\Delta t) + \frac{\Delta t}{\Delta T}q_A(t+\Delta t)}$$

where t is the current time,

ΔT is the time interval that values from the average time series are taken (1 hour),

$q(t+\Delta t)$ is the forecast traffic volume,

$q_{LR}(t+\Delta t)$ is the forecast traffic volume by linear regression model,

$q_A(t+\Delta t)$ is the forecast traffic volume from the model 7.

The model has been tested for 20-min. forecast. Thus, by substituting Δt = 1200 seconds (20 minutes) and ΔT = 3600 seconds (1 hour) the form change to:

$$\boxed{q(t+1200) = \frac{2}{3}q_{LR}(t+1200) + \frac{1}{3}q_A(t+1200)}$$

The model indicated a significant error improve. The mean absolute percentage error that was estimated is 14.8766. In **Figure 4.29** is shown the graphical comparison between the forecast and the actual time series.

4.4.3.2 *Forecast by combining Linear Regression and model 8*

This is the second combined model that has been tested. As it can be easily understood, this model is similar to the previous one. It combines the linear regression model with the model 8 that make forecasts by using an average time series and exponential interpolation. A weighting factor has been used in the same way as in the previous model. The form that forecasts the traffic volume after a time interval Δt ($0<\Delta t<\Delta T$) is:

$$\boxed{q(t+\Delta t) = (1-\frac{\Delta t}{\Delta T})q_{LR}(t+\Delta t) + \frac{\Delta t}{\Delta T}q_A(t+\Delta t)}$$

where t is the current time,

ΔT is the time interval that values from the average time series are taken (1 hour),

$q(t+\Delta t)$ is the forecast traffic volume,

$q_{LR}(t+\Delta t)$ is the forecast traffic volume by linear regression model,

$q_A(t+\Delta t)$ is the forecast traffic volume from the model 8.

Again the model has been tested for 20-min. forecast. Thus, by substituting Δt = 1200 seconds (20 minutes) and ΔT = 3600 seconds (1 hour) the form change to:

$$\boxed{q(t+1200) = \frac{2}{3} q_{LR}(t+1200) + \frac{1}{3} q_A(t+1200)}$$

The value of the error that this model indicated does not differ compared to the previous one. The mean absolute error that was estimated is 15.1044. In **Figure 4.30** is shown the graphical comparison between the forecast and the actual time series.

4.4.3.3 *Forecast by combining Linear regression and average time series*

This is the last model that in this thesis has been tested. It is similar to the two previous. A weighing function is also used in order to combine the two forecast terms. The first term is the linear regression model. Nevertheless, the philosophy of the second forecast term has been changed compared to the previous models. Instead of taking values form the average time series after one hour time period and gaining the 20th minute forecast by interpolation (models 9, 10), the forecast at the 20th minute is taken direct from the average time series. As before, more weight is assigned to the linear regression model. The form that forecasts the traffic volume after time interval Δt is:

$$\boxed{q(t+\Delta t) = a q_{LR}(t+\Delta t) + (1-a) q_A(t+\Delta t)}$$

where t is the current time,

$q(t+\Delta t)$ is the forecast traffic volume,

$q_{LR}(t+\Delta t)$ is the forecast traffic volume by linear regression model,

$q_A(t+\Delta t)$ is the value (or the forecast traffic volume) from the average time series,

a is the weighing factor.

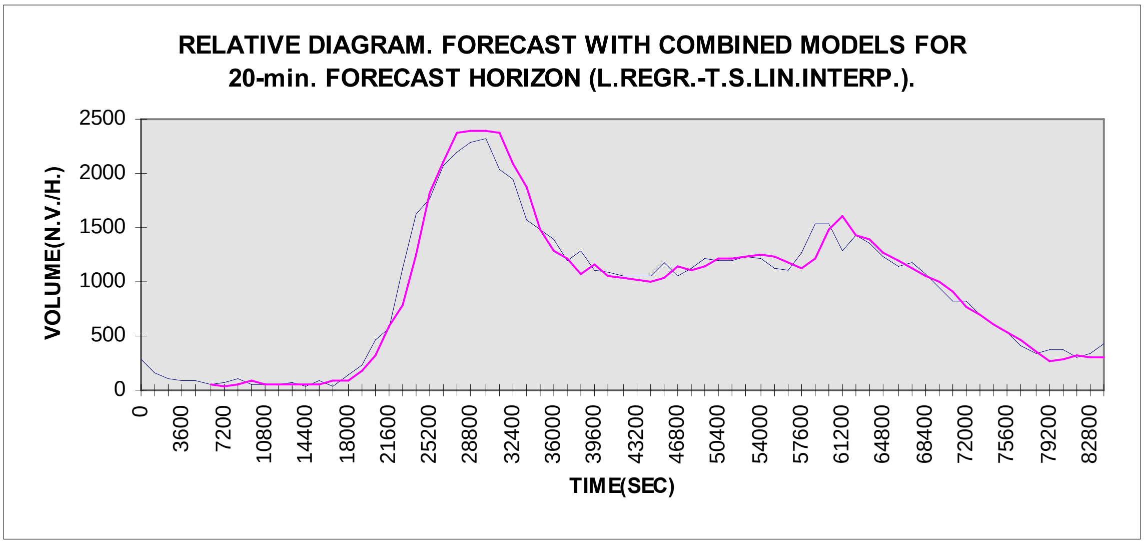


Figure 4.29 - Forecast by combining linear regression and model 7. Graphical comparison of the forecast and the actual Time Series (— actual, **— forecast**).

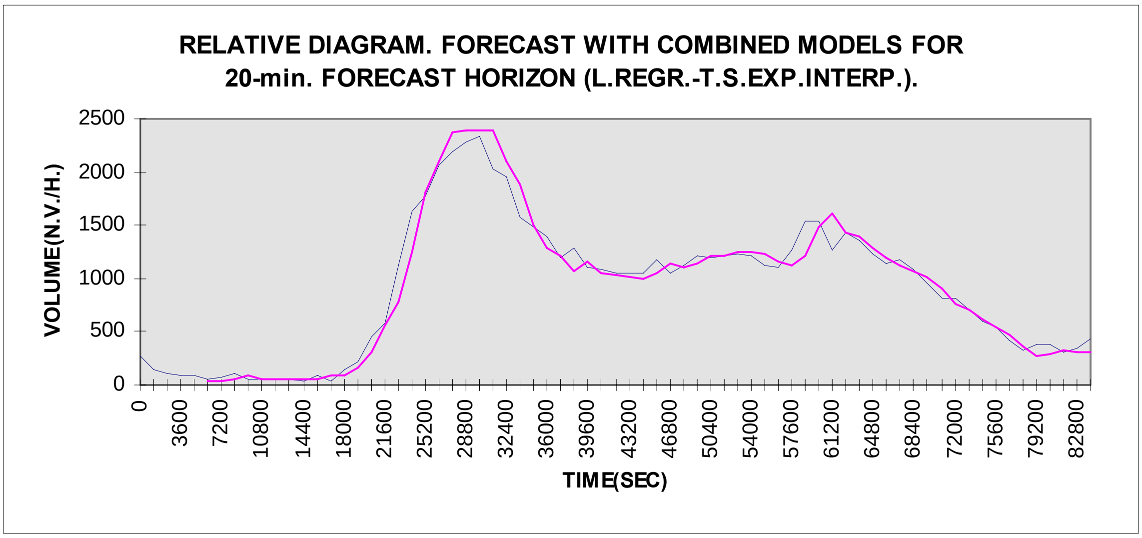


Figure 4.30 - Forecast by combining linear regression and model 8. Graphical comparison of the forecast and the actual Time Series (— actual, **— forecast**).

By substituting Δt = 1200 seconds (20 minutes) and a = 2/3 :

$$\boxed{q(t+1200) = \frac{2}{3} q_{LR}(t+1200) + \frac{1}{3} q_A(t+1200)}$$

An error improve occurred by applying this model. The mean absolute percentage error that was estimated is 13.2532. In **Figure 4.31** is shown the graphical comparison between the forecast and the actual time series.

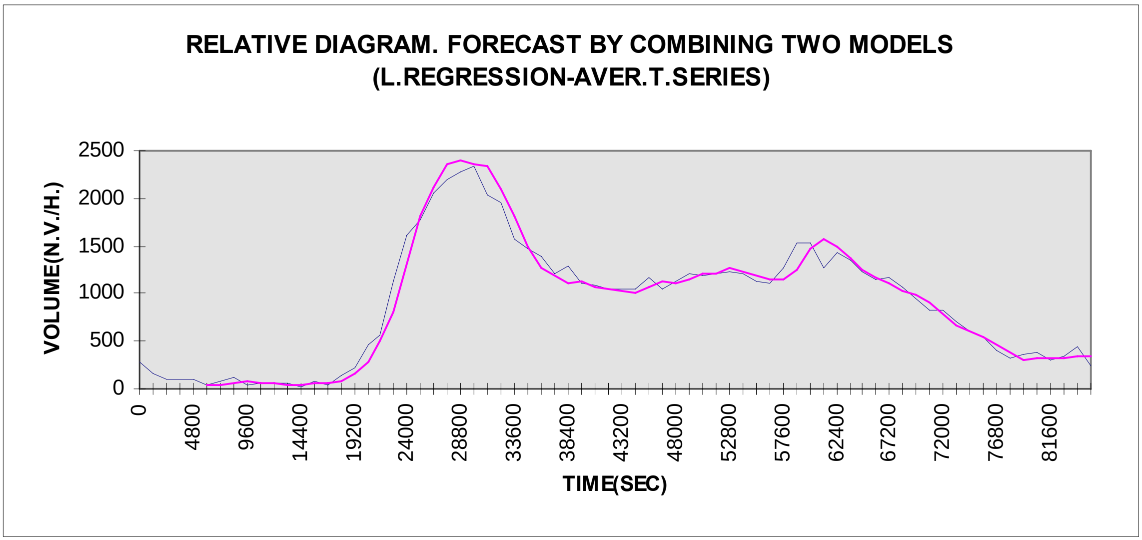


Figure 4.31 - Forecast by combining linear regression and average time series. Graphical comparison of the forecast and the actual Time Series (— actual, — **forecast**).

So far data elaboration, data categorization, and prognosis have been presented. That was the basic part of this thesis. Nevertheless, two important chapter are following where comments on the above results and the implementation on the AIDA are described.

CHAPTER 5

RESULTS ASSESSMENT

5.1 General

After the above analysis it is time to evaluate the above results and to make recommendations. This can be done dependent on two important criteria. The first is accuracy and the second is simplicity of computation. The need of an accurate estimate of the situation in the forecast model is obvious. The forecast data should be as near to the real data as possible. How accuracy can be measured has already been described in the previous chapter (§ 4.4.1). As far as the simplicity of computation is concerned, a computer takes significant time to read in the file on which data from previous forecasts are recorded and to look up each piece of information [1]. If the computations can be based on fewer words of information about the history of the observations, the computation will be faster. Not only is the reading speed per record increased, but there is more room in the memory program instructions. Thus, memory can be saved and the costs can also be limited. To criticize the performance of each model the model type is taken under consideration. Specifically, <u>type 1</u> model is defined as the model that predicts the following traffic situations by taking under consideration only the current day measurements and <u>type 2</u> model is defined as the model that predicts the following situations by taking under consideration only historical time series. Based on these criteria the models will be assessed. In **Figure 5.1** a list of the optimum MAPE for each model is presented in ascending order. In the following sections each model performance is described.

	MODEL	M.A.P.E.
1st	FORECAST BY COMBINING LINEAR REGRESSION AND AN AVERAGE TIME SERIES	13.25319
2nd	FORECAST BY COMBINING LINEAR REGRESSION AND MODEL 7	14.87663
3rd	FORECAST BY COMBINING LINEAR REGRESSION AND MODEL 8	15.10442
4th	FORECAST BY USING AN AVERAGE TIME SERIES AND EXPONENTIAL INTERPOLATION	17.98118
5th	FORECAST BY USING AN AVERAGE TIME SERIES AND LINEAR INTERPOLATION	18.1206
6th	LINEAR REGRESSION MODEL	18.67004
7th	IMPROVED BARTLETT REGRESSION MODEL	20.1561
8th	EXPONENTIAL SMOOTHING WITH DIFFERENCES AND TWO COEFFICIENTS	20.52421
9th	BARTLETT REGRESSION MODEL	21.34507
10th	EXPONENTIAL SMOOTHING WITH DIFFERENCES	21.3954
11th	EPONENTIAL SMOOTHING	22.49461

Figure 5.1 - List of the tested models. Optimum M.A.P.E. gained by each model.

5.2 Models performance

5.2.1 *Linear Regression Model*

The type 1 model with the lowest Mean Absolute Percentage Error (MAPE = 18.67004) is the linear regression model with five traffic volume entries. That means that satisfies the accuracy criterion in the best way, so the forecast values are very near the real values. The success of this model is eliminated by the fact that it needs the most data in the analysis area. It needs data from a time period of 100-min. (or 6000-sec.), so a big memory capacity is needed. A big number of computations also are demanded. These cause money and time costs which are countable disadvantages. Generally, the model forecasts the next situations very well since it follows the changes and it doesn't react slowly. If the costs mention above are judged not very important, this model is the best solution (as type 1 model) in forecasting the next traffic volumes.

5.2.2 *Bartlett Regression Model*

The Bartlett regression model with slope adjuster equal to 0.27 is the 9th model in the list of **Figure 5.1**. That means that the accuracy criterion is not satisfied well as by other models, so the real values are not forecast as well, too. The data which are needed are fewer compared to the previous model but they are still a lot. It demands 40-min. (or 2400-sec.) of data, so the number of computations and the memory demand are big. It also presents a late reaction to the values changes this can be easily realized by observing the graphical comparison in **Figure 4.16** where the forecast time series follows the actual time series. Thus, this model is not recommended as a good solution in forecasting traffic volumes.

5.2.3 *Improved Bartlett Regression Model*

Improved Bartlett Regression Model with slope adjuster equals to 15.43 is displayed in the 7th position of the MAPE list. Its MAPE (= 20.1561) is satisfactory, so the traffic volume forecasts are reliable. The remarkable advantage of this model is the small memory capacity demand since data from a time period of 25-min. are needed. It should be mentioned though that the calculations are quite big since the time segmentation is composed of 5-min. intervals. Observing the graphical comparison of **Figure 4.18**, it is obvious that this model shows a greater sensitivity to volume changes. Nevertheless, the problem of late reaction still presents itself (the forecast time series follows the actual time series). Considering all the above advantages and disadvantages, the improved Bartlett regression model can be characterized as a medium solution.

5.2.4 *Exponential Smoothing*

The model with the highest Mean Absolute Percentage Error (MAPE = 22.49461) is the exponential smoothing with smoothing parameter a = 1. That means that satisfies the accuracy criterion in the worst way, so the forecasts are far from the real values. The advantage of this model is the little data storage demand. It is only 20-min. data and the computations are very few. Only one term has to be stored at each forecast (one period ahead forecast, $\bar{q}_{old}$). Applying the smoothing parameter a = 1 means that the forecast follows exactly the actual values with a 20-min. phase difference. Even when a smaller parameter was applied, the problem was still the same and, of course, a worse MAPE was displayed. In conclusion the model seems to fail to forecast traffic volumes so it is not suggested as a good solution.

5.2.5 *Exponential Smoothing with Differences*

The exponential smoothing with differences and smoothing parameter a = 0.45 model is displayed in the 10th position of the MAPE list. It shows an improvement compared to the previous model but the error value is still big. The advantages and the disadvantages are the same with the exponential smoothing model. Little data storage is needed to carry out the calculations but it reacts lately to the volume changes. Generally, this model doesn't fail to forecast the next situations but an improvement is still needed.

5.2.6 *Exponential Smoothing with Differences and two Coefficients*

The exponential smoothing with differences and two coefficients with a = 0.41, b = 0.5 is the 8th model in the MAPE list. Its MAPE (= 20.52421) shows a great improvement compared to the two previous exponential smoothing models. It is nearly the same with the improved Bartlett regression model (MAPE = 20.1561), so it can also be characterized as satisfactory. As explained before, the great advantages of this model are the little data storage demand and the simplicity of computation. It has the smallest analysis horizon which is composed of one 20-min. time interval. Thus, the exponential smoothing with differences and two coefficients is the model that satisfies the second criterion in the best way. A disadvantage of the model is the phase difference that appears between the real values and the forecasts. Of course, the phase difference is improved compared to the previous models but it still exists. A trial to find a prognosis Time Series which could avoid this problem showed that for a = 0.6 and b = 0.3 an improvement occurred. Nevertheless, the MAPE increased up to 21.82318. The graphical comparison of **Figure 5.2** shows this Time Series. Finally, this type 1 model can be a very good solution in forecasting traffic volumes since it accomplishes both criteria in a satisfactory way. On the other hand, the phase difference problem can be solved by choosing the appropriate smooth parameters. It should be noticed that in this case the first criterion seems not to be well satisfied.

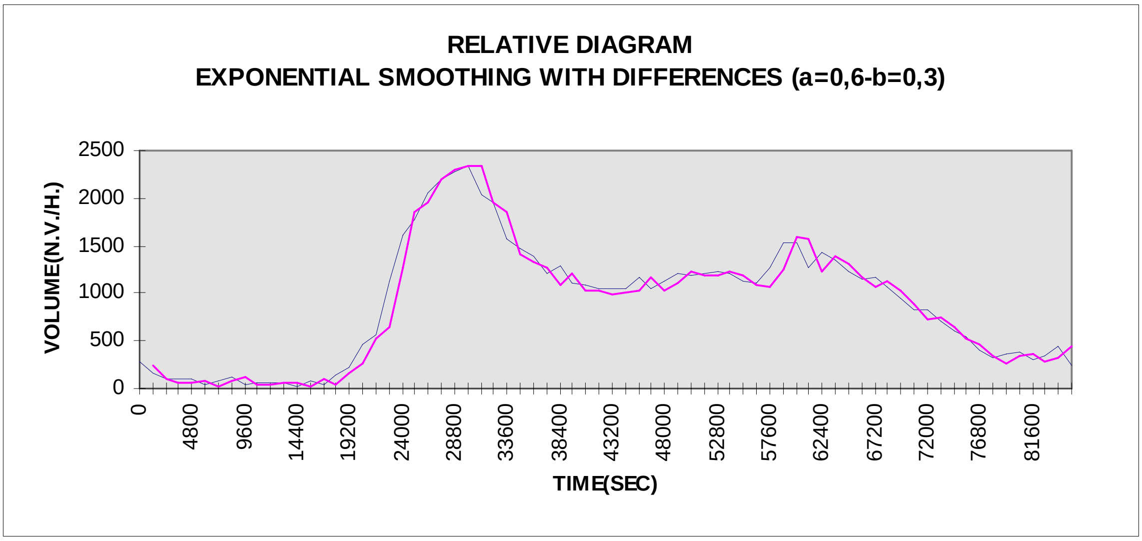


Figure 5.2 - A trial to avoid the phase difference problem.

5.2.7 *Forecast by using an average time series and linear or exponential interpolation*

The assessments of the models “forecast by using an average time series and linear interpolation” and “forecast by using an average time series and exponential interpolation” are being done together since their procedures and their performances are similar. These models are representatives of the type 2 models. Their advantage is that they predict the recurrent congestion with big accuracy. As it can be seen from the comparison figures (**Figure 4.26**, **Figure 4.28**) the phase difference problem doesn’t exist since the forecast time series is very close to the actual time series. An other advantage of these models is that they don’t demand complex computations since the forms that are used are simple interpolation forms. Nevertheless, the demand of memory capacity is remarkable because of the storage need of an average time series. As it can be seen in **Figure 5.1** they display a very good error value (MAPE = 18.1206, 17.9811 respectively) but this could be change depending on the number of non recurrent congestion or abrupt traffic volume changes. This is the main shortcoming of these models. As mentioned in chapter 4 the range of the error is analogous to the range of non recurrent congestion or generally to the range of the abnormal changes of the traffic situation. Finally, these models can not give a reliable forecast of urban traffic situations by themselves but they can give useful information by using them in combined models. This is the subject which the following two sections deal with.

5.2.8 *Forecast by combining Linear Regression and the models that use an average time series and linear or exponential interpolation*

As in the previous section, the assessments of the models "forecast by combining linear regression and model 7" and "forecast by combining linear regression and model 8" are being done together since their procedures and their performances are similar. These models can be characterized as the models with the more advantages compared to all the previous. The benefit that is gained by these combinations models is that they take advantage of the benefits of the type 1 and type 2 models. Thus, the recurrent congestion can be predicted since models type 2 do that and the abnormal changes can also well predicted because of the linear regression model. This means that the type 1 model give the sensitivity and model type 2 makes the model to take under consideration the normal (or usual) situations. The accuracy is improved by this combination. In **Figure 5.1** can be seen that these models have the second and the third position of the MAPE list (MAPE = 14.87663, 15.10442). The error value is depended again on the non recurrent traffic changes so a worse error value could be displayed. However, an improvement at the general forecast traffic situations is confidently gained. On the other hand, the disadvantage of these models is that they need more complex computations since they combine two models and memory costs are also greater. If this shortcoming is judged not very important, these models can be presented as a very good solution to the forecast traffic situation problem.

5.2.9 *Forecast by combining Linear Regression and an average time series*

This is the last model that has been tested in this thesis and the model that indicated the lowest error value (MAPE = 13.25319). Because it is a combined model of an average time series and type 1 model has all the advantages that have been already mentioned in the preceding section. Thus, the recurrent congestion can be predicted since values as forecasts are taken direct from a representative-normal time series and the abnormal changes can also well predicted because of the linear regression model. On the other side, the computations are less than in the above two models since the values from the average time series are taken direct without any other computations (i.e. interpolation). An other difference that can be remarked is that the previous models have the ability to predict the traffic situations even if the values from the average time series are given in a time period of 1 hour. On the contrary the present model demands values from the average time series every 20 minutes. It should be also mentioned that the weighing factor *a* of the model is an adaptable factor, so a further consideration can be done depending on the situation of the forecast traffic values. The value a=2/3 that has been taken is gained from the experience of the tested situation. In conclusion this model can be considered as the best solution if the shortcomings that mentioned above are not judged as important compared to the advantages and depending on the field that would be applied.

CHAPTER 6

COMBINATION OF PROGNOSIS AND AUTOMATIC INCIDENT DETECTION ALGORITHM (AIDA)

6.1 Proposed flow chart.

AIDA is flexible algorithm that can be used in different ways, so a lot of benefits can be gained. After the above trial to find an appropriate prognosis model it is time to find an approach to combine the prognosis with AIDA. A proposed implementation is shown in **Figure 6.1**. At the beginning the data can be categorized, in order to determine the feature of the time series. This can give a lot of useful information, so the various time series may be treated differently. In the second step AIDA processes the data and turns on an alarm when an incident or congestion occurs. If an alarm is turned on, a prognosis process will be executed. Predicting the future values of the traffic situation, the AIDA can be used again in order to find out if the future values will keep the alarm on in which case either actions (e.g. traffic coordination) should be done or the alarm will be turned off. When the alarm is off in the second step, a prognosis should be done, too. Thus, the AIDA will inform if the alarm will be activated, so that some actions can be done or if the alarm will be off, so no traffic problems will appear. As it can be easily understood, prognosis is implemented regardless of the alarm state. Every time that new data are received by a detector and are processed by AIDA, a new situation appears which could indicate a significant change. Thus, the forecast model should be informed and be able to make prognoses based on the recent values. But, why should a prognosis be made? This is the question that is to be answered in the next section.

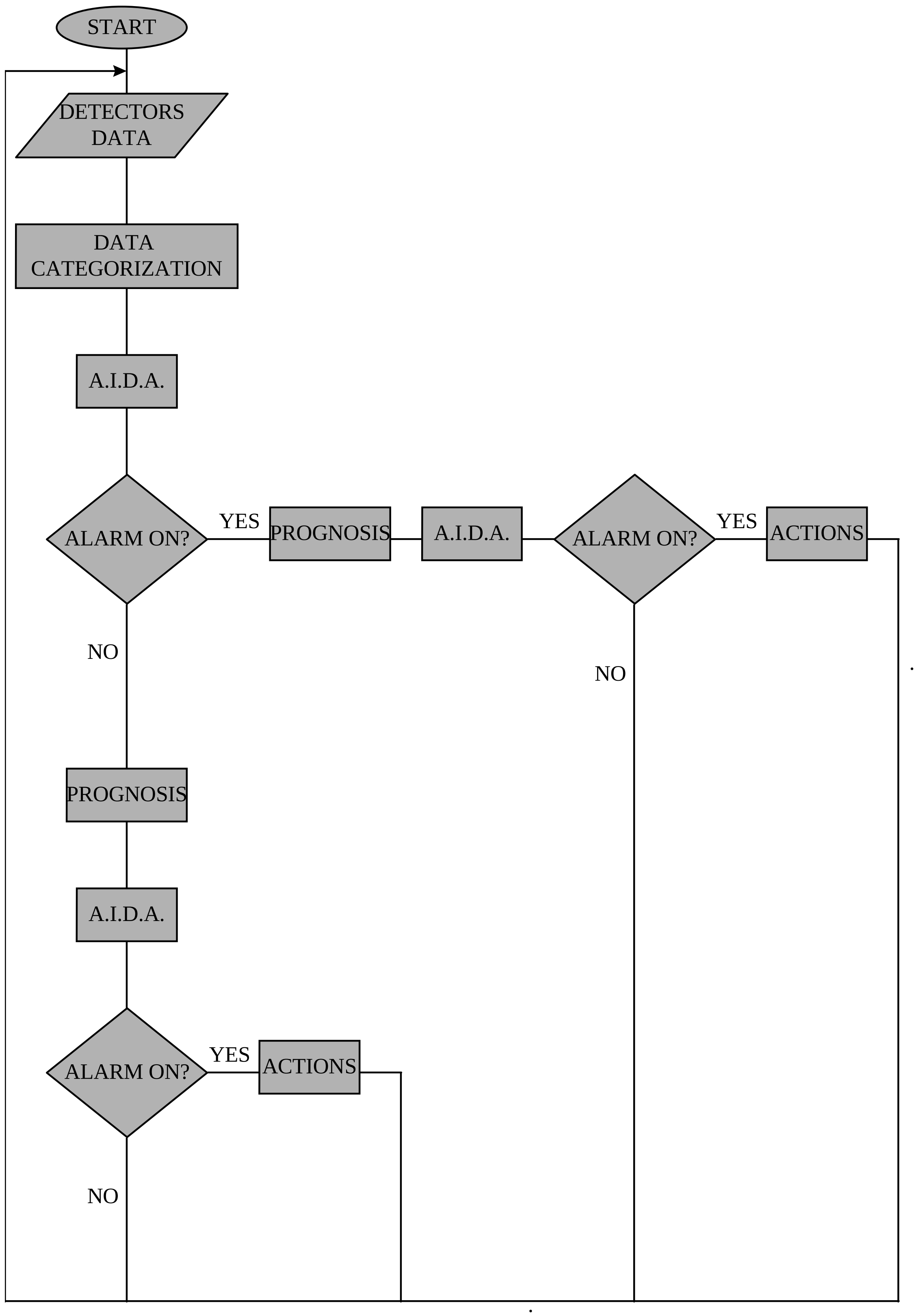


Figure 6.1 - Proposed prognosis implementation flow chart on AIDA.

6.2 The benefit that is gained

Forecasting is not a new problem. It has plagued management for centuries. Nevertheless, forecasting traffic situations in urban environment is a new approach that so far no one has ever tested. To make a prognosis is something very important as well as useful regardless of the magnitude that one wants to forecast. Knowing the future situation of a specified object can solve several problems in planning and decision making.

Forecast of the next traffic situations means knowledge of what is going to happen in the future. This knowledge can be used in order to make a decision how a traffic problem can be solved. When is known that an incident or a congestion is going to happen at the next 20-min. a fast and in time decision can be made. These decisions can be related with:

- control of signal lights, dynamic rerouting
- provision of information to drivers to encourage rerouting, postponement or abandoning of journey
- police early warning of incidents [2]

On the other hand, there is enough time to do actions and to criticize, in order to find an optimum solution. All the benefits which are gained so far with the existing Automatic Incident Detection Algorithm now can be gained better since the information of the traffic situation comes faster. These are:

- Improving efficiency and/or reducing congestion
- Removal of accident risk
- Improving access of emergency services
- A greater awareness of network conditions to enable managers to operate more rationally and effectively [2]

In conclusion, forecasting the future urban traffic situations can give useful information which can solve several problems. Because of the fact that urban traffic is strongly related with every citizen, solving such problems can improve the quality and the safety of life.

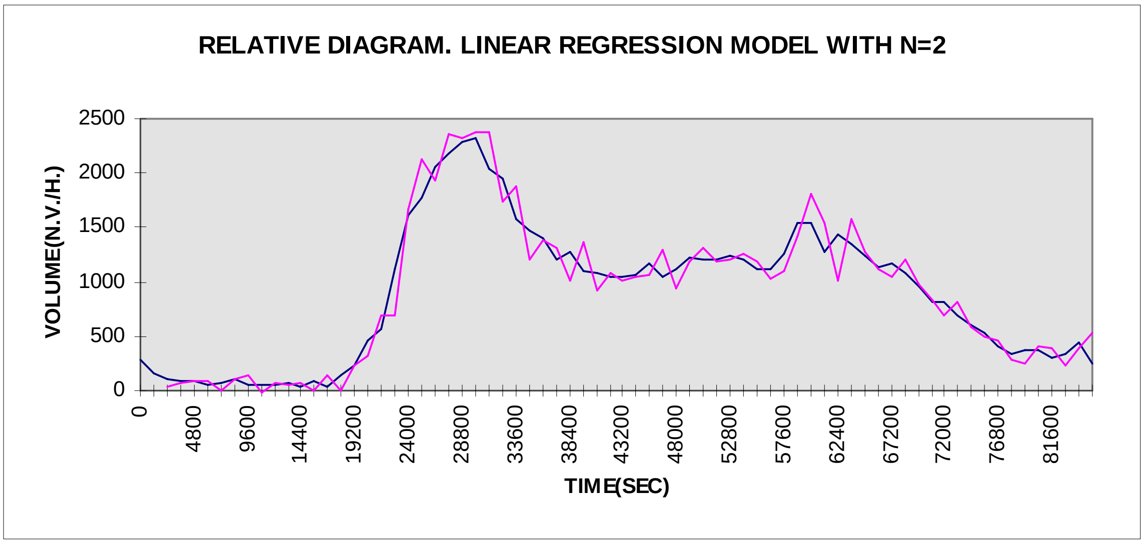
CONCLUSION

In this thesis the short term prognosis of signalized urban streets traffic situations has been examined with a 20 minute prognosis horizon. Data that had been taken from the Ingolstädter Straße field trial have been elaborated in order to be applicable to the proposal forecast models. A data categorization has been made based on the different traffic situations that are presented during the days of a year. This categorization shown that four day groups should be made. An error defined in order to estimate the accuracy of the tested models. That was the mean absolute percentage error which takes under consideration the level of the traffic volume. Eleven models have been tested that can be distinguished into three types. The first concerns the type of models (models 1 to 6) that their predictions are based on current day historical data and they indicated a sensitivity to the abnormal changes during the day. The model which indicated the minimum mean absolute percentage error of this type of models was the linear regression. The second concerns the type of models (models 7 and 8) that their predictions are based on historical time series (an average time series) in order to predict with great accuracy the recurrent congestion. This time series changes depending on the group of days that the tested day belongs. Both of the models indicated a similar accuracy. The third type of models concerns the combined models (models 9 to 11). They are combinations of the above two types. With this combination an improvement in the accuracy was gained. If the complexity of the calculations and their high memory demand that they present is not an important disadvantage the combination models that have described in this thesis can be the best solution at the problem of short term prediction on urban roads. Finally, a combination of automatic incident detection algorithm and a short term (20 minutes prognosis horizon) prognosis proposed where the data categorization has been taken into account. Prognosis is made regardless of the alarm status (incident or not) in order to have a continues knowledge of the next traffic situation. The application of prognosis of the traffic situations like this one that this thesis addresses can solve several problems and can improve the quality of every citizen’s life.

ANNEX

data flow terms.

AIDA step 2 algorithm.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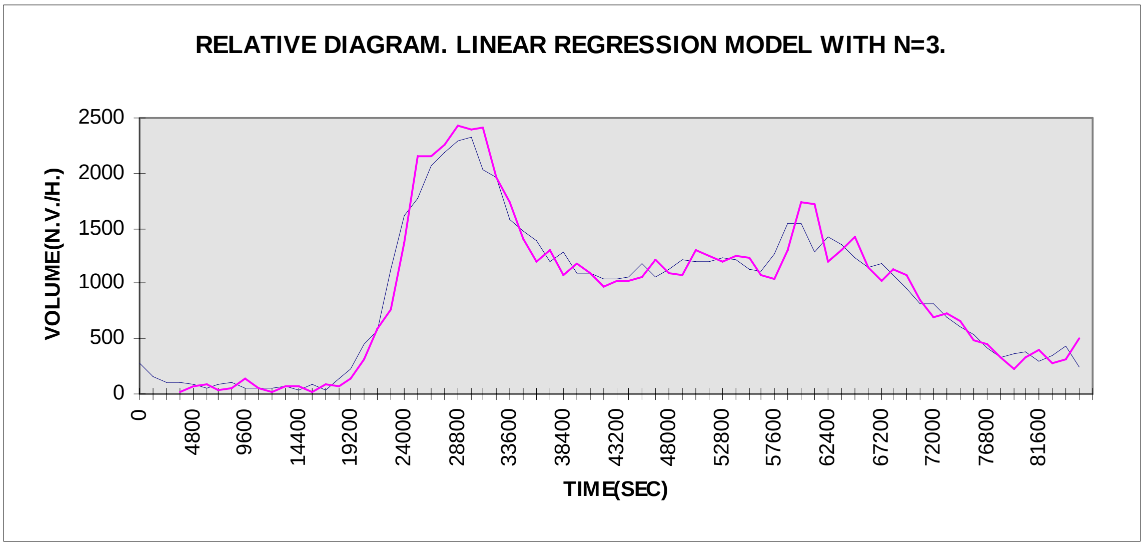
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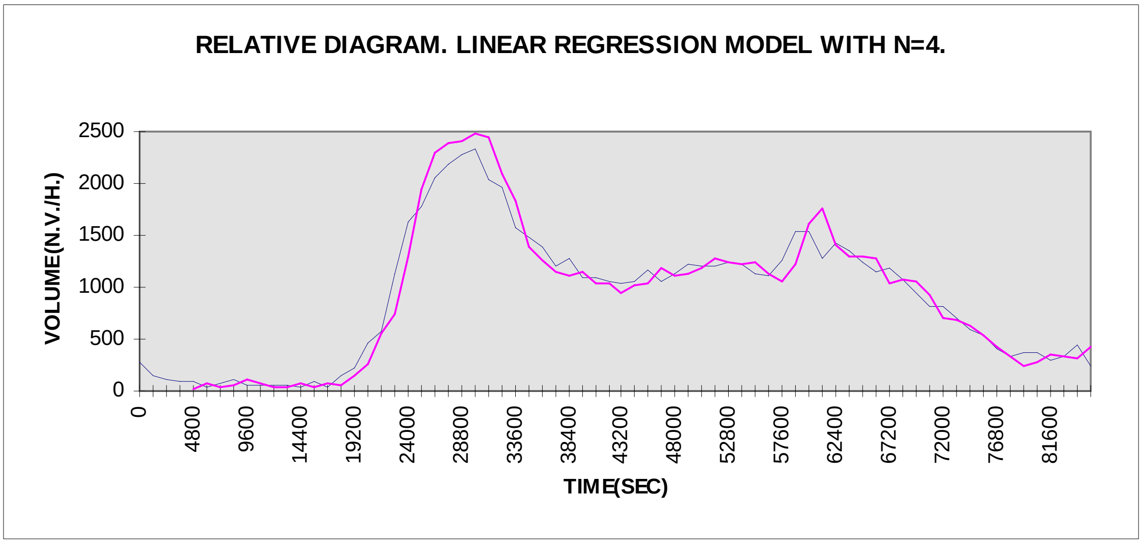
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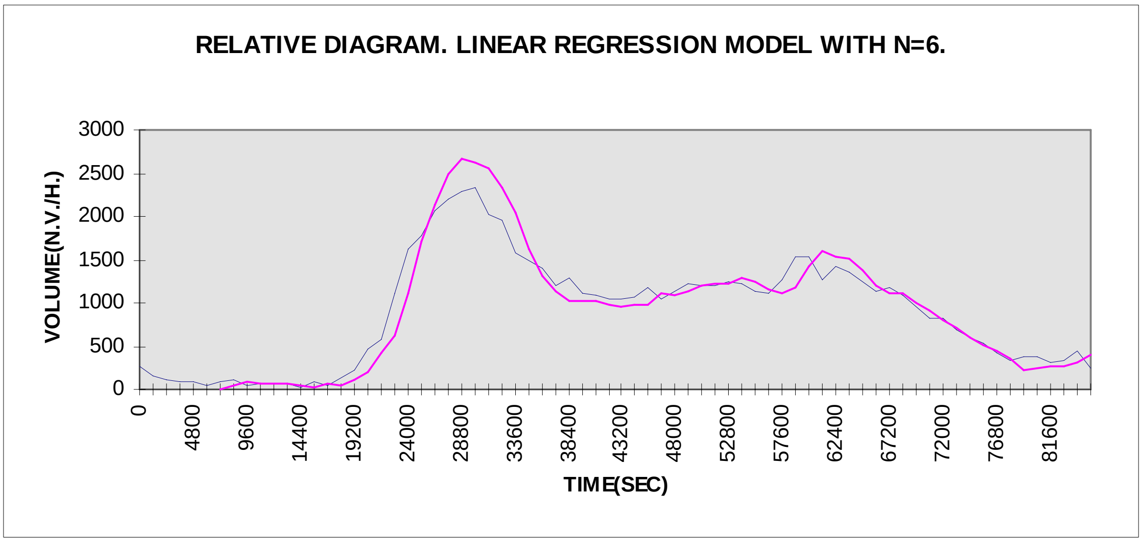
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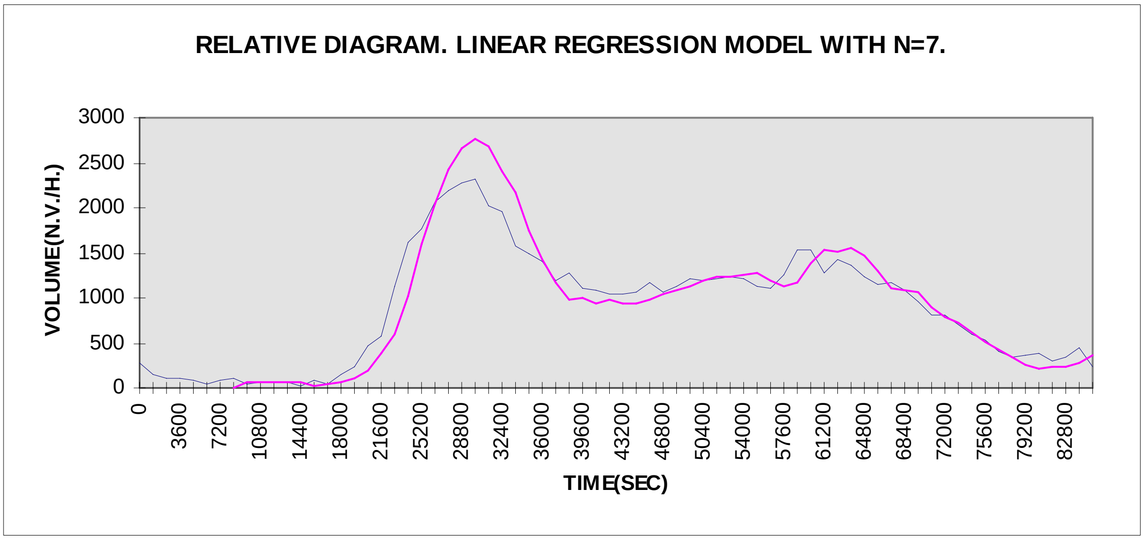
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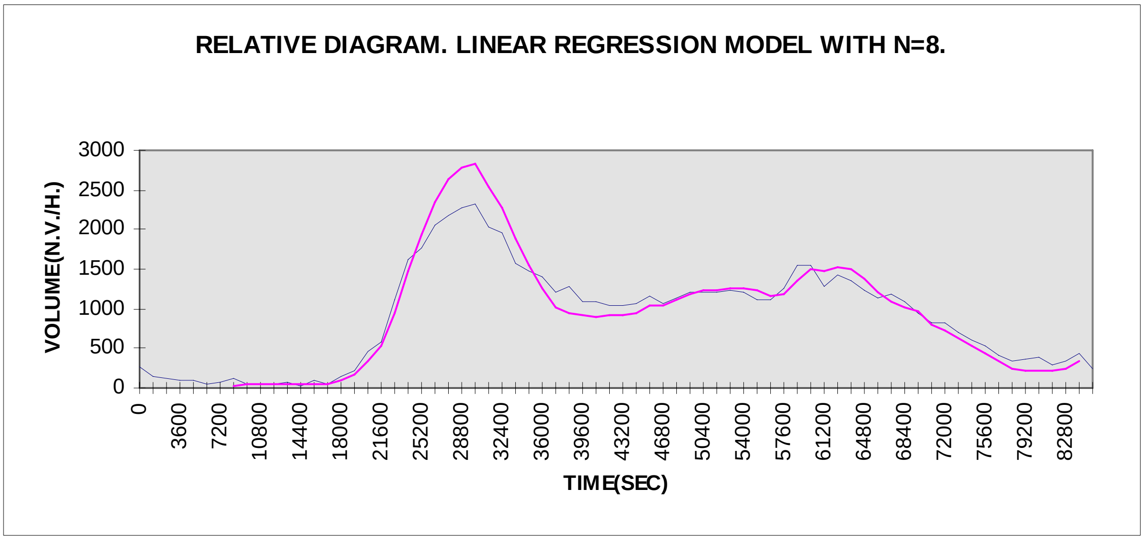
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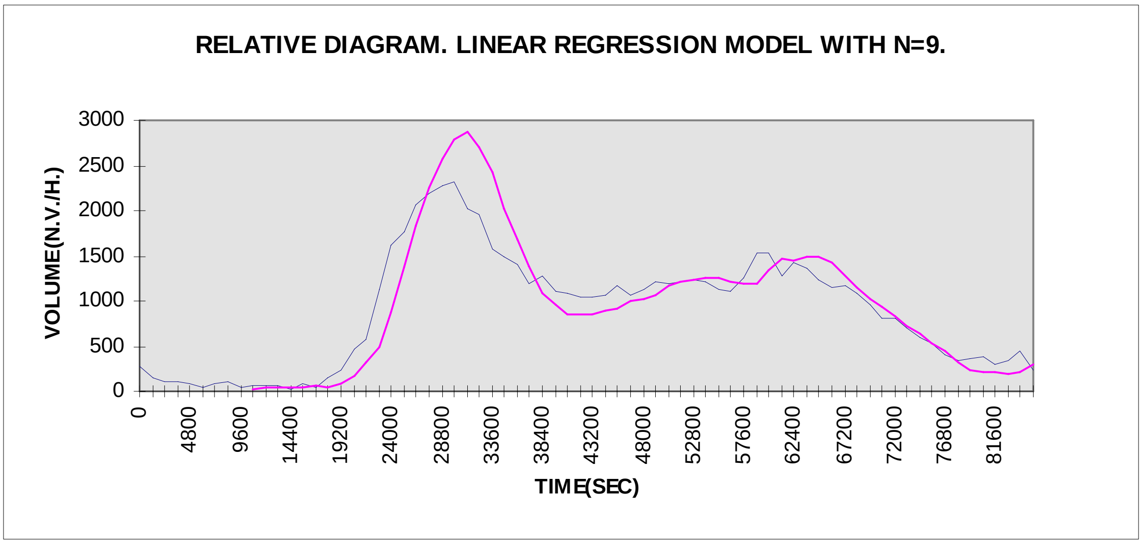
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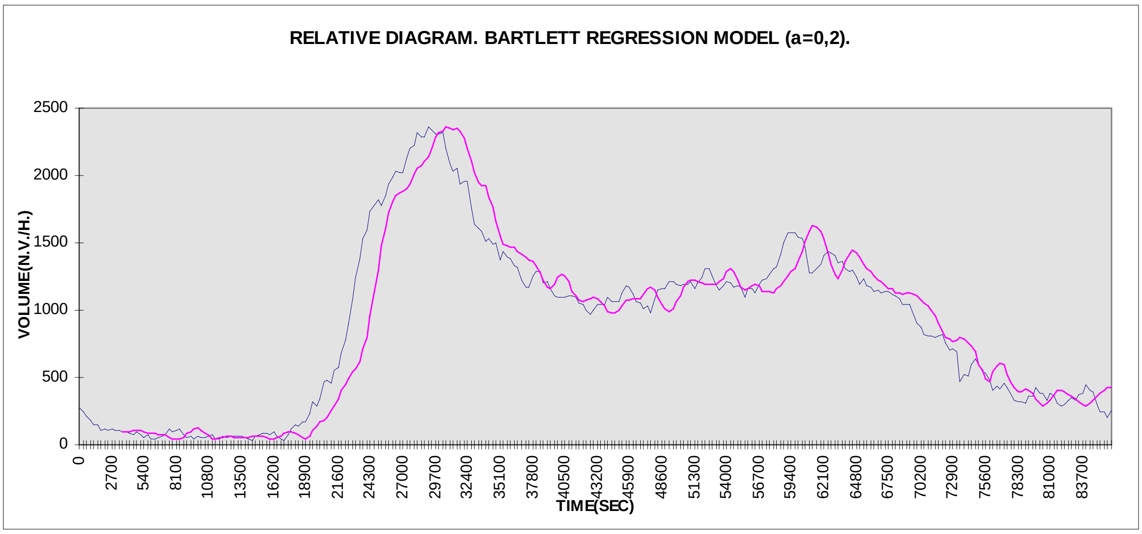
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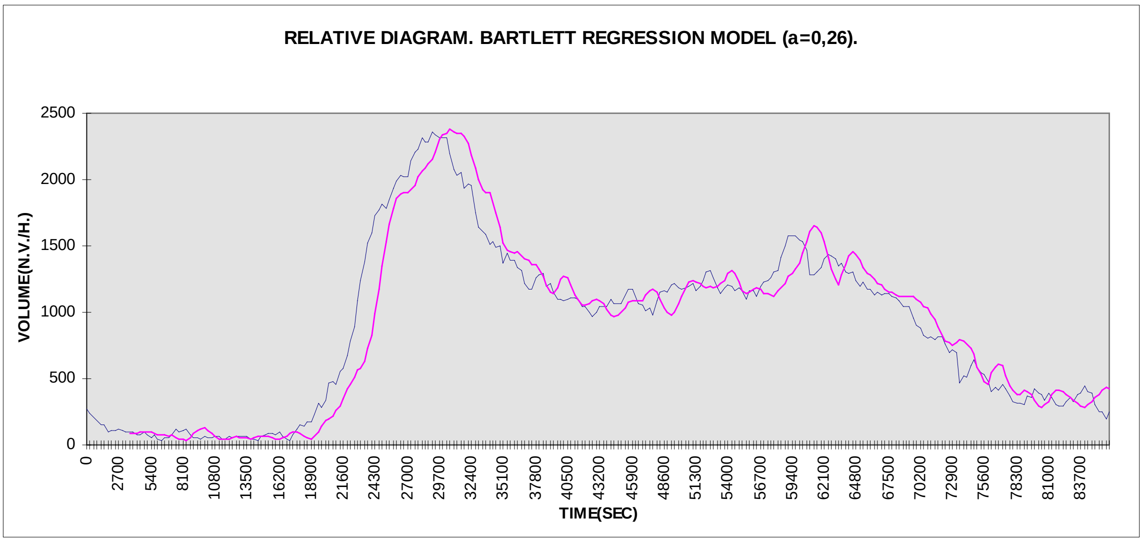
TIME(SEC)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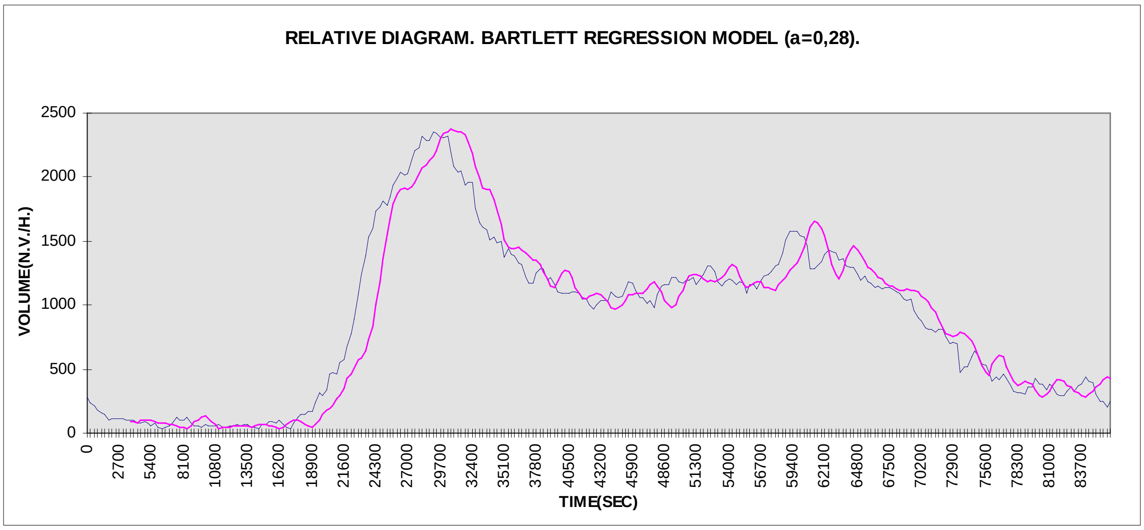
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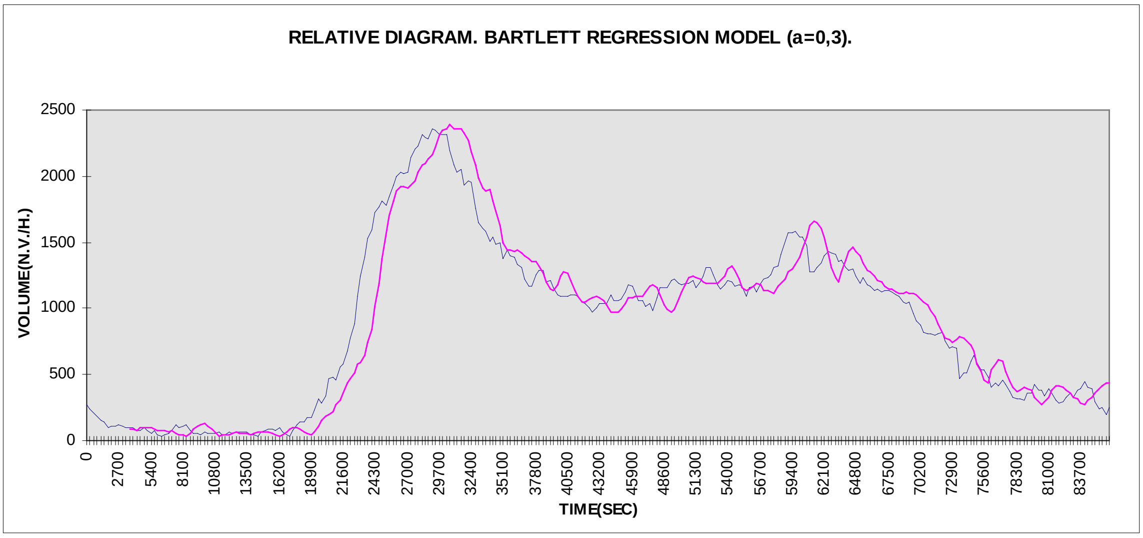
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45900
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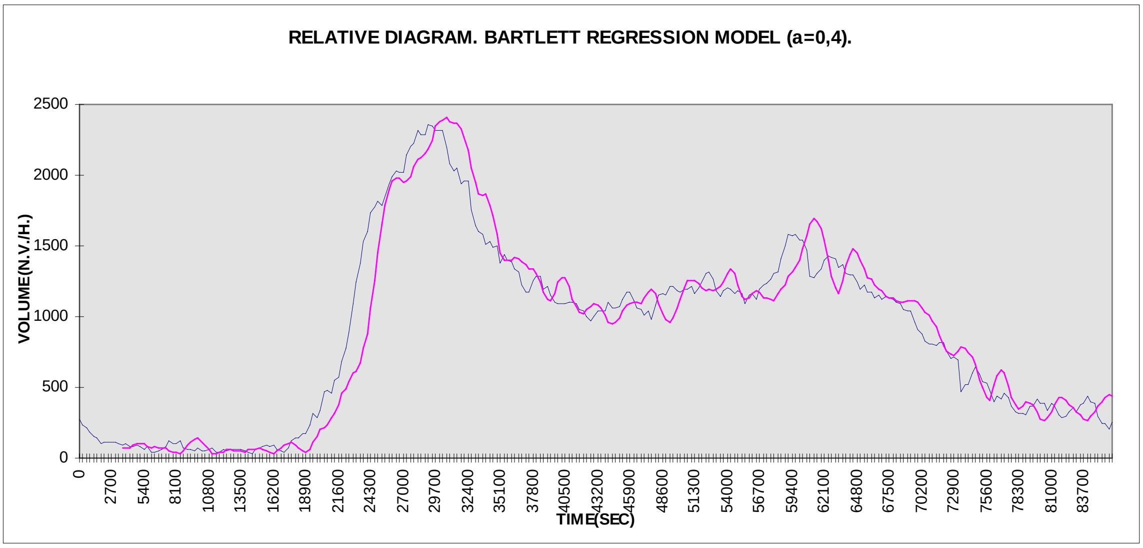
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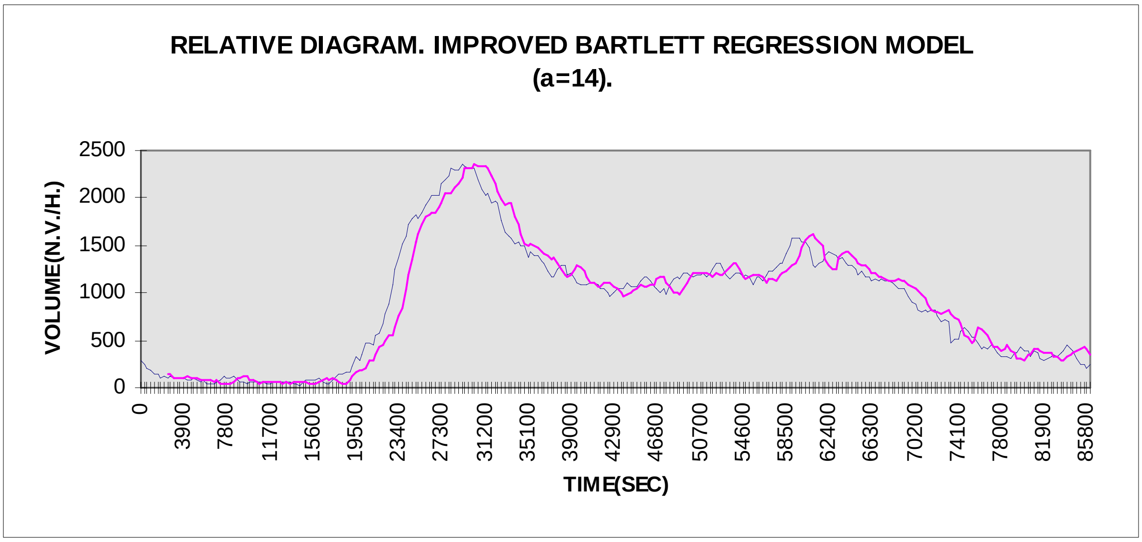
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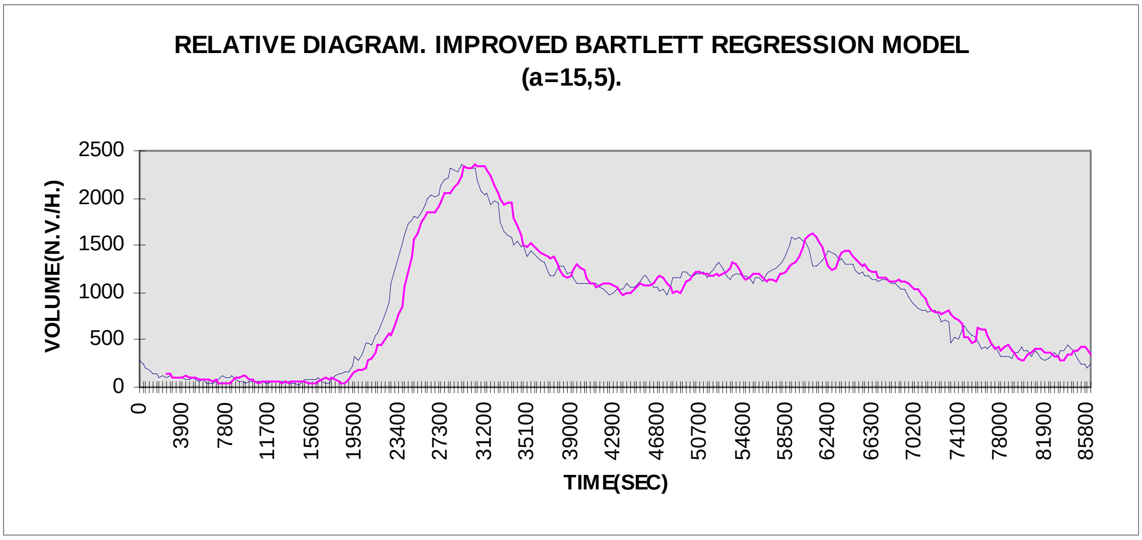
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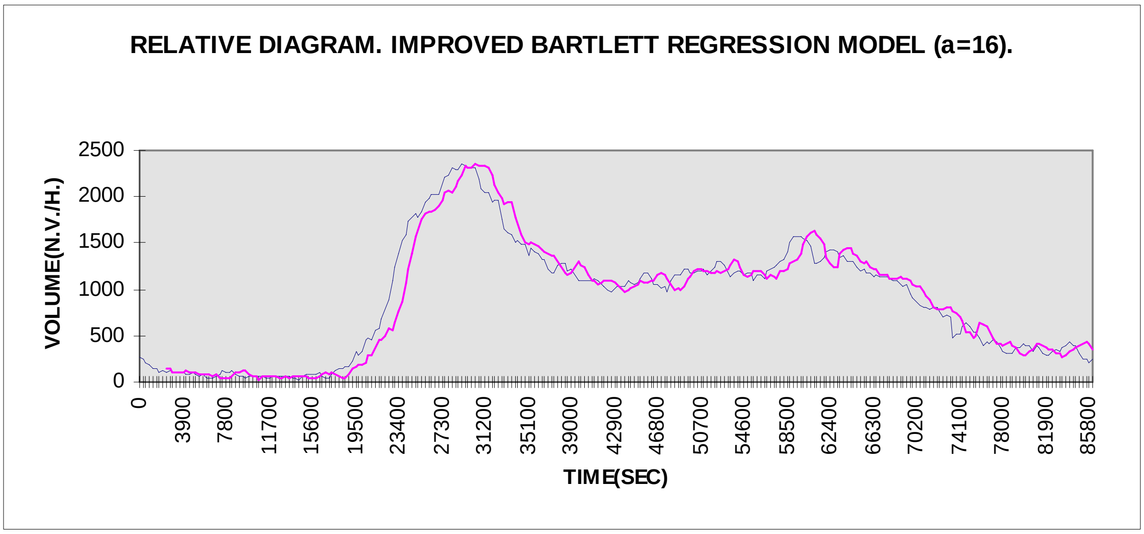
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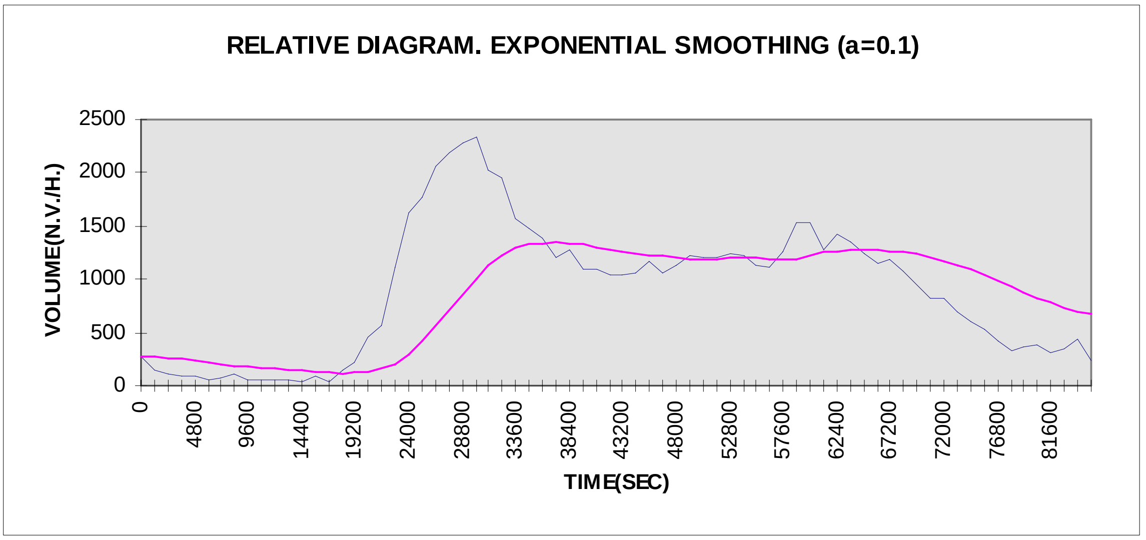
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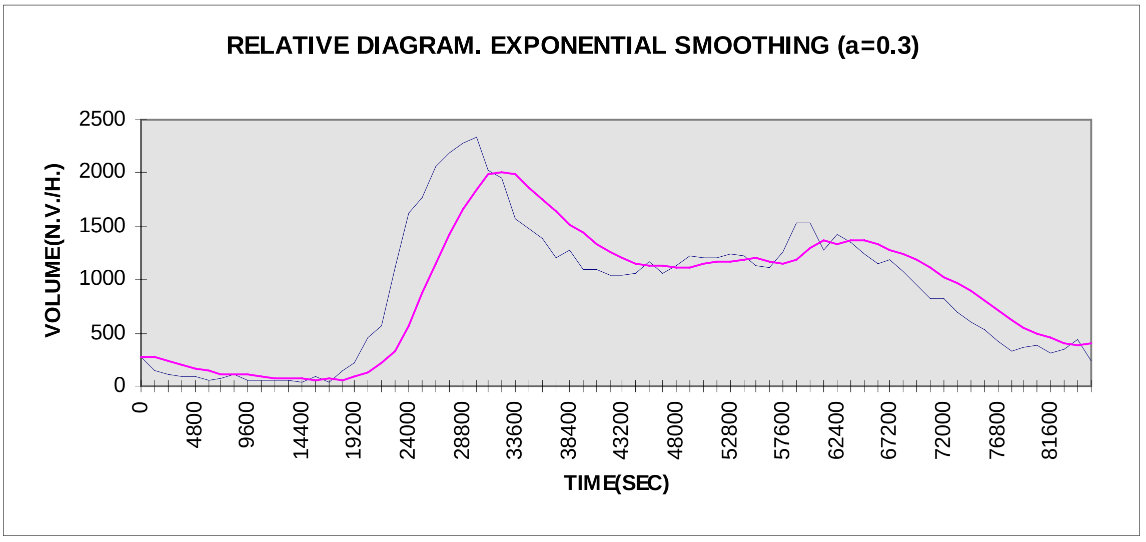
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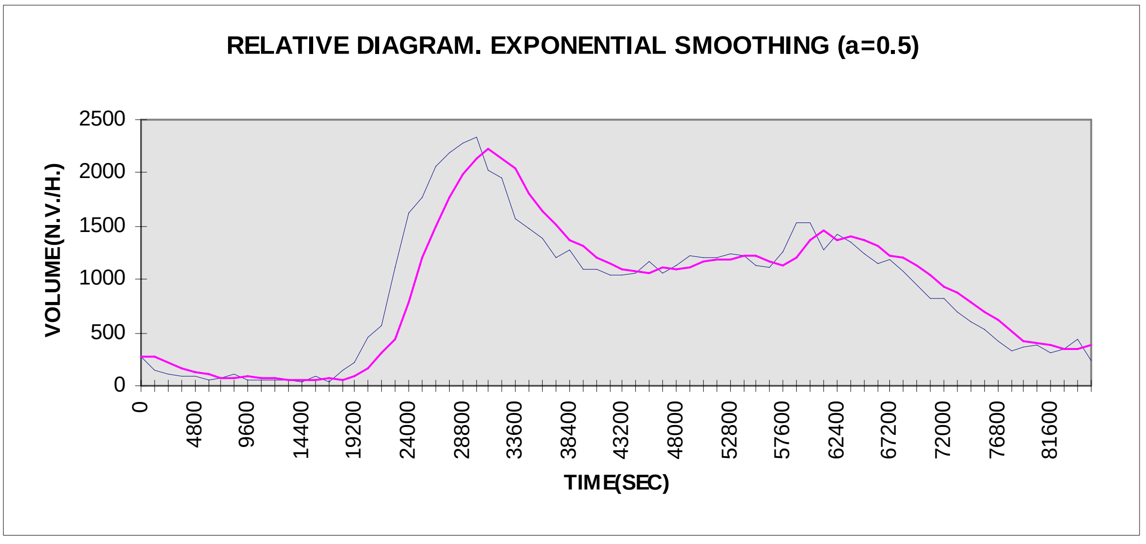
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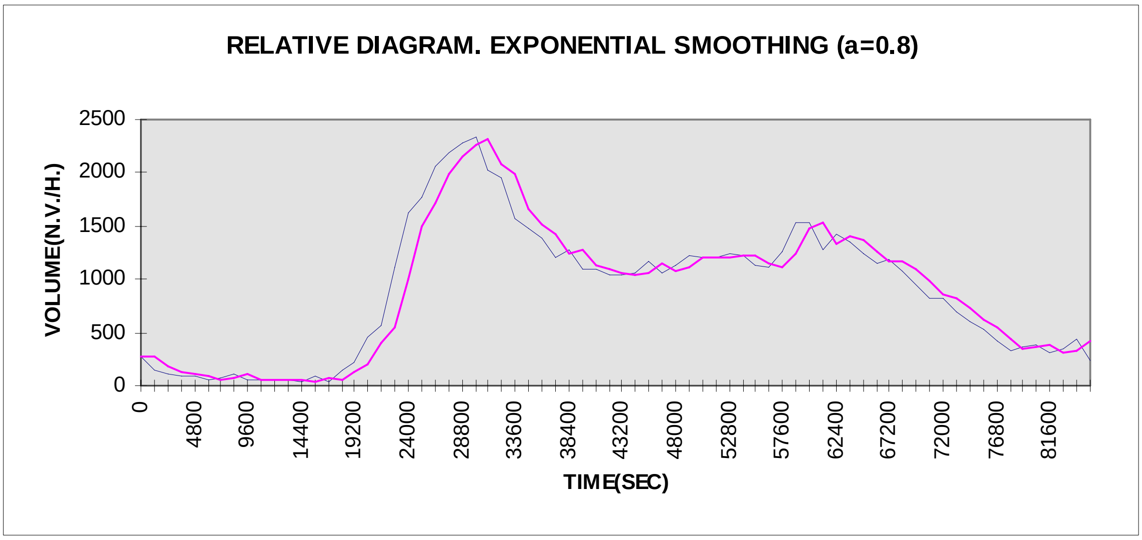

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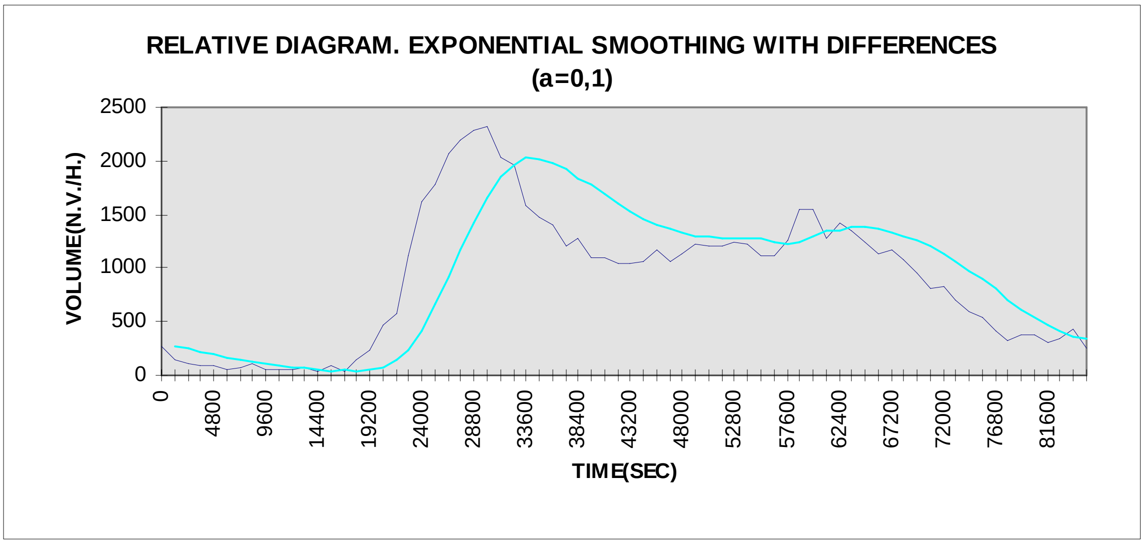

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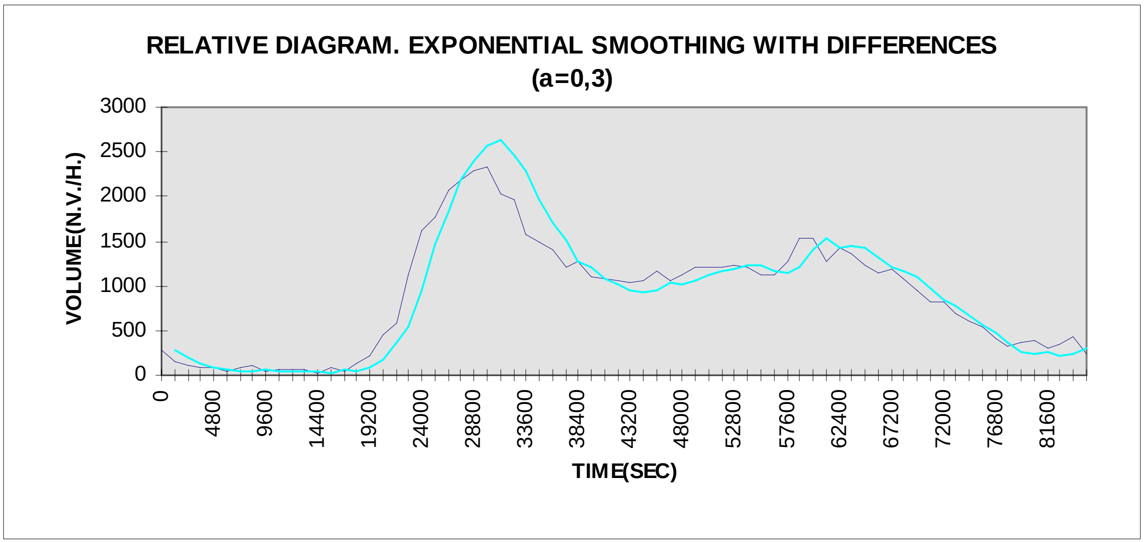

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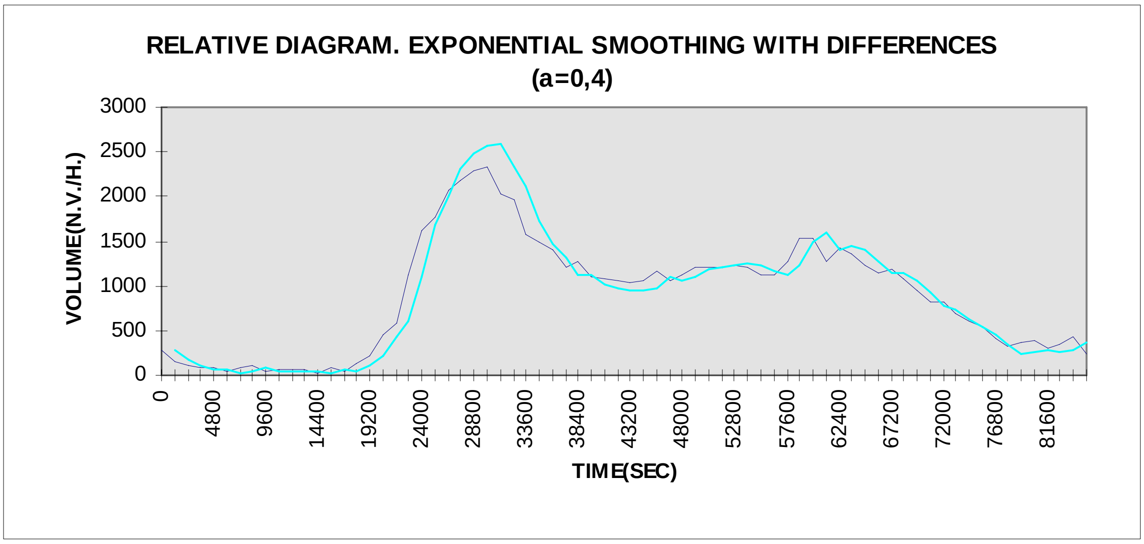
TIME(SEC)


RELATIVE DIAGRAM. EXPONENTIAL SMOOTHING WITH DIFFERENCES
(a=0,4)
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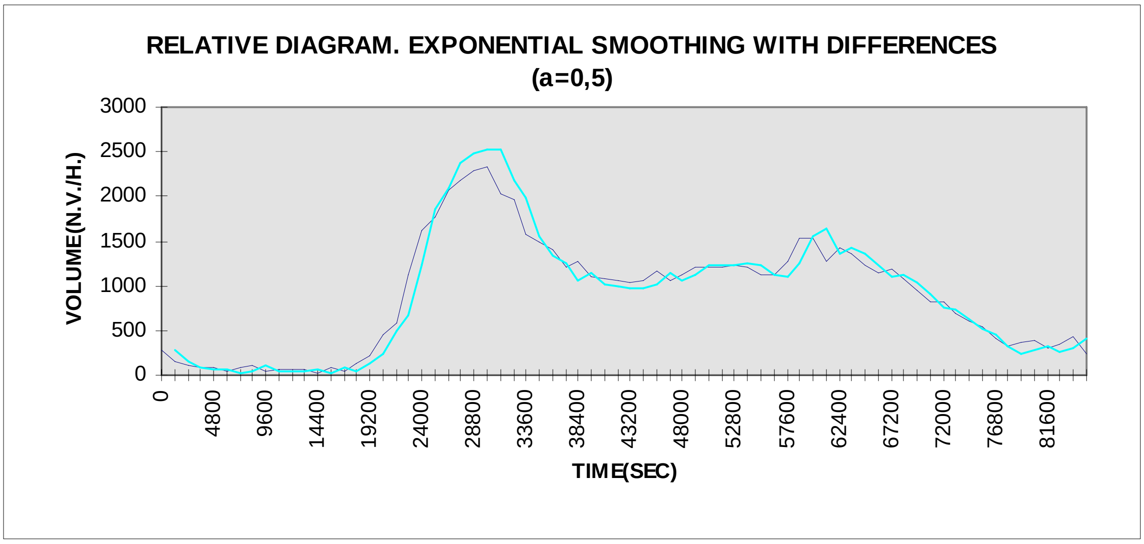
TIME(SEC)


RELATIVE DIAGRAM. EXPONENTIAL SMOOTHING WITH DIFFERENCES
(a=0,5)
VOLUME(N.V./H.)
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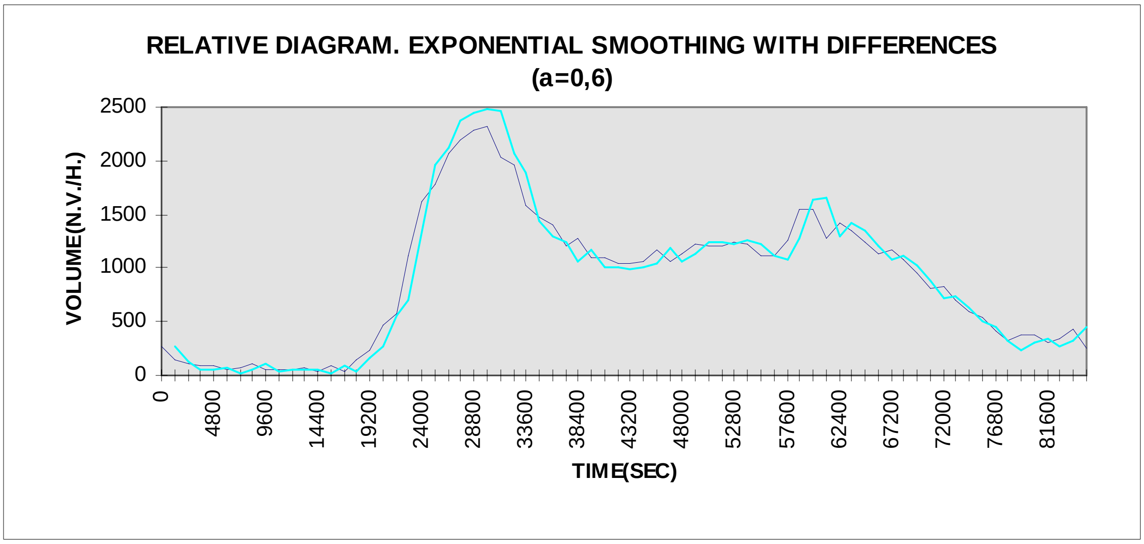
TIME(SEC)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(a=0,6)
VOLUME(N.V./H.)
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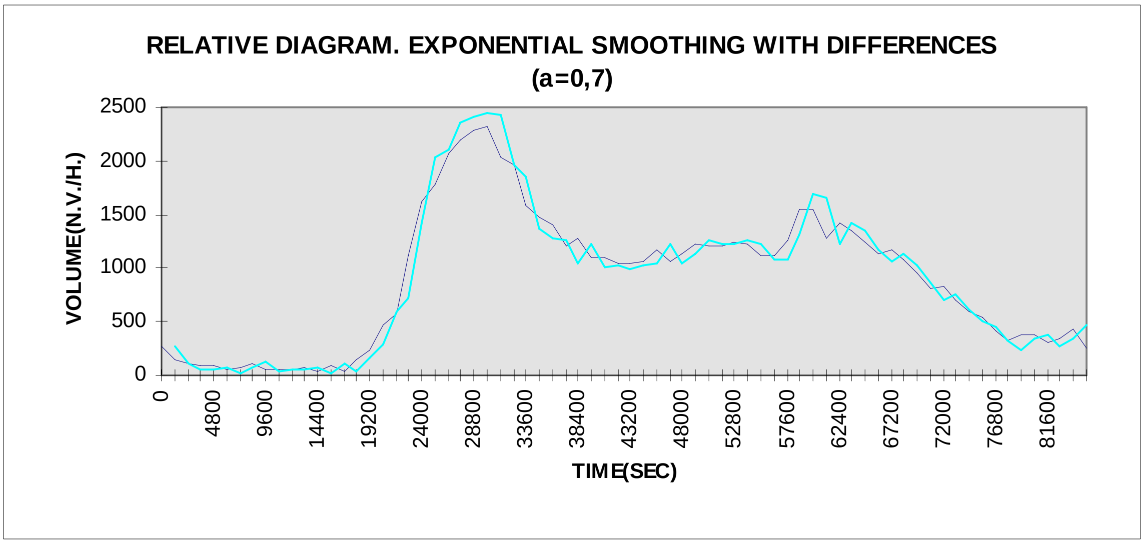
TIME(SEC)


RELATIVE DIAGRAM. EXPONENTIAL SMOOTHING WITH DIFFERENCES (a=0,7)
VOLUME(N.V./H.)
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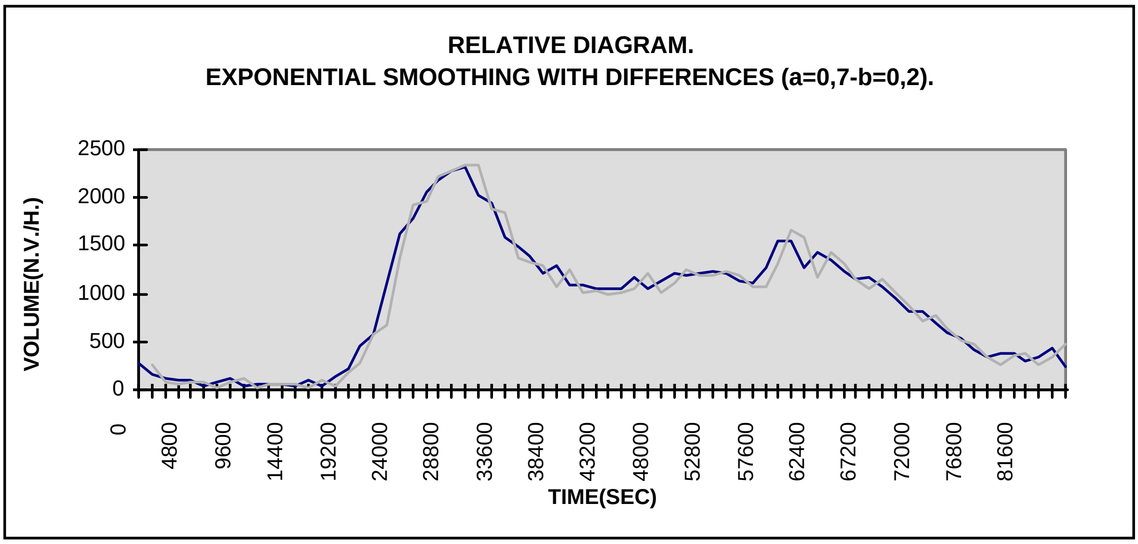
TIME(SEC)


RELATIVE DIAGRAM.
EXPONENTIAL SMOOTHING WITH DIFFERENCES (a=0,7-b=0,2).
VOLUME(N.V./H.)
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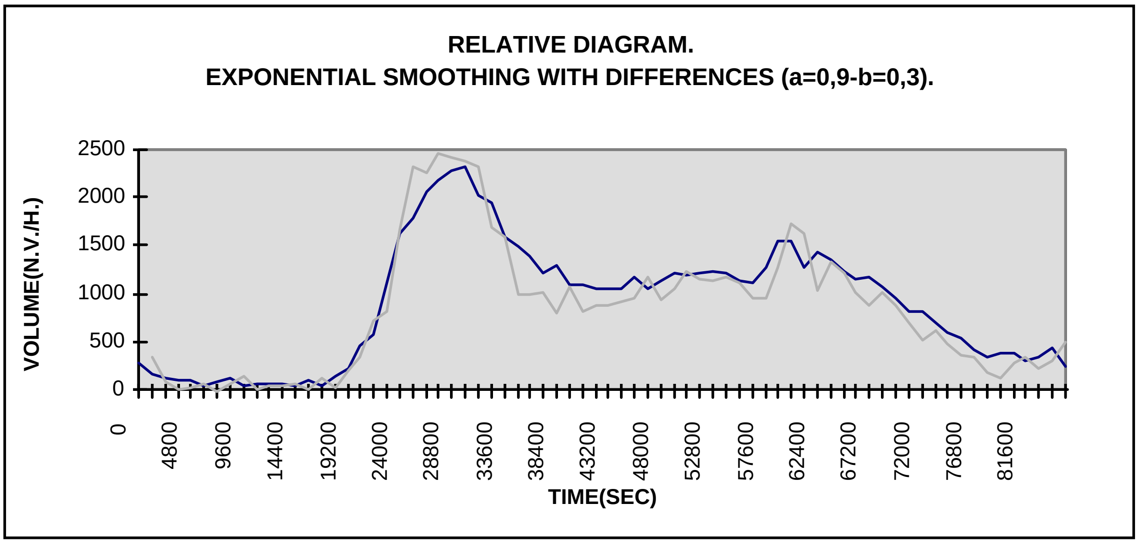
TIME(SEC)


RELATIVE DIAGRAM.
EXPONENTIAL SMOOTHING WITH DIFFERENCES (a=0,9-b=0,3).
VOLUME(N.V./H.)
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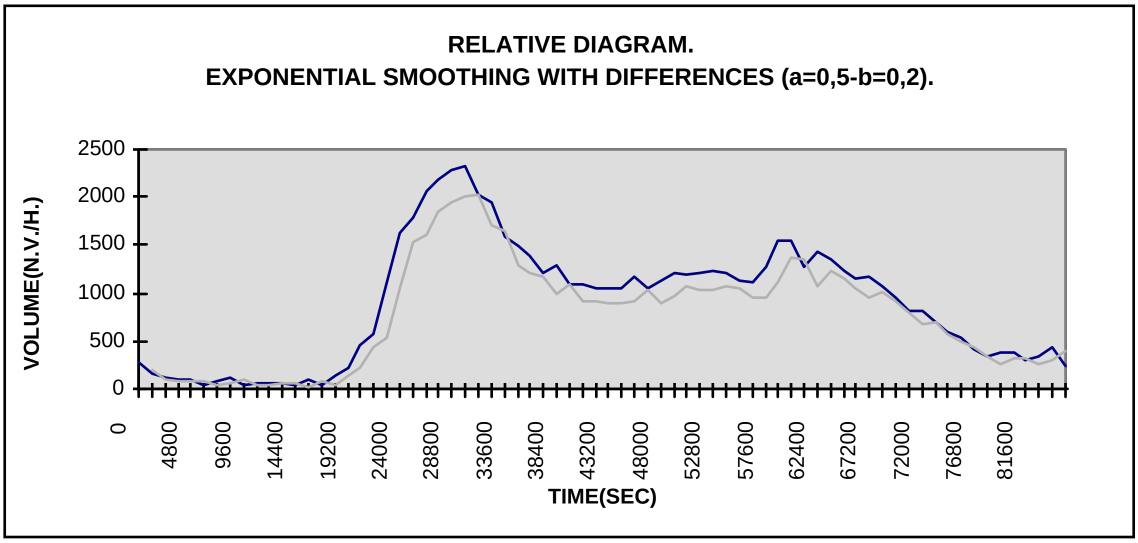
TIME(SEC)


RELATIVE DIAGRAM.
EXPONENTIAL SMOOTHING WITH DIFFERENCES (a=0,5-b=0,2).
VOLUME(N.V./H.)
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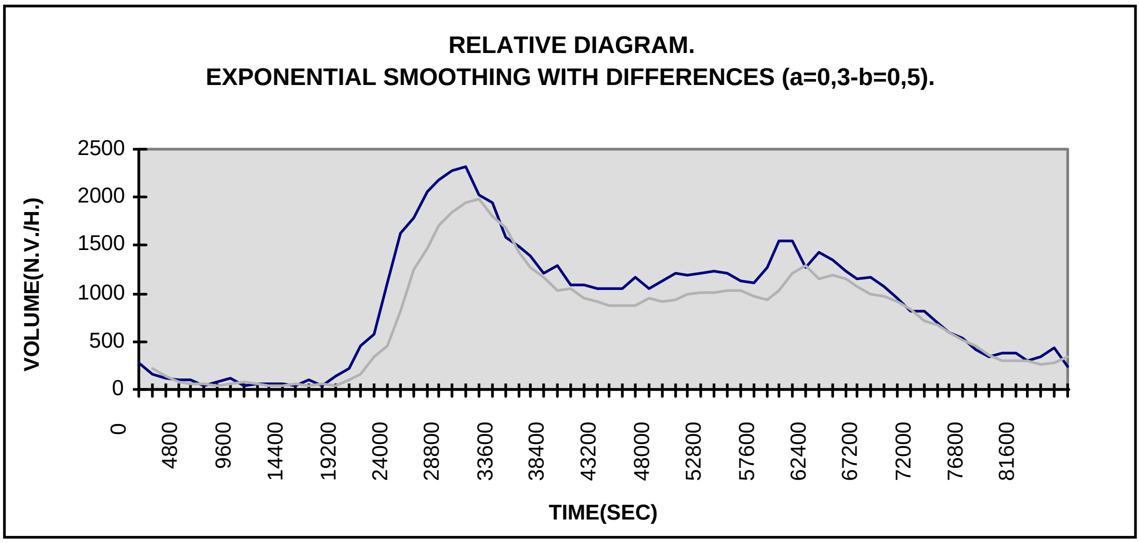
TIME(SEC)


RELATIVE DIAGRAM.
EXPONENTIAL SMOOTHING WITH DIFFERENCES (a=0,3-b=0,5).
VOLUME(N.V./H.)
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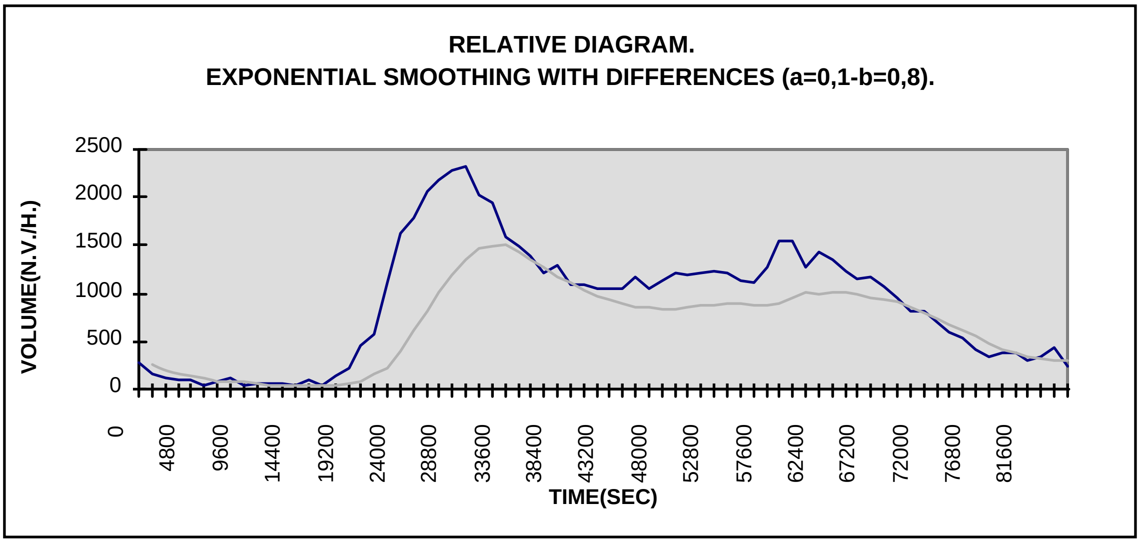
TIME(SEC)


RELATIVE DIAGRAM.
EXPONENTIAL SMOOTHING WITH DIFFERENCES (a=0,1-b=0,8).
VOLUME(N.V./H.)
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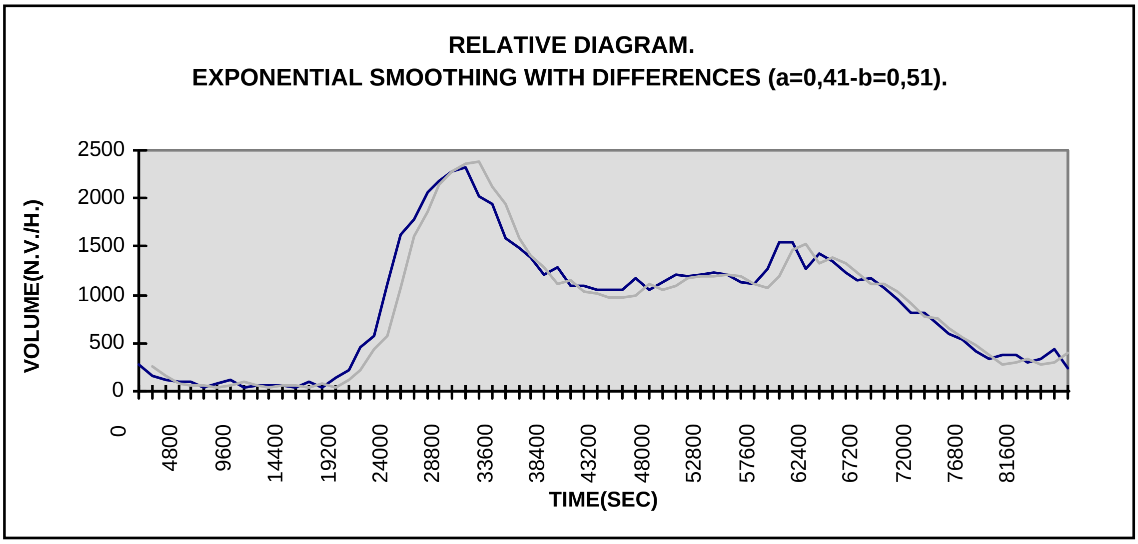
TIME(SEC)


RELATIVE DIAGRAM.
EXPONENTIAL SMOOTHING WITH DIFFERENCES (a=0,41-b=0,51).
VOLUME(N.V./H.)
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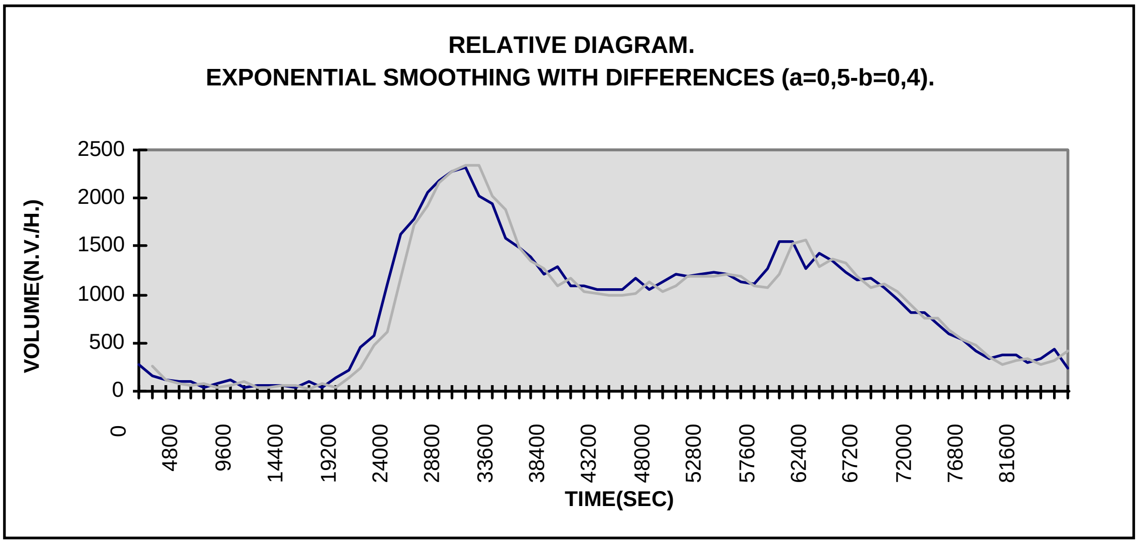
TIME(SEC)


RELATIVE DIAGRAM.
EXPONENTIAL SMOOTHING WITH DIFFERENCES (a=0,5-b=0,4).
VOLUME(N.V./H.)
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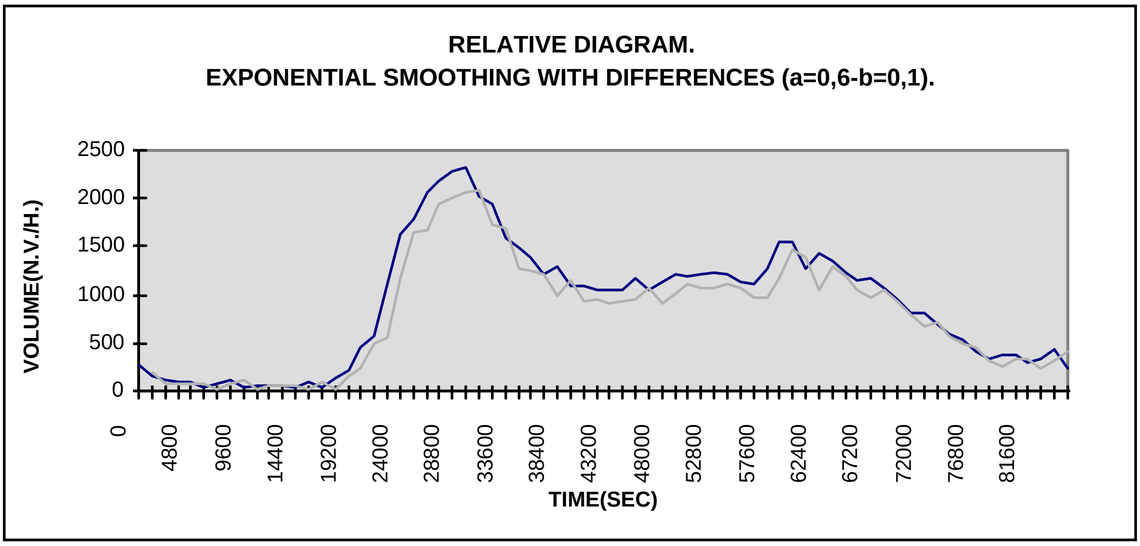
TIME(SEC)


RELATIVE DIAGRAM.
EXPONENTIAL SMOOTHING WITH DIFFERENCES (a=0,6-b=0,1).
VOLUME(N.V./H.)
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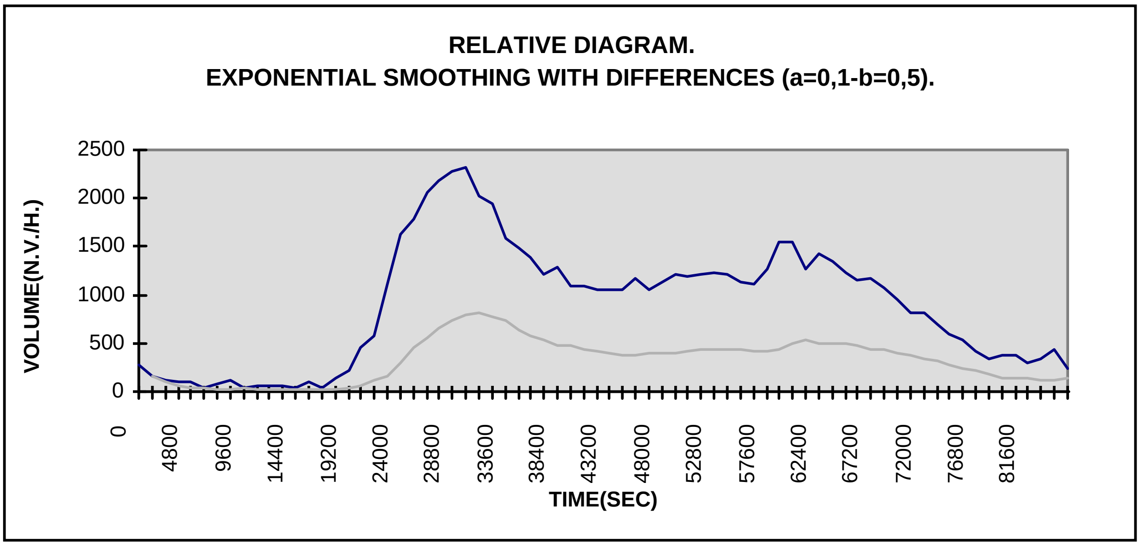
TIME(SEC)


RELATIVE DIAGRAM.
EXPONENTIAL SMOOTHING WITH DIFFERENCES (a=0,1-b=0,5).
VOLUME(N.V./H.)
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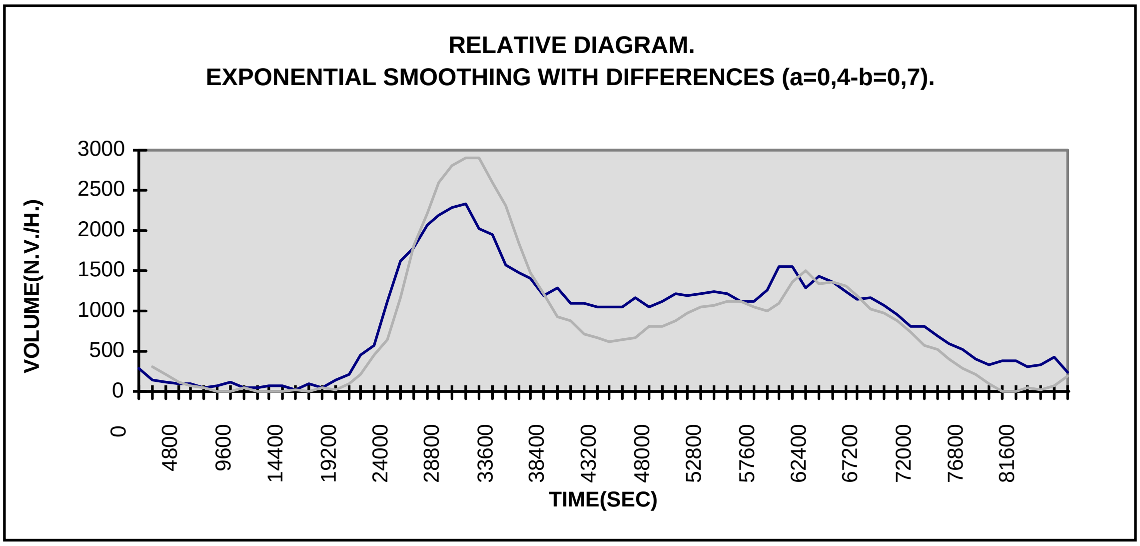
RELATIVE DIAGRAM.
EXPONENTIAL SMOOTHING WITH DIFFERENCES (a=0,4-b=0,7).
VOLUME(N.V./H.)
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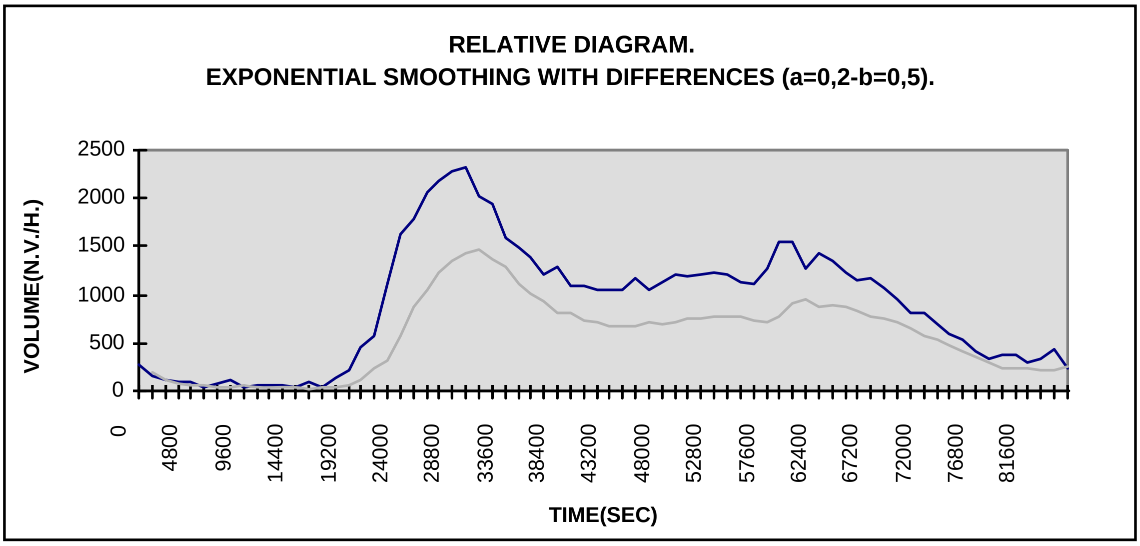
TIME(SEC)


RELATIVE DIAGRAM.
EXPONENTIAL SMOOTHING WITH DIFFERENCES (a=0,2-b=0,5).
VOLUME(N.V./H.)
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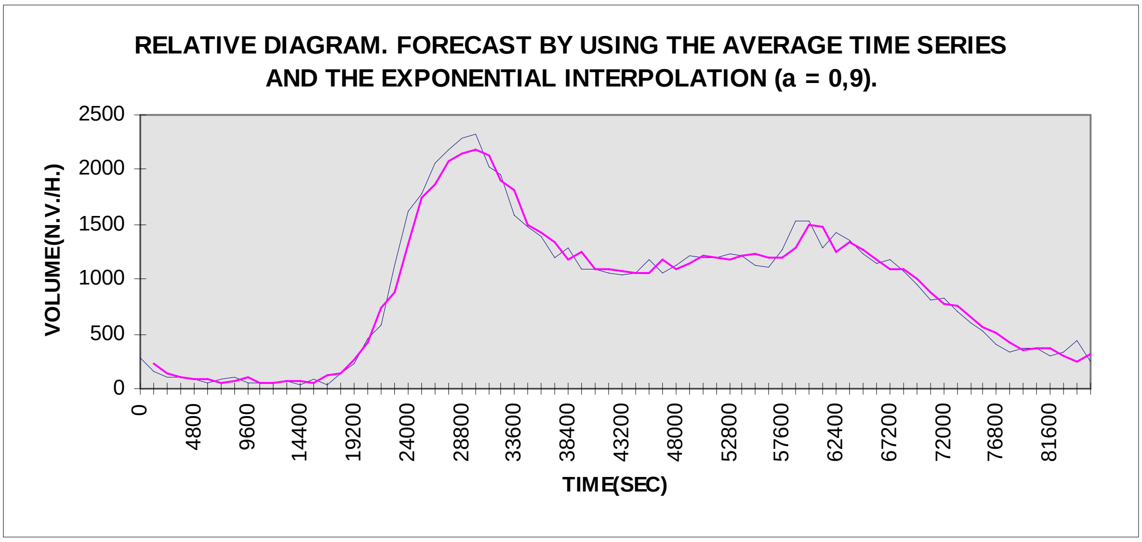
TIME(SEC)



RELATIVE DIAGRAM. FORECAST BY USING THE AVERAGE TIME SERIES
AND THE EXPONENTIAL INTERPOLATION (a = 0,9).
VOLUME(N.V./H.)
TIME(SEC)
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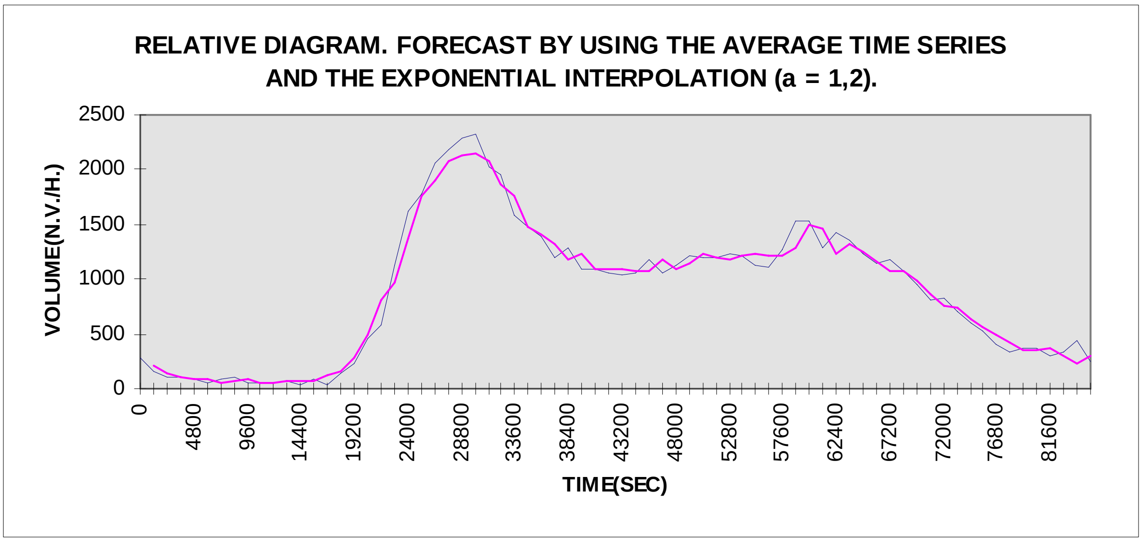

RELATIVE DIAGRAM. FORECAST BY USING THE AVERAGE TIME SERIES
AND THE EXPONENTIAL INTERPOLATION (a = 1,2).
VOLUME(N.V./H.)
TIME(SEC)
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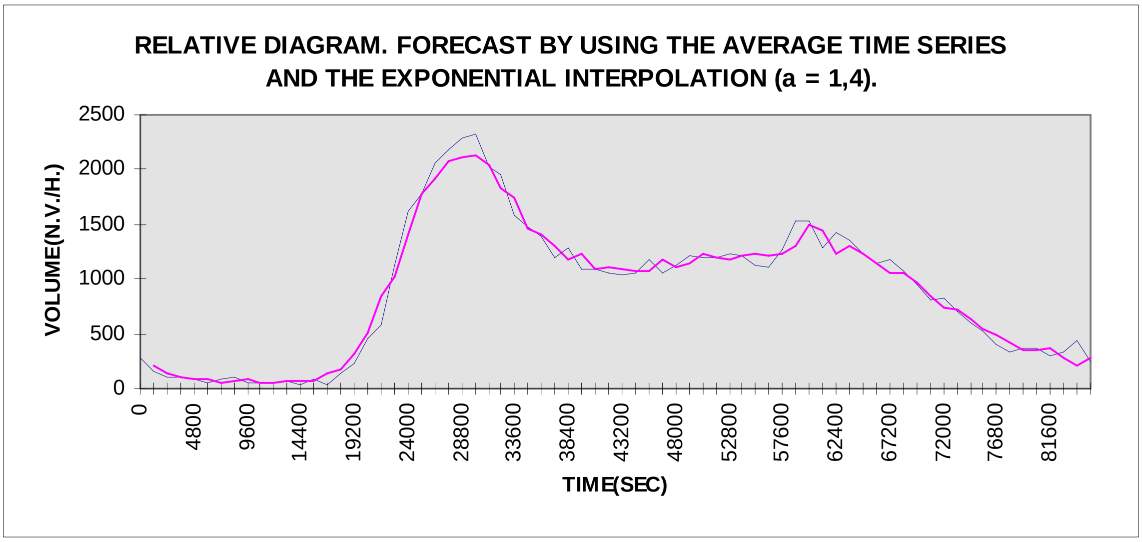

RELATIVE DIAGRAM. FORECAST BY USING THE AVERAGE TIME SERIES
AND THE EXPONENTIAL INTERPOLATION (a = 1,4).
VOLUME(N.V./H.)
TIME(SEC)
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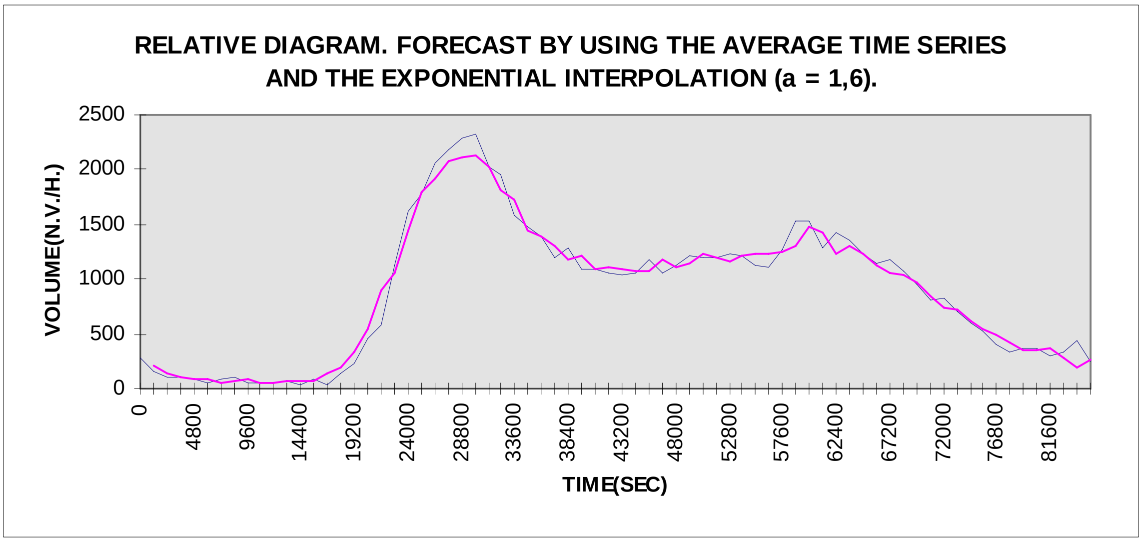
RELATIVE DIAGRAM. FORECAST BY USING THE AVERAGE TIME SERIES AND THE EXPONENTIAL INTERPOLATION (a = 1,6).
VOLUME(N.V./H.)
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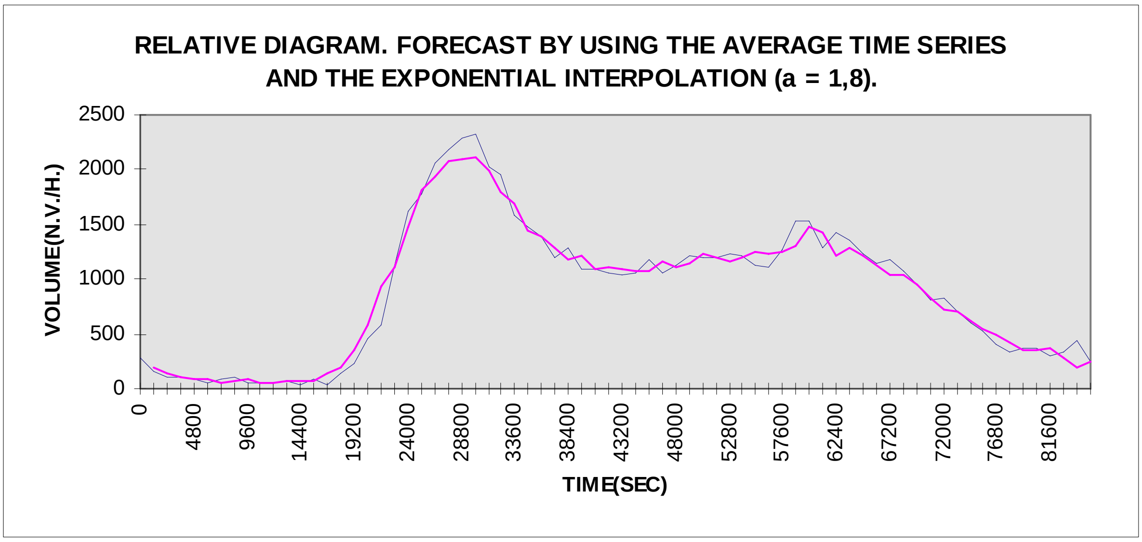
TIME(SEC)


RELATIVE DIAGRAM. FORECAST BY USING THE AVERAGE TIME SERIES AND THE EXPONENTIAL INTERPOLATION (a = 1,8).
VOLUME(N.V./H.)
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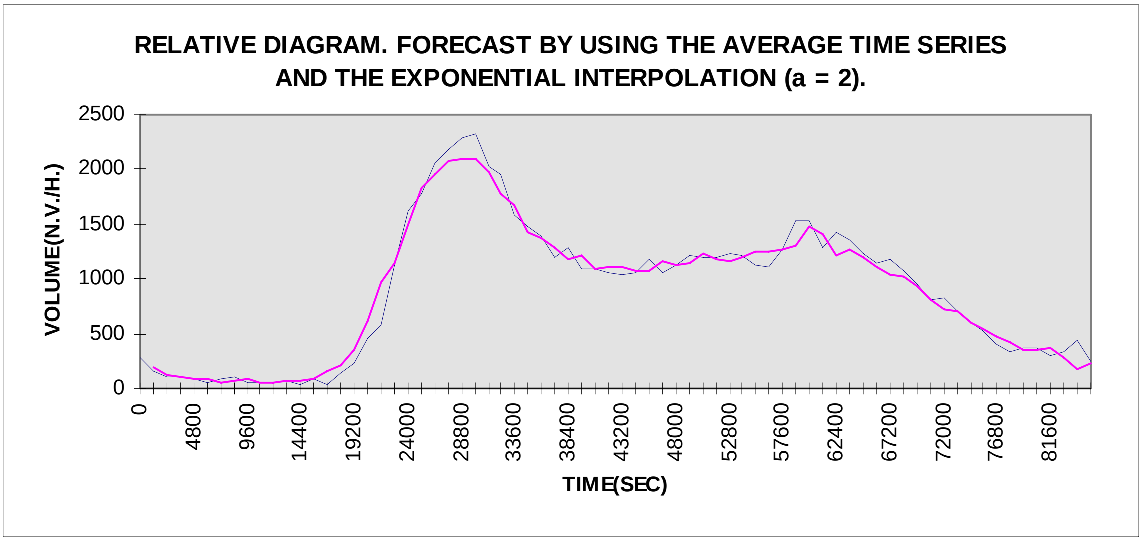
TIME(SEC)


RELATIVE DIAGRAM. FORECAST BY USING THE AVERAGE TIME SERIES AND THE EXPONENTIAL INTERPOLATION (a = 2).
VOLUME(N.V./H.)
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81600
TIME(SEC)

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GLOSSARY

1. **Traffic Volume**: The number of vehicles that pass through a road cross section in a define time interval is called traffic volume for the tested cross section and the tested time interval.[4]
2. **Traffic Density**: Traffic density is defined as the number of vehicles that travel in a specific time instate divided by the unit of length (normally is 1 kilometer) [4].
3. **Occupancy**: Occupancy is defined as the time that the measuring site area is occupied by a vehicle [4].
4. **Cycle time**: Cycle time is the time duration which is required for the complete traffic lights sequence [4].
5. **Inductive loop detectors**: Inductive loop detectors are detectors that measure the changes of the magnetic field caused by vehicles. Wire is placed in slots cut into the pavement and brought back to an amplifier/detector in the control cabinet [8]. They are easy to install and they cause small wear on the road surface.
6. **Double loop detectors**: Double loop detectors are used to measure high good vehicles. They are two sequential inductive loop detectors. They are described as the above inductive loop detectors.
7. **Harmonized average value**: The harmonic average is the reciprocal of the arithmetic average of reciprocals. The equation for the harmonic mean is:

$$\boxed{\frac{1}{H_y} = \frac{1}{n}\sum \frac{1}{y_i}}$$

   where H_y is the harmonic average,

   n is the number of values,

   y_i are the values which the harmonic average is estimated.

8. **Analysis Horizon (Area)**: Analysis horizon is the time area $t_a<t<0$ where the real measurements are collected and the estimated values are calculated.
9. **Prognosis Horizon (Area)**: Prognosis horizon is the time area $0<t<t_p$ where the calculated forecast values lie.
10. **Recurring congestion**: Recurring congestion is caused by combined effect of heavy traffic volume and inadequate capacity. This type of congestion is predictable and follows well defined temporal and spatial patterns [11].

Σχόλιο [NA1]:

11. **Non Recurring congestion**: Non recurring congestion is caused by traffic incidents which are unplanned physical obstructions or events occurring randomly in time and space, such as accidents, spilled cargoes, disabled vehicles, and debris on the road, which reduces the road capacity and creates perturbation in the traffic [11].