Statistics Netherlands

Discussion Paper

Traffic intensity as indicator of regional economic activity

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Index

Summary

In this study it is shown that it is possible to construct indicators of regional economic activity based on local traffic intensity data. Sensor readings on traffic flow from the NDW database were used to construct a monthly indicator of traffic intensity in the Eindhoven region. Some filtering was necessary to remove noise and to construct an indicator focused on economic activity. The Eindhoven region is a useful test case as it is focused on manufacturing. This means that business cycle indicators from the manufacturing industry survey can be used as a benchmark. The similarity and correlation between the survey data and the concept traffic intensity indicator were high, proving the link between traffic intensity and economic activity. Using the concepts developed here, it should be possible to construct fast and reliable indicators of local economic activity for many regions in the Netherlands.

Keywords

Traffic data, regional economic indicators, business cycle analysis, big data

1. Introduction

The importance for the economy of a good transportation infrastructure has long been acknowledged. However, there is another interesting link between transport and economic growth. Transport has become intimately connected to economic activity. It is not only anymore about the transport of commodities and finished goods, people also travel to get to work, clients and suppliers need to be visited.

Since 2005, the US Bureau of Transportation Statistics publishes a monthly transportation services index (TSI), now stretching back to 1979. It is based on a survey of both physical quantities transported and turnover of transportation services firms[Lahiri et all. (2003)]. It concerns the development of commercial transport, and does not relate to traffic flow measurements. Data on transport by road, rail, air, water and pipelines are collected. These are then combined into two separate indices, once concerning freight transport and another concerning passenger transport. These are then aggregated into the overall TSI. The relevancy here is that this transport services index has been shown to have a clear and strong relation with economic activity in the US. Lahiri et all. (2003) find that the TSI reliably identifies peaks and troughs in the US Business Cycle, with a lead of about 6 months. They also conclude that the freight index has a stronger link to the business cycle than the passenger transport index, and is therefore the more reliable indicator. Lahiry and Yao [2012] consider the usefulness of the transport services index for the US index of coincident economic indicators. They find a good coherence between the historic business cycle chronology and the TSI evolution. In their analysis, the TSI actually performs better than several of the current indicators included in the coincident index. Including the TSI would enhance the performance of the index of coincident indicators, not in the least as it suffers less from revisions than some other economic indicators.

These results indicate a potential important role of traffic data as an economic indicator. In the Netherlands, an extensive network for the monitoring of road traffic is in place. Different government entities have placed sensors to monitor traffic flow relevant to them, such as the state highway agency, provinces, and municipal governments. An important initiative was started to collect all these data in a central database, the NDW, to enhance their value by completeness and to make the data accessible to a wider audience. Thus it contains traffic flow data from highway sensors, but also from provincial roads, commercial parks and inside cities. Also, efforts keep being made to include more sensors in the database, thus extending its coverage. The database used to contain mainly data from the densely populated western part of the country, but now covers sensors in most of the country. All this means that the data in the NDW database are able to give a fine grained picture of road transport activity in the Netherlands.

This is what makes it valuable for this study. A countrywide road transport index would make a fine business cycle indicator for the whole economy, potentially even a leading one. However, using the data from individual sensors in a certain area, it is possible to construct local indicators of transport activity. The thesis here is that these can then be used as indicators of local economic activity. This would be highly valuable, as relatively little information is available on regional economic developments, certainly in the short term. Different parts of the country have different economic structures, and can therefore be expected to react differently to general business cycle developments. A fast and reliable regional indicator of economic activity would be of great use for policymakers and local firms alike. Traffic flow data have the potential to fulfil that role. They become available almost instantaneously, if that would be desired, and they are “hard” data, i.e. count data of real events. The link to economic activity is intuitive. And also very important, there are no revisions to traffic flow data, it gives an immediate final estimate.

This study will take the Eindhoven region in the south of the Netherlands as a test case. There are several reasons for this. The amount of data is just too large to do a proof of concept on the whole of the country. The Eindhoven region is not only geographically well defined (no overflow into another urban area), but also has an economic structure which is highly focused on manufacturing. This means that outcomes form the manufacturing industry survey, which asks firms about turnover development and expectations of other aspects of business, can be used as a benchmark for testing the plausibility of the regional traffic flow data as a regional economic indicator. This would be less clear cut for a region with a more mixed economic structure, for example with a large central government presence. If the Eindhoven case shows that there is a clear link between local traffic intensity and economic activity, it becomes plausible that traffic intensity indicators for other regions should be credible and useful indicators of local economic activity.

2. Data

The data used in this study were obtained from the National data warehouse for traffic information (NDW, www.ndw.nu). The aim is to collect data from all government road traffic monitoring operations in the Netherlands. It thus contains data from sensors on highways (A-roads), provincial roads (N-roads) and urban road networks (B-roads). This extensive coverage means that all types of traffic are captured, and different selections for different uses can be made. Unfortunately for the purpose of economic analysis, the database goes back only to 2010 or later for most sensors.
There are different types of sensors, which yield different types of information. However, all register vehicle flows, the number of vehicles passing per minute, average speeds, and travel times between sensors. The classic traffic sensor, a detection loop in the road, tends to be older and just registers the passing of a vehicle. Newer sensors tend to be camera’s, which also give information on vehicle type. There are 3-class sensors and 5-class sensors, which can distinguish the following types, based on detected vehicle length:

Table 1; Detection categories 3-class traffic sensor

Category	Description	Detection length
1	Motorbikes, cars, vans	<5.6m
2	Single lorries, busses	>5.6m - <12.2m
3	Articulated lorry	>12.2m

Table 2; Detection categories 5-class traffic sensor

Category	Description	Detection length
1	Motorbikes	>1.85m - <2.4m
2	Cars and vans	>2.4m - <5.6m
3	Single lorries	>5.6m - <11.5m
4	Busses	>11.5m - <12.2m
5	Articulated lorry	>12.2m

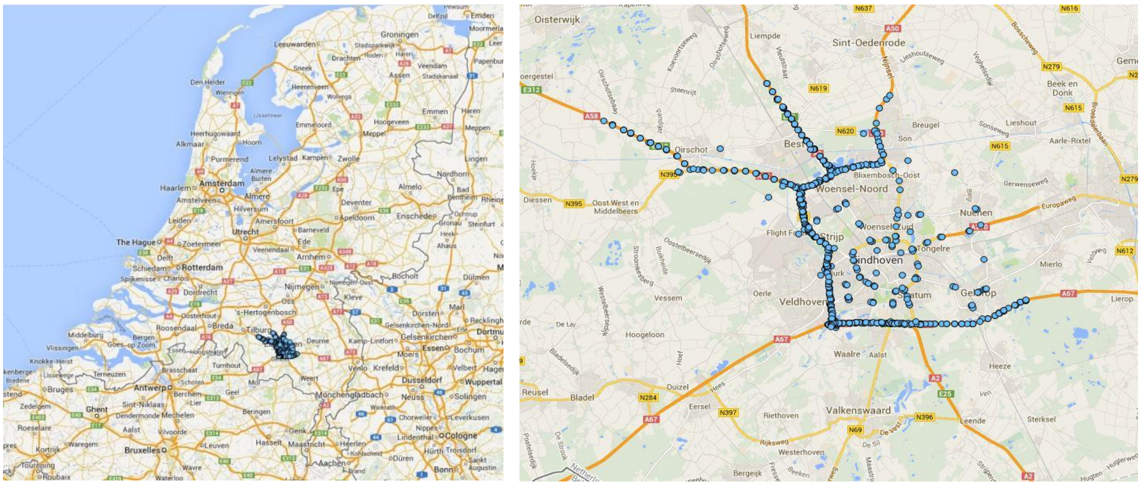
This distinction can be very useful for tailoring the data for monitoring specific types of activity, however the majority of sensors is still of the single class type.
The NDW files contain a lot of information per sensor, the NDW-data format contains 47 fields. A lot of those concern quality control or data not relevant for this study. Here, the following fields were selected:

Table 3; Selected fields from NDW data

field	Description
periodStart	Start of measurement period (YYYY-MM-DD hh-mm-ss)
periodEnd	End of measurement period
vehicleFlow	No. of vehicles passing per minute
measurementSiteNumberOfLanes	Number of lanes
measurementSide	Direction
specificLane	Lane number
specificVehicleCharacteristics	Length class
locationForDisplay_latitude	Latitude
locationForDisplay_longitude	Longitude
LOC_DES	Junction/fork/through
ROADNUMBER	Roadnumber (i.e. A2 etc.)
ROADNAME	Name

This constitutes already a serious data reduction, which is quite important as the total size of the dataset is rather large. The study concerns itself with the Eindhoven region, defined as the 4-digit postal code region starting with 56**. Using the R GEO-package, the relevant traffic sensors were selected by their GPS coordinates. Figure 1 shows the locations of the sensors around Eindhoven.

Figure 1; Positions selected traffic sensors, in and around Eindhoven



As every combination of location, direction, lane and vehicle class is registered as a separate “sensor” in the NDW data file, the total for the Eindhoven region comes to 662. Quite a few of these are not always active, or not for the whole period, so in practice the number of sensors used in the computations lies somewhere between 200 and 300.

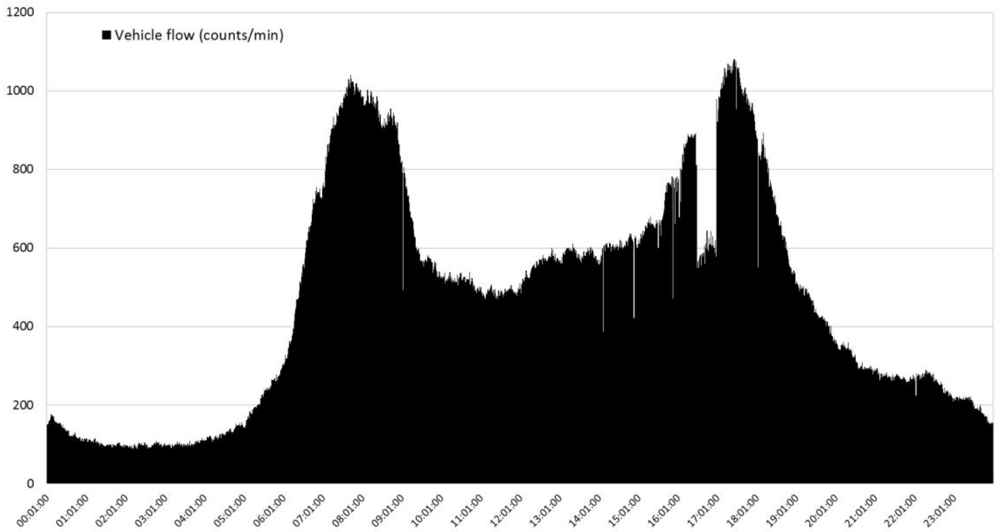
The focus in this study is on the link between economic activity and traffic intensity, i.e. the number of vehicles on the road. Therefore the vehicle flow (i.e. the intensity measure) is the measurement of interest. Average speeds and travel times are less relevant, and were ignored. To ensure control over data integrity and for accurate filtering, it was necessary here to use registrations of vehicle flow on a minute by minute basis. Therefore, the period between period start and period end is one minute, and either one can be used as time stamp.
This means that the size of the total dataset is rather large, even though only one region is considered and the data cover only three years, from 2011 to the beginning of 2014. The original data downloaded from NDW consisted of 3565 csv-files, amounting to about 1TB of data. On the whole, this is a huge data destruction exercise, going from 3565 files and 1TB via an intermediate 36 files amounting to about 50 mB to 1 time series of only a few kB.

3. Methodology & Results

3.1 Exploratory analysis

The first phase of the research consisted of an explanatory study using minute by minute data average vehicle flow of a single day in the Eindhoven area. A simple minute average of all vehicle types over all road types for all sensors was computed, without any filtering. The results are shown in graph 3.1, and immediately a number of interesting features are visible.

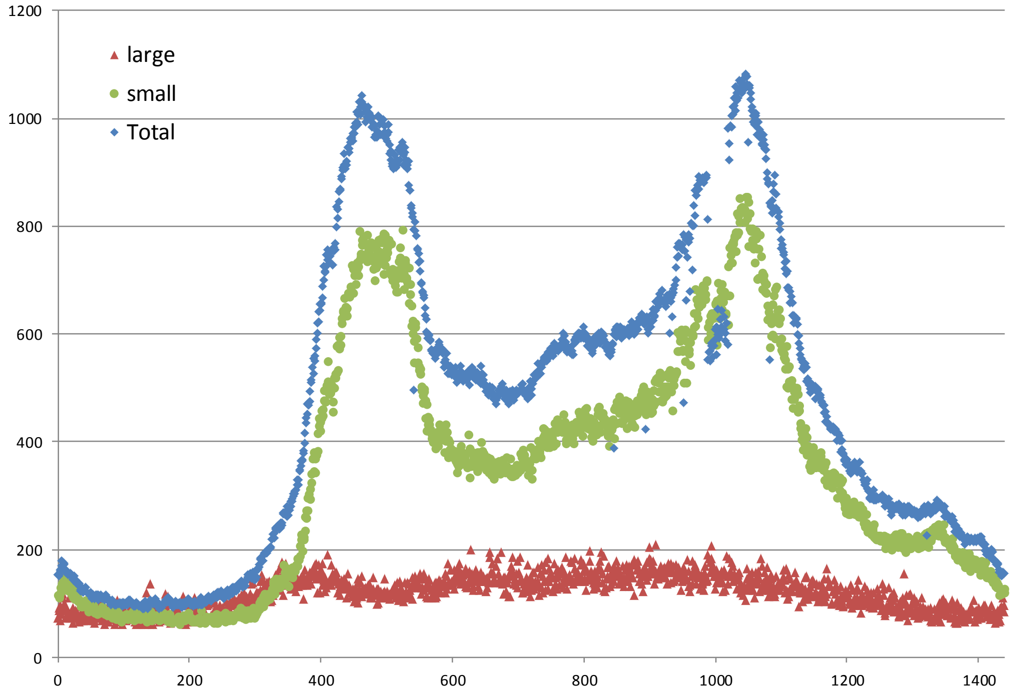
Graph 3.1 ; Average vehicle flow intensity per minute in Eindhoven region on Tuesday January 14th .



There are two distinct peaks in traffic intensity, one relating to the morning rush hour, the other to the evening one. Also, the data can be rather noisy, with sudden temporary drops in intensity which are virtually for certain connected to measurement errors. These can be of several different types. Individual sensors can (temporarily) be out of commission, data transmission for one or a group of sensors can fail, or data registration for one or a group of sensors can fail, for shorter or for longer periods. The sudden and more lasting drop in intensity between 16.00 and 17.00 can be due to either a traffic jam or a group sensor problem. These are all things which need to be taken into account when designing the data processing methodology.

By making a number of different selections, the data can be further explored. An interesting option is to investigate whether the different vehicle classes have different patterns in time. This is potentially very relevant, as focusing on one type of vehicle class can yield both more relevant results (for example only busses & lorries) and yield a data reduction. Graph 3.2 compares registered vehicle intensities for small (cars) with those of large ones (lorries and busses).

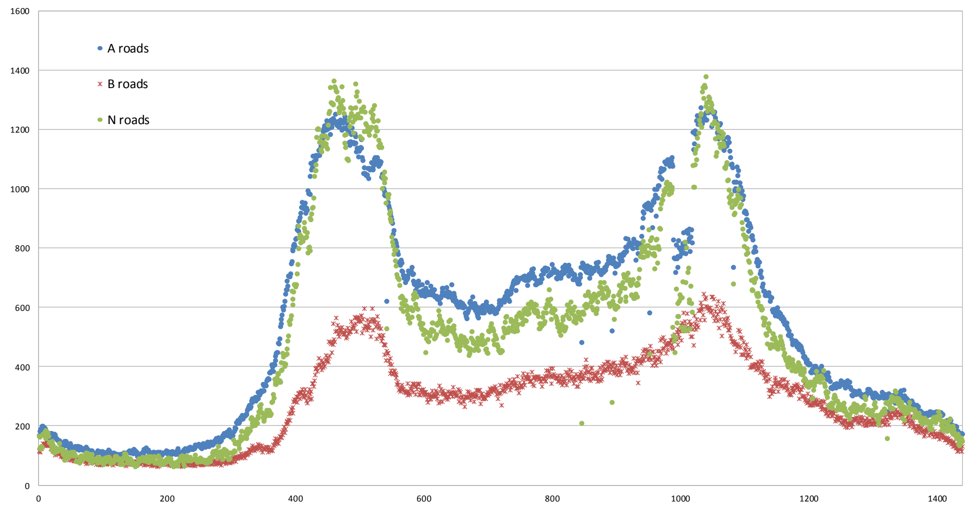
Graph 3.2; Average vehicle flow intensity per minute in the Eindhoven region on Tuesday January 14th separated according to vehicle type (small= class 1 or 1+2,large=class 2+3 or 3+4+5)



What immediately becomes clear is that the registered intensity of large vehicles is much smaller than for small vehicles. Connected to this, the data for that class are also much noisier. What barely can be seen is that the peaks during the day for large vehicles tend to lead those of small ones. Overall, the safest choice seems to be to include all vehicle types in the analysis, thus resulting in the most representative results. Also, the majority of the sensors is not yet able to distinguish between vehicle classes.

A second analytical option is to consider the potential difference in pattern between different road types. Urban (B) and provincial (N) roads will contain more local traffic, whilst highways (A) will also contain a fair share of passing traffic. Graph 3.3 shows that patterns during the day are roughly comparable for all road types, though the rush hour peaks seem to be more pronounced in the A and N-road traffic flows. Another important observation which can be made here is that the flow data from the A-roads is less noisy that those of the B and N-road sensors, a not unimportant characteristic.

Graph 3.3; Average vehicle flow intensity per minute in Eindhoven region on Tuesday January 14th separated according to road type (A=highway ,N=provincial, B=urban)



3.2 Data processing methodology

Based on the conclusions drawn from the preceding analysis, the following data processing methodology was devised:

1.Use minute data.
2.Select the A-road sensor data.
3.For each day, remove all sensors which register 0 intensity for more than 20% of the day.
4.Sum over all vehicle class intensities and compute an average over all lanes per sensor per direction.
5.Remove all data from Saturdays and Sundays
4.Use a Butterworth filter to remove the noise. Perform this data cleaning on a per day and per sensor basis.
5.Focus on rush-hour data, i.e. use only observations between 7.00 and 9.00 and 16.00 and 18.00.
6.Compute the daily average over all sensors
7.Compute a monthly average to arrive at the final indicator

There were two main considerations which lead to the process described above; the need to correct for faulty sensors and noise, and the need to reduce the size of the dataset as soon as possible. The second reason is not trivial, even using the power of the R data.table package, processing the data only for this one region took three full days (72 hours) on a 2.6 GHz 8-core processor with 64 GB RAM. I will give a short explanation as to the considerations which lead to each step.

1. Use minute data.

Only working with minute registrations gives one full control over the data

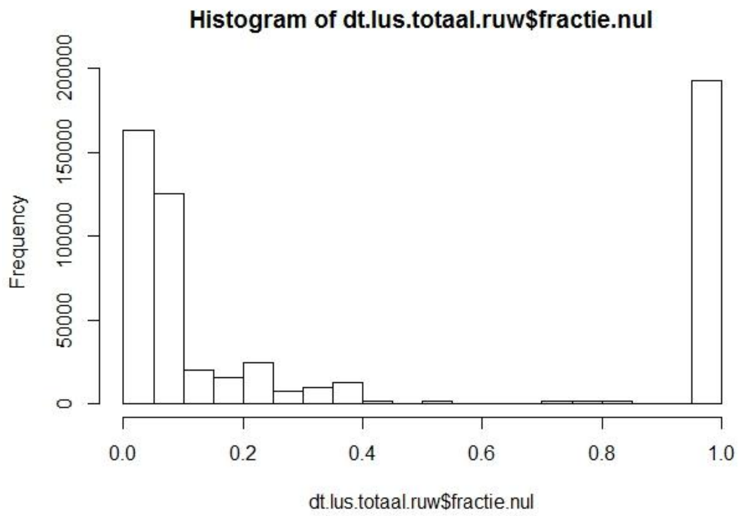
2. Select the A-road sensor data.

This is a data reduction decision. The A road data seemed to be the least noisy. Focusing on N and B roads could result in more locally relevant data.

3.For each day, remove all sensors which register 0 intensity for more than 20% of the day.

As graph 3.4 shows, there is a significant number of sensors which register 0 during the whole or a large part of the day. These are either defective sensors, or sensors which are in the registry but not present or transmitting data on the specific data considered. Removing these leads to a significant reduction in noise and more realistic esimates.

Graph 3.4 Histogram of the number of sensors registering 0 for different fractions of the day over a 10-day period.



4.Sum over all vehicle class intensities and compute an average over all lanes per sensor per direction.

Data reduction is necessary to arrive at the final estimates.

5. Remove all data from Saturdays and Sundays

Traffic on working days will be much more relevant for tracking economic activity. It also diminishes the potential issues of registering traffic related to large public events (festivals e.d.) which tend to take place in the weekends.

4. Use a Butterworth filter to remove the noise. Perform this data cleaning on a per day and per sensor basis.

The Butterworth filter is a frequency filter, designed to have an as flat as possible frequency response. It was used here as a low-pass filter to remove some of the observation to observation noise of the individual sensors.

5. Focus on rush-hour data, i.e. use only observations between 7.00 and 9.00 and 16.00 and 18.00.

This step leads both to data reduction and more precise results. Traffic during rush hours is probably more singularly connected to economic activity than during the day or night.

6. Compute the daily average over all sensors

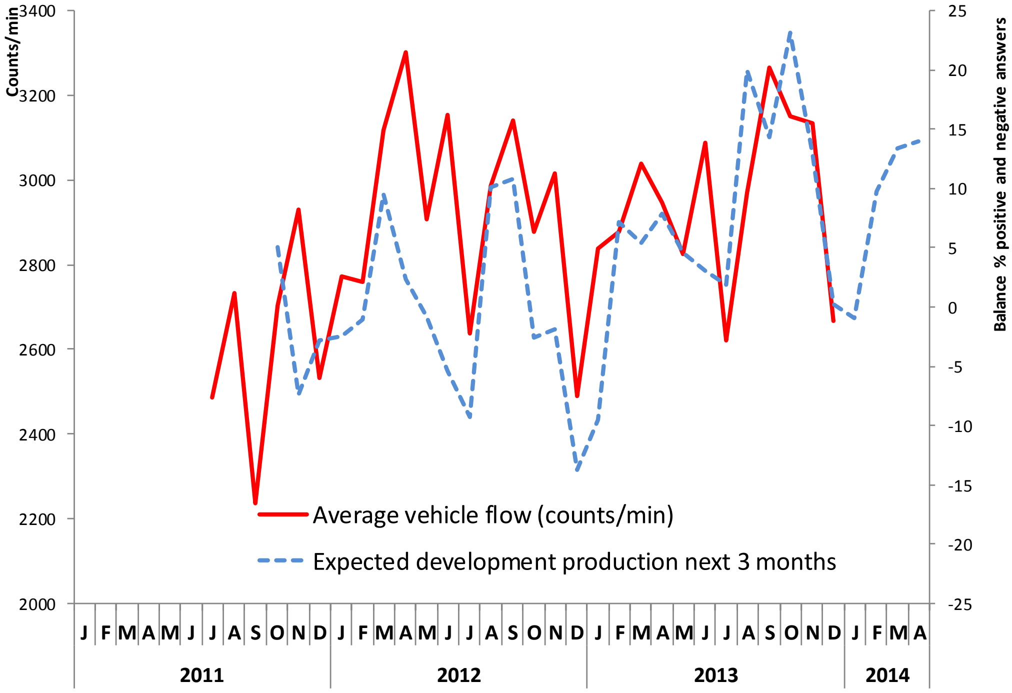
7. Compute a monthly average to arrive at the final indicator
Monthly averages are less noisy and robust than daily or weekly ones. The influence of days with traffic jams and other issues averages out or becomes smaller. And most reference economic indicators tend to be monthly as well. If more extensive filtering is employed (i.e. developing steps to identify days with large traffic jams etc. as outliers), weekly indicators are probably viable as well. Daily ones will probably be too volatile to be of much use.

3.3 Results – concept indicator

With the methodology described in the previous section, a concept traffic intensity indicator for economic activity can be computed. This is simply the monthly average computed in the final step of section 3.2. The next step is to assess the plausibility of this indicator; does traffic intensity contain relevant information on economic activity? To test this, a benchmark is necessary. Here data from the manufacturing sentiment survey will be used. These are known to be very good business cycle indicators, with a strong and proven relation to short-term economic developments. They are also relevant here for two other reasons. It concerns a survey of the manufacturing industry, and as stated before the Eindhoven region is a manufacturing hub. The survey outcomes are also available per province, and Eindhoven is the dominant region in the province of Noord-Brabant. This means that the data from this survey should have a strong connection to economic activity in the Eindhoven region. And graph 3.5 shows this to be the case.

The evolution of the traffic intensity indicator tracks that of expected production development, an important business cycle indicator, amazingly well. Peaks and troughs coincide, meaning that the traffic intensity index should be able to signal important turning points in economic activity. The close relationship between the two indicators is confirmed by the computed correlation, which is maximal at 0.56 at lag 0, meaning that the series are coincident . With some further processing, notably seasonal adjustment, the coherence between the two series can probably be improved even further. Another important option is to perform trend-cycle decomposition, which could improve focus on the business cycle component and remove some noise. Unfortunately, the traffic intensity series is too short at the moment for both types of filtering.

Graph 3.5; Monthly indicator of average rush hour vehicle flow in the Eindhoven area compared to expected production development in the manufacturing industry for the province of Noord-Brabant.



There might be a more direct filtering option to improve the results. There has recently been much development in the field of so-called blind source separation. This concerns the situation that one has a signal which is a mix of different signals, but there is no further knowledge about the sources or type of the component signals. The key technique for this is independent component analysis (ICA)[Hyvärinen and Oja (2000)]. The goal of independent component analysis is to split the signal into components which are as statistically independent as possible. This is in contrast to the more familiar principal components analysis, where the aim is to find common components which explain as much as possible of the variance of the data. Another difference is that ICA only works on non-Gaussian data. This is actually a fundamental property of ICA. The basic setup is that there are n observed signals x which are a mix of m independent source signals via a mixing matrix A.

$$x = As$$

The idea now is to find an unmixing matrix W which can be used to derive the original signals s from the observed data x:

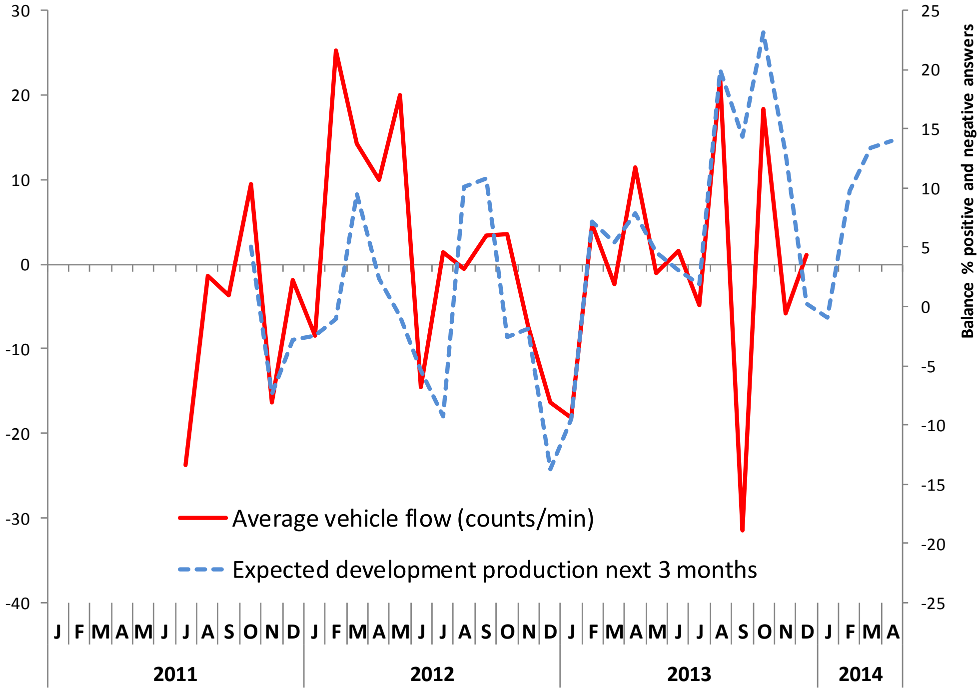
$$s = Wx$$

ICA now opens up a way to identify W. The underlying idea is that the central limit theory states that the distribution of an independent random variables tends towards a Gaussian distribution, irrespective of the distributions of the components. Thus, the sum of two independent random variables will be closer to a Gaussian distribution than the two separate distributions. The idea is now to find a method to decompose the signal by maximizing the non-Gaussianity of the resulting components. Options are to maximise kurtosis, minimise negentropy or minimise the mutual information. The first component extracted will be the strongest non-Gaussian, the next will be orthogonal to the first and so on. The FastICA algorithm, available in R, performs these calculations.

The problem is that ICA in principle requires the number of observed signals n to be larger than the number of sources m. When using aggregated vehicle flows per minute, there is only one signal. Fortunately, Mijovic et al [2010] offer a solution. They suggest creating artificial signals by splitting the original signal into separate modes. For this, they suggest using either wavelet analysis or empirical mode decomposition (EMD). They prefer the latter one, as it seems to have more separating power. EMD decomposes complex, single channel signals into oscillatory modes called IMF's . The algorithm automatically determines the number of IMF's, for details see Huang et al. [1998].

For the series of average vehicle flow intensities by minute, the EMD algorithm identified 10 oscillatory modes, see the graphs in appendix B. The 10 independent components which resulted from feeding these mode signals into the ICA algorithm can be found in appendix A. When looking at the components, it is clearly visible that these are not random artefacts. Some are noise, such as components 5, 6 and 9, but that is to be expected as the original series contains noise. Components 2,3,7 ,8 and 10 are clearly cyclical though, some with a trend component (3, 10), others representing daily cycles (8). Components 1 and 4 are very interesting, as they seem to identify the daily rush hour peaks. Identification of relevant components is done here by visual inspection. A more rigorous approach would be to use spectral analysis to identify the relevant ones. Here, components 1, 2, 3, 4, 7, and 10 were selected. These were back transformed to EMD modes, and then to a monthly indicator. This indicator is shown in graph 3.6.

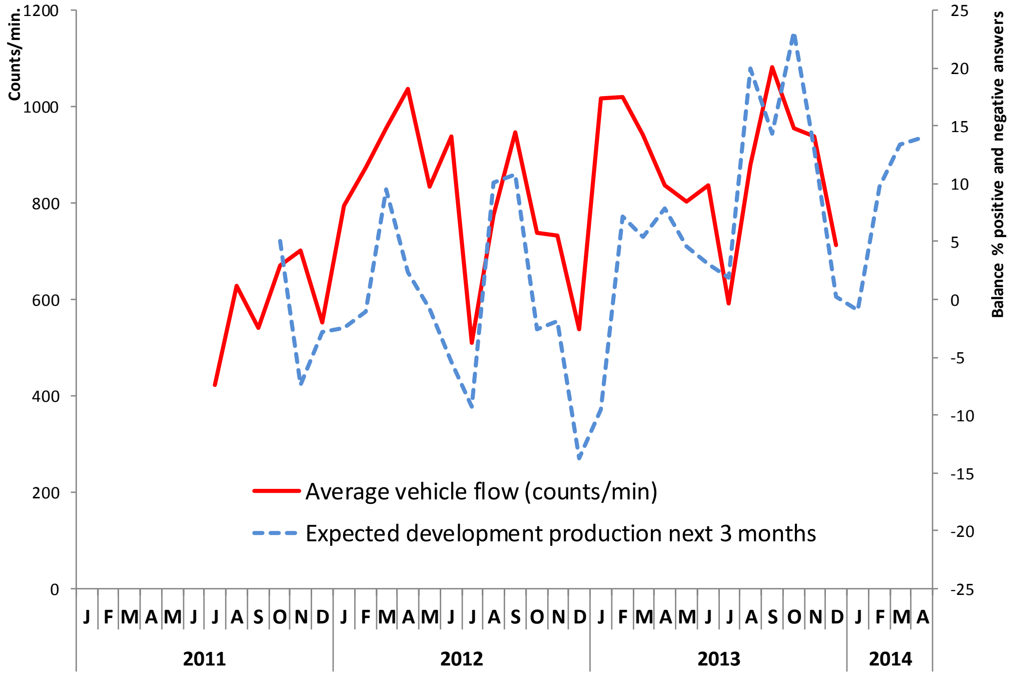
Graph 3.6; ICA-filtered monthly indicator of average rush hour vehicle flow in the Eindhoven area compared to expected production development in the manufacturing industry for the province of Noord-Brabant.



At first sight, this new traffic intensity indicator seems to track production expectations better, at least when considering the succession of peaks and troughs. Correlation however is lower than for the unfiltered indicator, at 0.386 (lag 0). Perhaps some fine-tuning of the ICA-process could remedy this, , Mijovic et al [2010] state that ICA is sensitive to noise and offer a solution, not implemented here.

Another option to improve the traffic intensity indicator is to use the EMD-algorithm to filter out the most relevant signal. Similar to the ICA selection, the most relevant EMD oscillatory modes were selected and turned into a monthly, rush hour based indicator. Modes 1, 2, and 5 (appendix B) were selected, and the resulting monthly indicator is shown in graph 3.7. This filtered indicator is smoother than the simple average one presented in graph 3.5, though correlation is a again a little lower at 0.523 (lag 0). A somewhat lower correlation is a price worth paying for a smoother and therefore more informative indicator.

Graph 3.7; EMD-filtered monthly indicator of average rush hour vehicle flow in the Eindhoven area compared to expected production development in the manufacturing industry for the province of Noord-Brabant.



4. Conclusions

Fast and detailed information on economic conditions and changes therein are ever more in demand. A notable desire is for more regional information, as economic developments tends to vary across a country. The economic structure of the Netherlands is certainly not homogenous geographically. Unfortunately, most regional economic indicators are either not available at high frequencies, or not detailed enough (e.g. relating to provinces or even groups of provinces).

Traffic data might help here. These are available at high frequency and with high geographical detail, for each region in the country. This study aimed to establish whether it would be possible to construct an indicator of regional economic activity based on local traffic intensity data. The link between transport activity and economic growth is well known. The question is whether "simple" traffic intensities at the regional level can yield a useful economic indicator.
The results in this study show that this is certainly the case. The region of Eindhoven in the Netherlands was chosen for a proof of concept. This region is a manufacturing hub, with a focused economic structure. It is also geographically well defined.

From the Dutch NDW database, traffic flow data per minute for all sensors in the Eindhoven region were downloaded. After several filtering steps, these were compiled into a monthly indicator of average traffic intensity in the region. The filtering steps were necessary to remove noise and data from defective sensors, and to focus on developments most relevant for economic activity. Only data from weekdays and during the rush hour periods were used, and the analysis was limited to traffic on highways (A-roads). But even this relatively simple methodology already resulted in a very good indicator. When compared to a benchmark business cycle indicator, the expected development of production in the manufacturing industry for Noord-Brabant, the traffic intensity indicator exhibited a remarkable similarity. Peaks and troughs in both series coincided, and correlation was respectable at 0.56. The coherence could probably be increased by the application of seasonal corrections, but unfortunately the series is too short for that. A longer time series would also allow for trend-cycle decomposition, which could further increase the relevancy for monitoring economic activity. Two advanced signal processing techniques, independent component analysis and empirical mode decomposition were tested here. These result in a smoother and more informative indicator, though at the cost of a small decrease in correlation with production expectations.

Another option for further research is to focus on sensor readings from provincial and urban roads, possibly enhancing the focus on local economic activity.

The overall conclusion is that local traffic intensity readings contain relevant and clear information on regional economic activity. The methodology described here could be applied to all regions in the Netherlands, leading to new potentially very useful information on economic developments.

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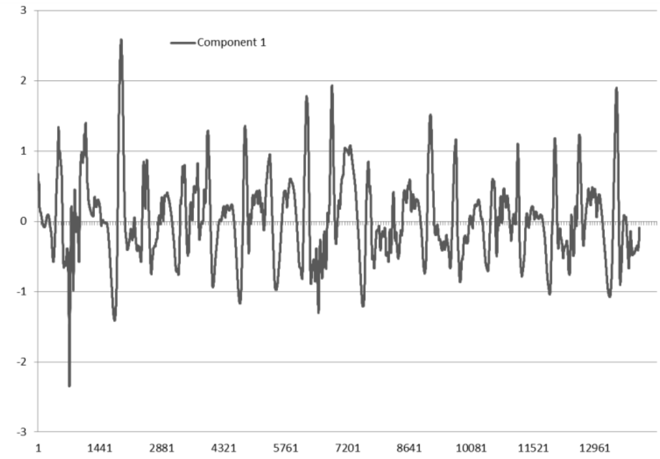
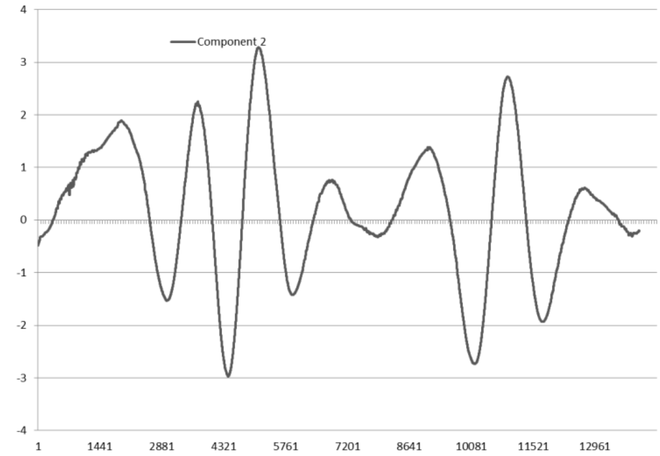
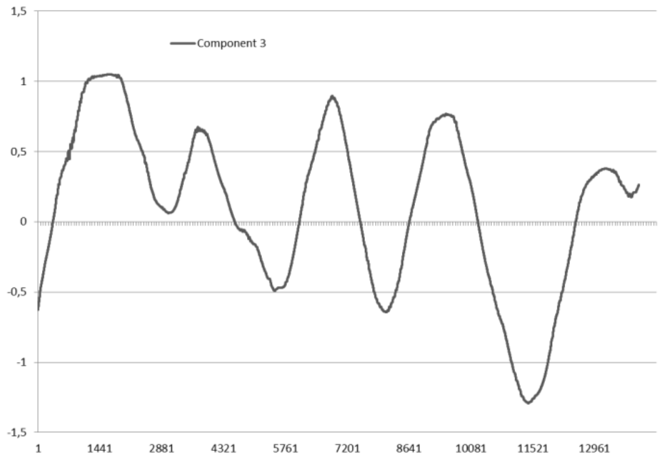
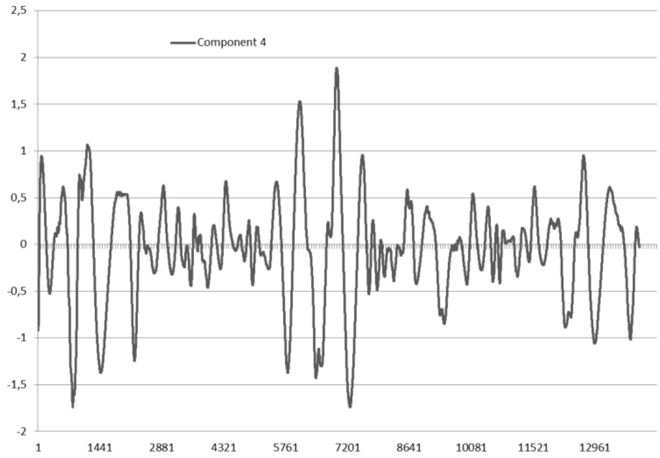
Appendix A

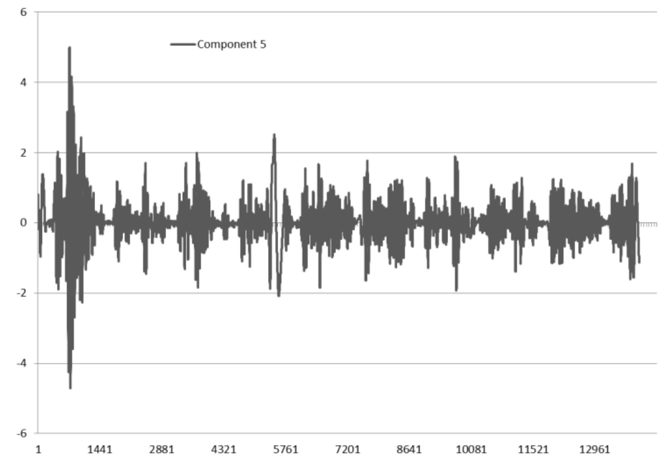
Graphs of components identified by ICA (10 day sample)








Component 4
2,5
2
1,5
1
0,5
0
-0,5
-1
-1,5
-2
1
1441
2881
4321
5761
7201
8641
10081
11521
12961


Component 5
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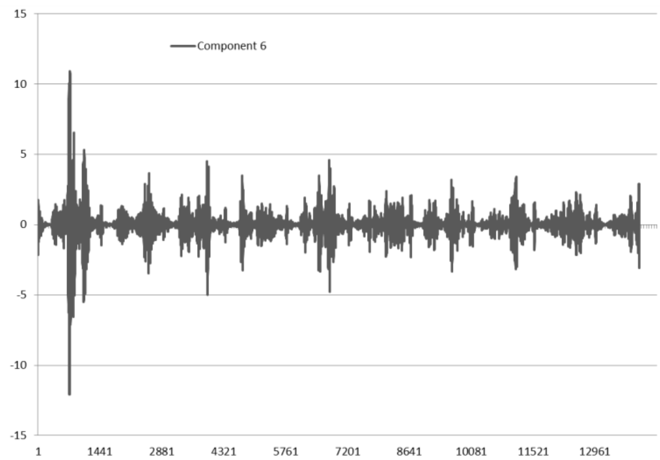
Component 6
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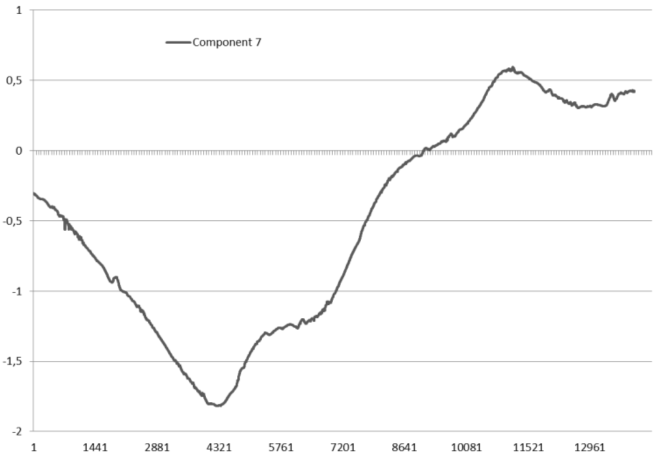
Component 7
1
0,5
0
-0,5
-1
-1,5
-2
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7201
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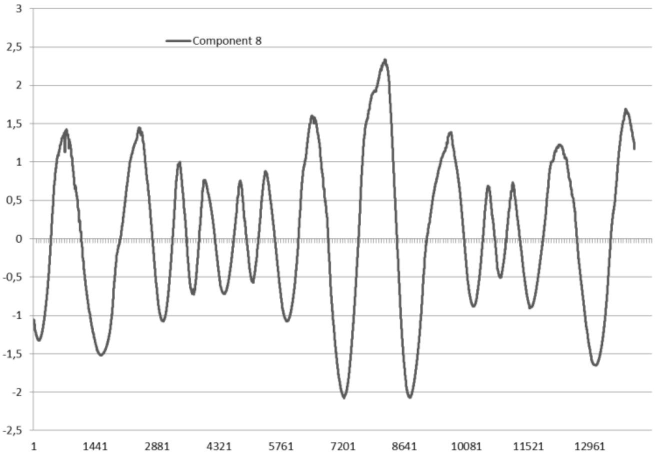
10081
11521
12961

Component 8
3
2,5
2
1,5
1
0,5
0
-0,5
-1
-1,5
-2
-2,5
1
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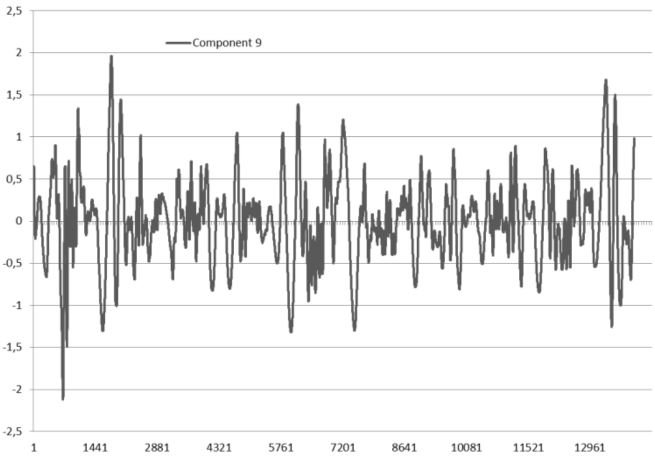
2881
4321
5761
7201
8641
10081
11521
12961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5761
7201
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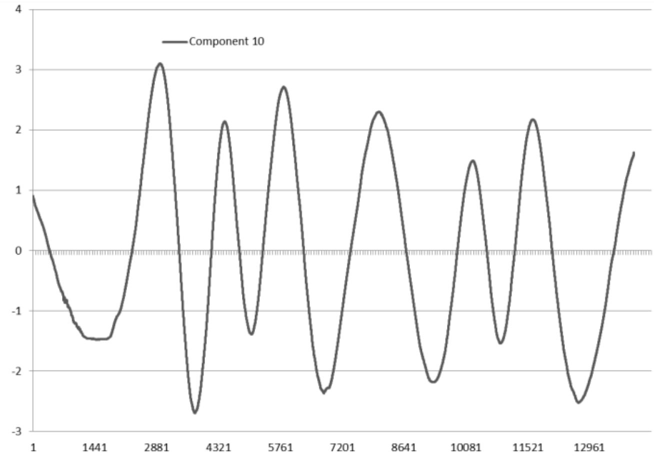
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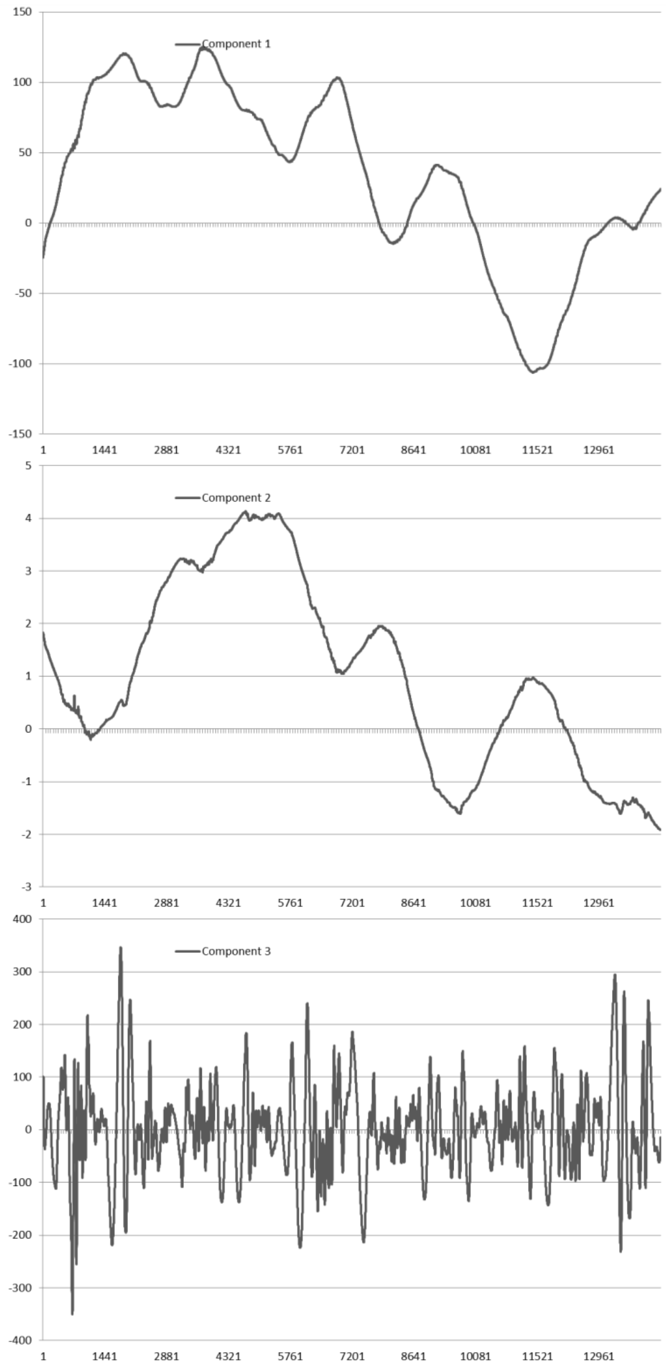
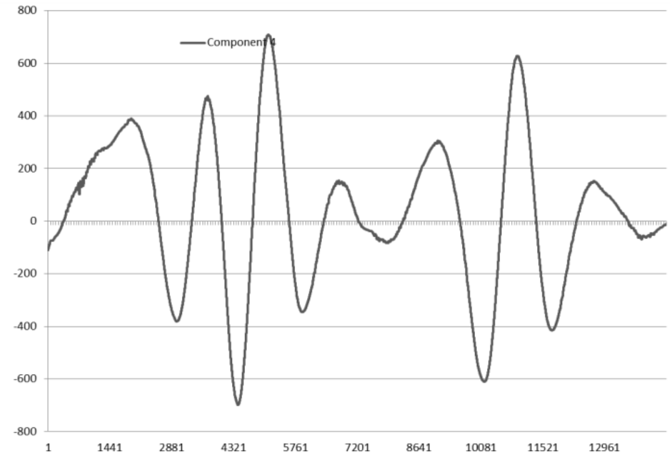
3
2
1
0
-1
-2
-3
1
1441
2881
4321
5761
7201
8641
10081
11521
12961

Appendix B

Graphs of modes from EMD analysis (10 day sample)

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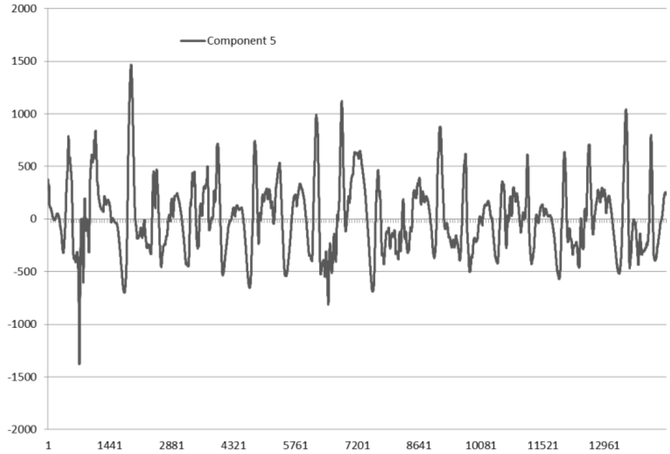
5761
7201
8641
10081
11521
12961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500
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1
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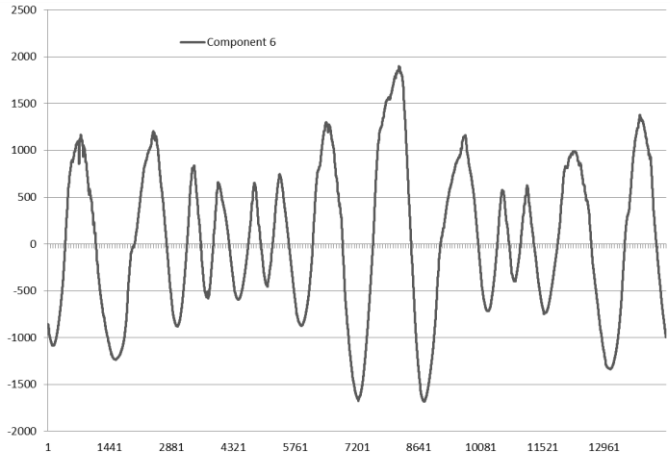
4321
5761
7201
8641
10081
11521
12961


Component 6
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1500
1000
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-1500
-2000
1
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2881
4321
5761
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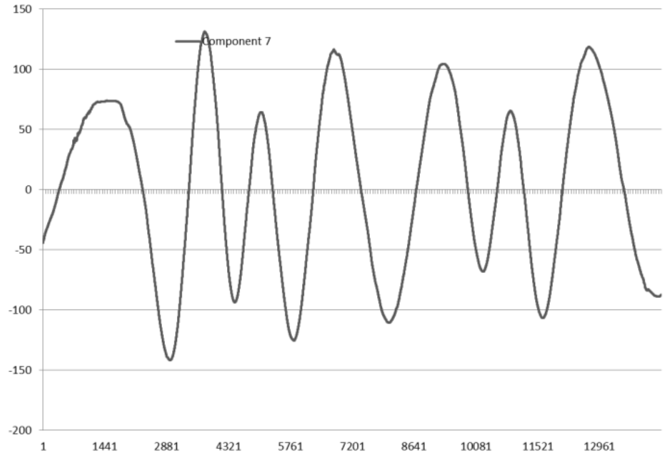
8641
10081
11521
12961


Component 7
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100
50
0
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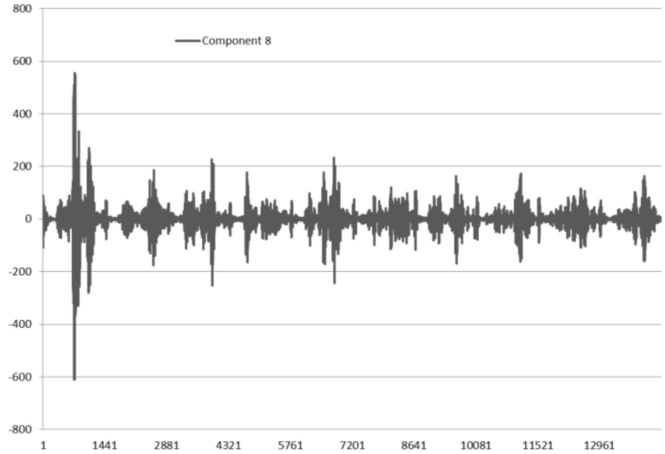
-100
-150
-200
1
1441
2881
4321
5761
7201
8641
10081
11521
12961


Component 8
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600
400
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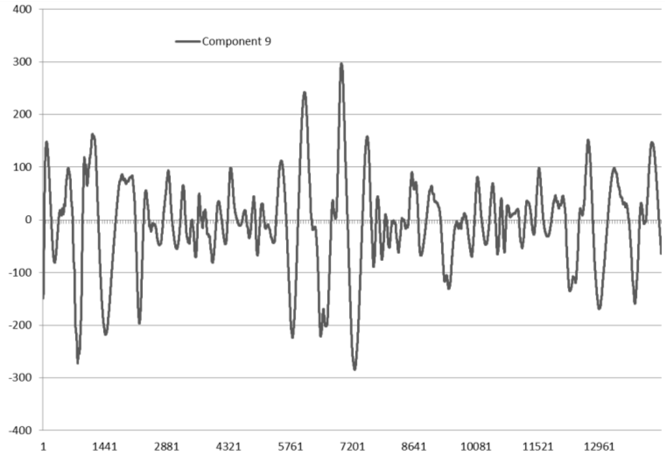
-400
-600
-800
1
1441
2881
4321
5761
7201
8641
10081
11521
12961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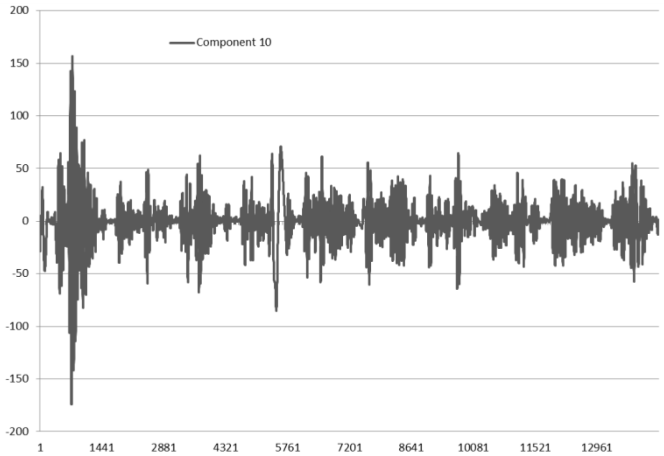
-300
-400
1
1441
2881
4321
5761
7201
8641
10081
11521
12961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100
50
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-50
-100
-150
-200
1
1441
2881
4321
5761
7201
8641
10081
11521
12961

Explanation of symbols

.	Data not available
*	Provisional figure
**	Revised provisional figure (but not definite)
x	Publication prohibited (confidential figure)
–	Nil
–	(Between two figures) inclusive
0 (0.0)	Less than half of unit concerned
empty cell	Not applicable
2013–2014	2013 to 2014 inclusive
2013/2014	Average for 2013 to 2014 inclusive
2013/’14	Crop year, financial year, school year, etc., beginning in 2013 and ending in 2014
2011/’12–2013/’14	Crop year, financial year, etc., 2011/’12 to 2013/’14 inclusive

Due to rounding, some totals may not correspond to the sum of the separate figures.

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