

Estimating Baseline Travel Times for the UK Strategic Road Network

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Abstract—We present a new method for long-term estimation of the expected travel time for links on highways and their variation with time. The approach is based on a time series analysis of travel time data from the UK’s National Traffic Information Service (NTIS). Time series of travel times are characterised by a noisy background variation exhibiting the expected daily and weekly patterns punctuated by large spikes associated with congestion events. Some spikes are caused by peak hour congestion and some are caused by unforeseen events like accidents. Our algorithm uses thresholding to split the data into background and spike signals, each of which is analysed separately. The background signal is extracted using spectral filtering. The periodic part of the spike signal is extracted using locally weighted regression (LWR). The final estimated travel time is obtained by recombining these two. We assess our method by cross-validating in several UK motorways. We use 8 weeks of training data and calculate the error of the resulting travel time estimates for a week of test data, repeating this process 4 times. We find that the error is significantly reduced compared to estimates obtained by simple segmentation of the data and compared to the estimates published by the NTIS system.

Index Terms—Travel Time, Traffic Congestion, Prediction

I. INTRODUCTION

The UK is considered world-leading in its ability to collect and process real-time data from its road network. Highways England are responsible for making this data available through the National Traffic Information Service (NTIS) [1]. Highways England collects speed, flow, travel time and other data on the Strategic Road Network using sensors on the road and in vehicles. The basic building blocks of the Strategic Road Network are the so-called links. They are segments of motorway, with a length varying between 500 and over 20000 metres. The links on the network incorporate thousands of induction loops at different sites, which report their measurements to a centralised system. NTIS data is used to assign a traffic profile to each link on the network. Each profile contains, with a resolution of one minute, the expected travel time at any given time of day, understood as the average time to transverse said link. Historical travel time data within the same link is used to compute expected future travel times.

Currently, generating these profiles makes use of a combination of an Exponentially Weighted Moving Average (EWMA) and heavy time-dependent segmentation (manual clustering), although the exact methodology is not made public.

Here, using NTIS travel time data, we present a novel method for generating profiles for a complete week, such that they do not require segmentation or an underlying model, only requiring statistical and spectral analysis of previous data.

The available literature on travel times is extensive but most recent research in focuses on short-term forecasting and not on the long term [5] [6]. From a methodological point of view Machine Learning and Statistical Methods take most of the attention [7], different approaches can be found: using historical data [8] [9], neural networks [10]. Others take closer approaches to this paper differentiating between peak and non-peak [11], using spectral analysis [12] [13] or Locally Weighted Regressions [14] [15] [16] [17] [18] [19]. Comparisons between some of these studies and others can be found in [20], [21], [22] and [23].

Most of these methods have been specifically tuned for the conditions on which they have been developed and transferability to other sites is often not evaluated. To assess the transferability of this method, it is tested on three different motorways. The method here presented, uses a combination of spectral analysis, tree decisions and local regression.

II. EXAMPLES OF TRAVEL TIMES

The most direct variable for measuring the state of traffic over a length of road is the vehicles’ travel times. The instantaneous travel time for a given segment of road is the average time that the vehicles currently in it are taking since they enter the segment until they exit it.

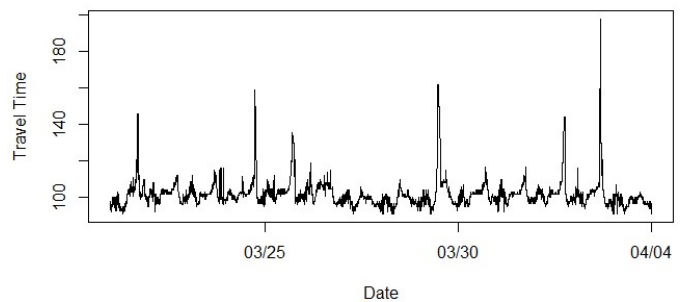


Fig. 1. Travel times on link 117007401 in the M6 over three weeks.

As it can be seen in Figure 1 the travel time remains within a vaguely predictable pattern most of the days, with bounded minima during nights corresponding with the free flow time and with some outliers below this value corresponding to speeding drivers. Travel time will meaningfully rise as people leave to work and add load to the motorways. This collective behaviour will create the morning traffic jams, which in our data, are partially replicated during the evening rush hour, normally finding a plateau in between. After this, the travel times slowly decay towards the night period of free-flow regime. In Figure 1, it can also be seen that there are a series of excursions out of this oscillating yet bounded typical behaviour. In these, the travel time can increase several times fold the usual values. These extreme oscillations are much less predictable both in intensity and inter-oscillation period than the recurrent congestion described previously.

III. CURRENT TRAFFIC PROFILES

In this section, current approaches towards the generation of Traffic Profiles will be described, in line with how these are calculated in the United Kingdom.

A. Use of Exponentially Weighted Moving Average

One currently used way for creating Traffic Profiles consists in applying an EWMA on the same minute of every day, with the implicit assumption that similar road behaviour can be expected at the same time of the day. Changes happening in a given time of the day, will be smooth enough across dates so their trend can be appropriately approximated by the EWMA. In these algorithms the next Travel time forecast $\hat{x}(i, d+1)$ on the i -th minute of a given day d , for a memory parameter $\alpha \in [0, 1]$ and with measured travel time x_i^d , will be:

$$\hat{x}_i^{d+1} = \alpha * x_i^d + (1 - \alpha) * \hat{x}_i^d \quad (1)$$

The main problem when using an EWMA is the manner in which the memory decays. Recent measurements are weighted more heavily than events in the past, if an extreme fluctuation occurs, the following forecasts will be biased, partially replicating this event and over-estimating the travel times until enough new measurements have been taken to dissipate this effect.

B. Segmentation

In addition, to acknowledge the specific differences between some special dates in the year, and the difference between days of the week, this family of methods requires the use of heavy date based segmentation. The EWMA will be applied across dates which fall in the same category (i.e. Mondays, weekends, Christmas Day, ...). If this is combined with the shortcomings presented in Section III-A, some long reaching effects are generated, which can propagate for weeks into the future predictions, but do not have any reflection on the observed travel times, as it can be seen in Figure 2. Furthermore, in order to generate a valid segmentation, an experienced team is necessary, since the needs of the process can geographically vary, given that the EWMA approach tends

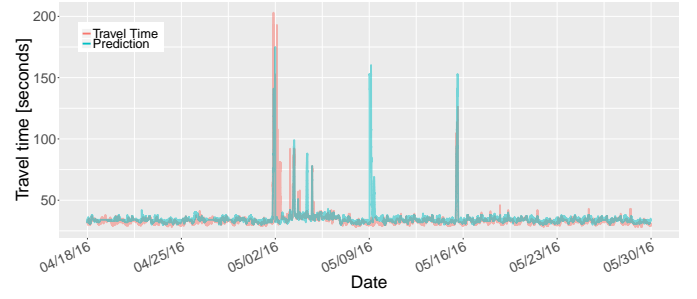


Fig. 2. Example of the current algorithm predicting increases in travel times for several weeks after a peak is seen in the measured travel times (25/04/2016)

to better approximate endemic congestion. This dependence can lead to the creation of legacy systems which may not be well understood after a few years, decreasing their usability over time unless extra effort is put into transmitting this knowledge and continually train new staff.

IV. DATA

A. Data Gathering and Selection

Data was gathered from 3 different Motorways in England. The M6 and M11 were selected due to their high usage and combination of recurrent and outstanding congestion. The M25 was selected on the base that it is the most used Motorway in England on a daily basis, suffering from chronic congestion.

- The dataset for M6 comprises 90 days (12 complete weeks) of data (07/03/2016-05/06/2016) across 14 links.
- The dataset for d M11 comprises 90 days (12 complete weeks) of data (07/03/2016-05/06/2016) across 25 links.
- The dataset for M25 comprises 75 days (10 complete weeks) of data (07/04/2017-20/06/2017) across 61 links.
- Links were discarded if they had more than 10% of missing data or if they contained any entry or exit ramps.
- Whenever missing data was detected for 10 or less minutes, it was linearly interpolated.
- Whenever missing data was detected for over 10 minutes, it was left as missing values.

In the case of the M6 and the M11 the first 8 weeks are used to predict one complete week ahead. One week later, the process is repeated, deleting the oldest week of training data and incorporating measurements of the week predicted in the previous step. This is performed 4 times. In the case of the M25, 6 weeks of data were used for training and the process as described above is performed 3 times.

B. Data Contents

For each link on a specific date, the required input data consists of one entry per minute, containing:

- Measured travel time
- Profile (expected) travel time

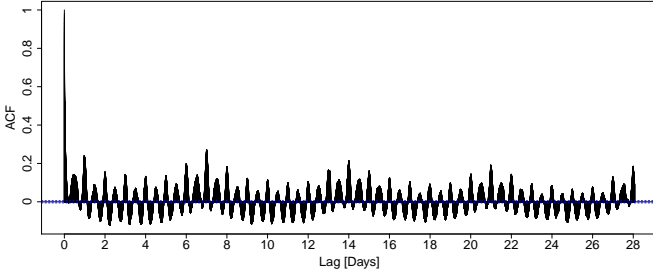


Fig. 3. Autocorrelation function of a link in the M6 over a period of 4 weeks, showing seasonal patterns on the daily and weekly periods.

V. TRAVEL TIME PREDICTION ALGORITHM

Given the cyclic nature of traffic, the aim was a prediction algorithm that could account for the periodic variations and endemic congestion while being resilient to fluctuations and rare events. This algorithm also should:

- Be robust, mitigating the propagation of isolated events into future forecasts, unlike methods using EWMA.
- Not require the use of time segmentation and be valid for regular and "special" dates.
- Be location agnostic, the internal parameters should be set algorithmically based on the data.
- Have Gaussian, mean 0, uncorrelated residuals.
- Near flat Trend term, given the different time scales between seasonal cycles and changes in the general motorway flow.

A. Naive Segmentation

To obtain an accurate comparison of the performance of the algorithm developed in the following subsections, an example of basic segmentation was coded. This involved a weighted combination of the training data points using uniform weights. In this way, for the i -th minute of a week and using a training set composed of the previous of n weeks, the Naive Segmentation (NS) profile is:

$$\hat{x}(i, n) = \sum_{\text{week}=1}^n \frac{x_n^i}{n} \quad (2)$$

B. Decomposition in Background and Spikes

During exploratory data analysis we found that, from the point of view of travel times, traffic operates in two differentiated regimes that we denominated Background and Spikes.

- Background:
 - Stable around a mean value.
 - Oscillates with small amplitude and high frequency.
 - Suitable for spectral filtering.
- Spikes:
 - Zero most of the time. Quickly go to extreme values.
 - Oscillates with great amplitude and low inter-oscillation frequency, creating far reaching effects.
 - Suitable for seasonal decomposition.

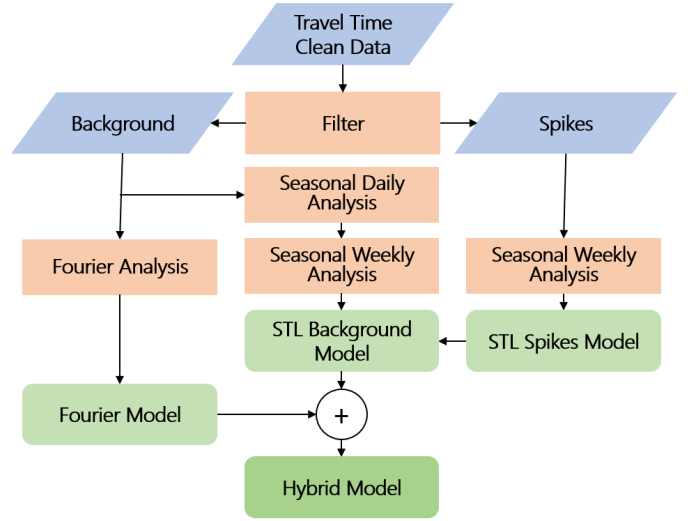


Fig. 4. Schematic of data streams in the algorithm.

This decomposition, assuming Gaussian noise ξ , signal of the form:

$$\text{Travel Time}_t = \text{Background}_t + \text{Spikes}_t + \xi \quad (3)$$

The objective was to separate them in such a way that times of smooth operation are captured as part of the Background and used for spectral analysis, attempting to mitigate the prediction error induced by the high frequency oscillations and obtaining a basic view of what can be daily observed. Meanwhile, the spikes, including the recurring and non-recurring congestion, were treated separately searching for seasonality in larger time scales than those in which the background oscillates, as suggested by Fig. 3. Ideally, after this step, the remainder should only contain isolated large rare events deviating from the profile and white noise.

To prevent the differing lengths of the links from affecting this decomposition, for this step, all travel times were normalized according to their corresponding link's free flow time, defined as the time to transverse the length of the link at the maximum legal speed allowed by the motorway. However, this step only mitigates the non-regularity of the time series, since there are drivers who do not follow these limits. A threshold was heuristically set, as seen in Table I to separate the two components in the different regimes from the normalised travel times on a per-motorway basis, although better results can be obtained by setting each link individually. Intuitively, this threshold scales with the amount of recurring congestion in a link. Whenever a data point was above the threshold, it was flagged as belonging to a spike.

For this purpose, an indicator function was defined, taking for every minute the value:

$$\delta_t^{\text{spike}} = \begin{cases} 1, & \text{if } x_t > \text{Threshold} \\ 0, & \text{otherwise} \end{cases} \quad (4)$$

TABLE I
TRAVEL TIME NORMALISATION THRESHOLDS

Motorway	Threshold
M6	1.1
M11	1.2
M25	1.4

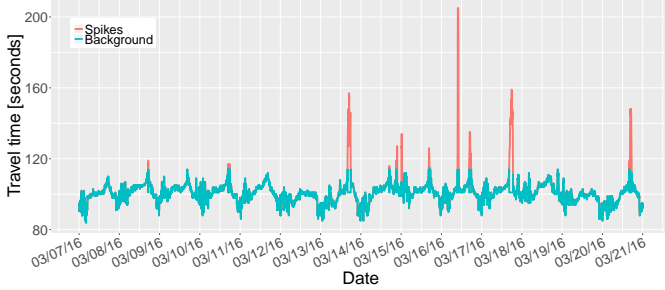


Fig. 5. Decomposition time series in background and spikes

C. Spectral Component

The main difficulty when dealing with the Background signal is the low amplitude, high frequency fluctuations that can be found almost ubiquitously. Signal smoothing can be performed by completely removing a range of frequencies while the information bearing bands are retained. For this task, the Fast Fourier Transform (FFT) [4] was used as follows:

- 1) Calculate Background Power Spectrum using FFT
- 2) Remove frequencies corresponding to periods under 4 hours and over 1 week
- 3) Repeat for all n weeks in training set
- 4) Apply EWMA to the modified weekly Power Spectra
- 5) Compute the Inverse Transform

D. Seasonality Component

Seasonal-Trend Decomposition based on LOESS (STL) [2] was chosen for the seasonality analysis since it can handle any type of seasonality, allowing the user to control how it changes over time as well as the smoothness of the trend-cycle while being robust to outliers [3].

Below, the sequence of steps taken to extract the Seasonality Components that can be observed in Fig. 3 is described in line with Fig. 4. Note that this should be applied to the n training weeks as a single time series.

- 1) Decomposition of Background for daily seasonality
- 2) Extract and sum the series corresponding Trend and Remainder from Step 1
- 3) Decomposition of output from 2 for weekly seasonality
- 4) Add daily and weekly Seasonal components from Step 1 and Step 3 to obtain global seasonality
- 5) Average seasonality across training weeks
- 6) Linearise Trend term from output of Step 3
- 7) Add linearised trend to seasonality obtained in Step 6
- 8) STL Decomposition of Spikes for weekly seasonality

9) Extract Spike's Seasonality corresponding to the number of weeks for forecasting

10) Add Spike's Seasonal component to the output of 8

To ensure a successful decomposition, after Step 3 Background's Remainder should be zero mean, Gaussian distributed. Background's Trend should have a near zero slope. This should also hold after Step 8.

E. Seasonal-Spectral Hybrid Profile

In order to create the final Seasonal-Spectral Hybrid profile (Hybrid), one of the two forecasts generated in the previous points is taken, depending on what is the identified regime:

$$\text{Hybrid} = \text{Seasonal} * \delta_{\text{spike}} + \text{Spectral} * (1 - \delta_{\text{spike}}) \quad (5)$$

VI. ACCURACY RESULTS

In this section the accuracy of the algorithm described above is compared against the Published Profiles and the NS Model. For each temporal point i , the Mean Average Percentage Error (MAPE) is defined below:

$$\text{MAPE} = \frac{\left(\sum_{i=1}^n \frac{\|x_i - \hat{x}_i\|}{x_i} \right)}{n} \quad (6)$$

For complete Motorways, the Root Mean Squared Error (RMSE) has been calculated for each temporal point i as:

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^n (x_i - \hat{x}_i)^2}{n}} \quad (7)$$

In both cases the error for a Link is defined as the average MAPE or RMSE across all prediction points. The error for a Motorway is defined as the average of the error across all its links.

A. Accuracy by Quantile

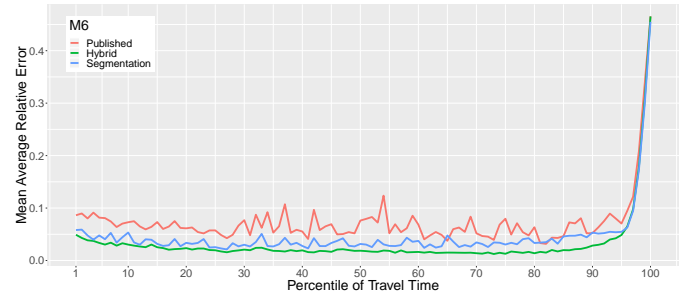


Fig. 6. Average accuracy results in M6 across percentiles of travel time.

Here, the accuracy of the algorithm is compared against the Published Profiles and the NS Profile across all percentiles of travel time. As it can be seen in Figs. 6, 7 and 8, the Hybrid Profile has a higher accuracy than the Published Profiles and the NS Model for all percentiles of travel time except for the most extreme values where they all perform poorly. The most meaningful difference occurs between percentiles [50 – 95], where the Published Profile starts to suffer from higher inaccuracy.

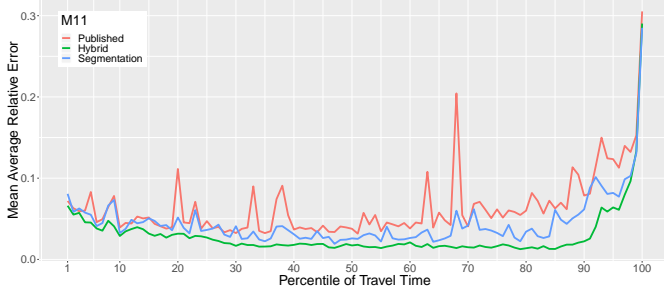


Fig. 7. Link average accuracy results in M11 across percentiles of travel time.

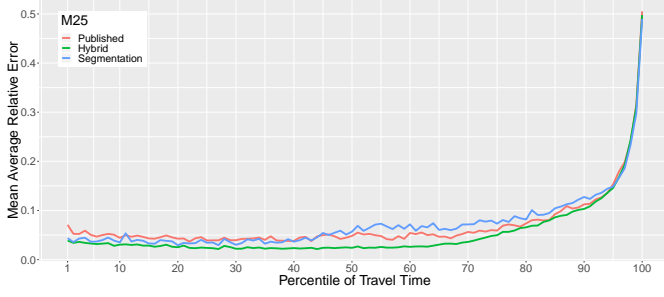


Fig. 8. Link average accuracy results in M25 across percentiles of travel time.

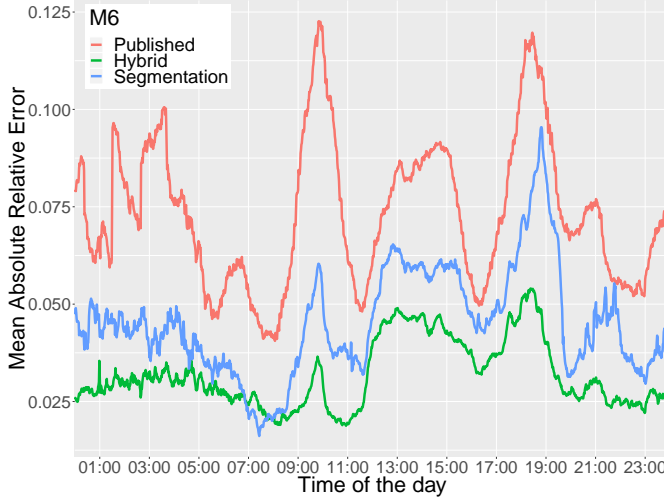


Fig. 9. Link average accuracy results in M6 across times of the day.

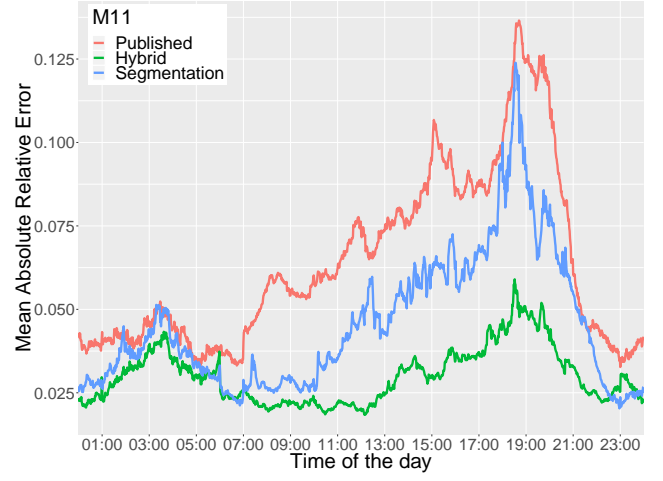


Fig. 10. Link average accuracy results in M6 across times of the day.

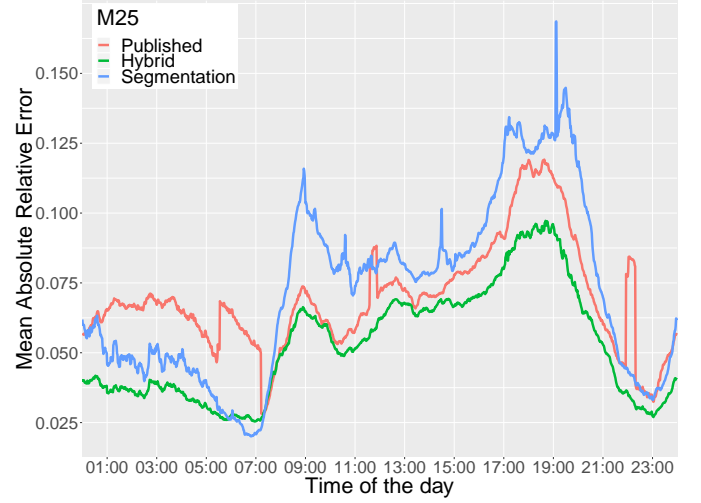


Fig. 11. Link average accuracy results in M25 across times of the day.

B. Daytime Error

Here, the accuracy of the algorithm is compared against the Published Profiles and the NS Profile across the times of the day. As it can be seen in Figures 9, 10 and 11, the Hybrid Profile has a higher accuracy than the Published Profiles and the NS Model for all times of the day, all locations and training lengths. The most relevant improvement occurs during the morning and evening peak hours, where the algorithm presented in this paper does not accuse meaningful performance worsening relative to the morning plateau when

TABLE II
MARE DISTRIBUTION PER MOTORWAY

% rel. error	<-25%	-25% to -15%	-15% to -5%	-5% to 5%	5% to 15%	15 % to 25%	>25%
M6	1.58	0.60	3.77	88.01	5.97	0.06	0.01
M11	0.80	0.35	4.07	86.15	7.97	0.49	0.15
M25	3.85	2.73	10.42	75.12	7.29	0.33	0.28

compared with the other two profiles.

In the case of the M6 and M11, where the training set is richer, the error at peak times is reduced by at least 50% in all cases, reaching as much as 68.7% in the case of the M6 morning rush. In the case of the M25, which is congested on a regular basis, the errors in the Published Profile during peak times are slightly lower than on the other cases, indicating that, given the use of EWMA, this recurrent congestion is better captured by it. Even in this case, the proposed algorithm performs significantly better than any of the other two, except for a brief window between 6-7AM when it is outperformed by the NS Model.

TABLE III
MARE PER LINK ON M6

Link	MARE
117007401	0.0211
117007501	0.0421
117007601	0.0246
117007801	0.0480
117007901	0.0308
117008401	0.0331
117009102	0.0269
117011901	0.0235
117012001	0.0446
117012101	0.0262
117012201	0.0431
117012301	0.0275
117016001	0.0360
123025901	0.0189

TABLE IV
GLOBAL MARE & RMSE PER MOTORWAY

Motorway	MAPE [%]	RMSE [s]
M6	0.0318	0.0368
M11	0.0300	0.0355
M25	0.0552	0.0667

VII. FUTURE WORK

The algorithm presented above meets the requirements described in Section V except for an heuristically set threshold. One potential way of reaching compliance with these requirements is to perform the decomposition by applying a Wavelet Transform and separating background from spikes based on statistical analysis of the transformed time series in terms of how their Wavelet coefficients oscillate over time within a scale level. In the future a sensitivity analysis should be conducted to explore the limits of the algorithm in terms of minimum training data set, as well as maximum performance with increased training.

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