On-street Parking and Park and Ride Prediction with Interpretable Time Series Models

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ABSTRACT

Today's parking policy is increasingly focused on reducing cars in urban areas. In this paper it is demonstrated how interpretable time series models can be used to analyze the impact of public transport and tariff changes using parking transaction data of 3,594 on-street selling points and 8 Park and Ride (P&R) locations in Amsterdam, the Netherlands. Benchmarked with a Seasonal Naive model, Error Trend Seasonality Models, Seasonal Autoregressive Integrated Moving Average models and Interpretable Multivariate Long Short-Term Memory models are compared, each with external variables included (ETSX, SARIMAX and IMV-LSTM, respectively). The ETSX model achieved the lowest RMSE values for each of the locations. According to this model, a tariff increase led to decreased parking demand in the centre, but increased demand in peripheral areas and most P&R locations, a new metro line resulted in less parking in the centre and COVID-19 measures decreased the parking demand by 10% until almost 100%.

CCS CONCEPTS

• **Applied computing** → **Transportation**; **Forecasting**; • **Computing methodologies** → *Neural networks.*

KEYWORDS

time series forecasting, urban transportation, parking behavior, lstm, cnn, auto-regressive models, ets, exogenous regressors, variable interpretability, park and ride, on-street parking, off-street parking

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1 INTRODUCTION

From lots of parking [23] to replacement of parking lots [25]: parking management has changed immensely during the past decade. As automobility increased, while each car needs on average four parking spaces [23, 30, 38], the demand for parking accelerated. To satisfy this high demand minimum parking requirements have become the norm in many cities, such as in America [37], suburban Canada [8], Australia [39] and later in India, Malaysia and the Philippines [3]. Environmental consequences of plentiful parking manifest themselves in open space and diversity losses [31] and air pollutants caused by cruising for parking [37]. As a counter-reaction, today's parking policy makers increasingly aim to *discourage* instead of support car use in dense urban areas [31].

In this case study, we will focus on the impact of these changes in Amsterdam, the Netherlands. Due to its high population density, rich mix of functions and narrow streets, public space is scarce. About 11% of this space is taken up by parked cars [22]. While on average a car spends 95% of its existence parked [21] more than 40% of residents' cars do not move at all on any given day [22]. To reclaim the city's livability and accessibility, Amsterdam has launched a plan [7] to reduce car use in the city center, while stimulating public transport, walking and cycling. By 2025 11.2 thousand parking locations will be replaced with pedestrian and bicycle lanes, city parks and playgrounds. Parking tariffs have increased, car sharing systems are enhanced, park-and-ride supply is expanded and the public transport network is extended with a new metro line, the North South Line (NSL).

With the goal to investigate the impact of these changes on the parking demand in Amsterdam, time series models with external variables are developed using parking transaction arrivals of eight Park and Ride (P&R) locations and 3,594 selling points for on-street parking. These models do not only predict the parking demand, but also assess how the demand is affected by external variables. Analyzed are weather, holiday and event variables, spatial features, the opening of the NSL, parking tariffs and the intelligent lockdown in the Netherlands due to COVID-19. With a Seasonal Naive model as a benchmark, we compare Seasonal Auto-regressive Integrated Moving Average models with exogenous regressors (SARIMAX), Error, Trend, Seasonality models with exogenous regressors (ETSX) and Interpretable Multivariate Long Short-Term Memory (IMV-LSTM) models. The following research questions are addressed:

(1) How can variable importance with respect to the prediction of the target variable be assessed in time series models?
(2) What are the changes in parking behavior in Amsterdam as a result of the policy measures?

These questions are examined in the following sections. The next section discusses the related literature. After analyzing the data for this case study, the model methodology is described. Subsequently, the performance of the models is compared and the results from the best performing model are analyzed. Finally, this paper is concluded with a summary of our findings and suggestions for future research.

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Table 1: Comparison variables from literature about parking prediction models.

Research	Time patterns from models	Time patterns from features	Weather	Holiday	Event	Area type	Traffic flow	Parking other locations	Tariff change	Public transport change	COVID-19
[2]	×	×	×	×							
[5]		×									
[9]		×	×		×						
[10]		×	×	×							
[11]	×		×	×	×						
[12]	×	×	×			×	×				
[26]		×	×	×				×			
[33]		×	×	×	×	×	×				
[34]		×	×	×	×		×				
[35]	×	×	×	×	×	×	×				
[44]	×	×	×	×	×	×					×
This research	×		×	×	×	×		×	×	×	×

2 LITERATURE REVIEW

There are multiple ways to investigate parking behavior. Richly studied in parking behavior research are discrete choice models [15–17, 20, 27, 28, 40, 42]. Alternatively, the impact of external factors on the parking behavior can be investigated with time series models with external variables included. Prominent in parking behavior research are Recurrent Neural Network (RNN) models, such as LSTM models and Gated Recurrent Unit (GRU) models. For example, Zhang et al. [44] presented a periodic weather-aware LSTM with event mechanisms for parking behavior prediction. In a similar study, Arjona et al. [2] developed LSTM and GRU models with weather and temporal variables for forecasting parking availability in three European cities and a city in the USA. Other models commonly used for the task of parking behavior analysis are random forest models, for instance by Provoost et al. [34] and Feng et al. [10]. Moreover, Lu and Liao [26] developed a Naïve Bayes classifier to predict the on-street parking occupancy in San Francisco, USA. It was found that addition of external variables is a powerful method to not only enhance the model performance, but also to investigate the parking behavior. In Table 1 external variables in the relevant literature are summarized. Most frequently examined are temporal variables (e.g. structural temporal, holidays and events) and weather variables. However, none of the papers assessed the impact of major traffic and transportation changes, such as a new public transport line and a parking tariff change. Instead, analogous papers apply statistical tests [41] or probit models [24]. This paper contributes to previous studies by proposing an approach to investigate the impact of major policy changes using time series models.

3 DATA

The dataset used in this work consists of more than 22 million parking transactions from 3,594 on-street selling points and 8 P&R locations in Amsterdam, the Netherlands, provided by National Parking Register (NPR). Per hour, per selling point the number of arrivals and the total sum of parking duration is measured. The measurement period is from March 1, 2018 to April 30, 2020, totalling at 792 days. During this time the NSL is opened (22 July, 2018) and parking tariffs have increased (14 April, 2019). Figure 1 and 2 illustrate the P&R locations and the number of selling points per neighborhood and tariff zone, respectively. The P&R locations are positioned in peripheral areas. Because paid parking applies for all locations inside the A10 Ring road, more selling points are located in the city centre compared to outside. Fewer selling points are located in the heart of the center because multiple streets in the old city centre are closed to car traffic.

3.1 Data pre-processing

Figure 3 summarizes the data preparation steps applied.

3.1.1 Data cleaning. First, transactions with a total parking duration of less than 5 minutes and more than 1 week are removed, as these are most likely result of measurement errors [32]. This eliminates 1.96% of the observations. The parking arrival data still may contain anomaly points, that are, points that deviate from the collective common pattern of the majority of the data points. These points are detected with the Amazon Sagemaker Random Cut Forests algorithm [13]. This algorithm is more flexible than setting a threshold with predetermined limits and takes the structure of multiple dimensions into account. This property enables to detect anomaly points in time series data, which have an additional time dimension. An anomaly point is retained if it occurs during a holiday or scheduled event. With 1,000 random cut trees, only 0.001% appeared to be an anomaly. The removed data points are then imputed with Kalman filter imputation [43] using a Seasonal Naive model as an input.

3.1.2 Feature addition. The coordinates of the selling points are derived from Amsterdam Open Data. Subsequently, location zones from two spatial levels are obtained, which are 56 parking tariff zones and 80 neighborhoods. Each parking tariff zone has a different parking tariff regulation. Hence, these are indicative to assess changes in parking behavior as a result of the tariff change. On the other hand, the neighborhoods are more fine-grained. This enables to investigate more detailed information (e.g. on events nearby). Next, the explanatory variables in Table 2 are retrieved.

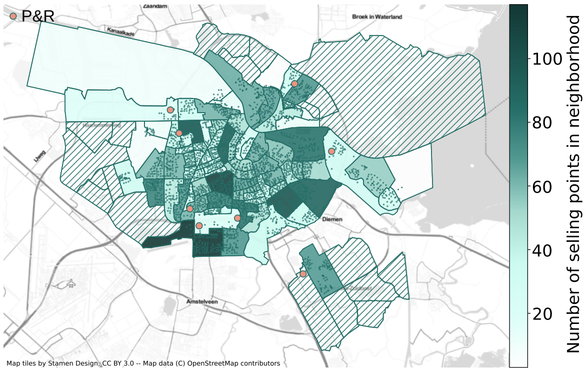

Figure 1: Spatial arrangement selling points per neighborhood and Park and Ride locations.

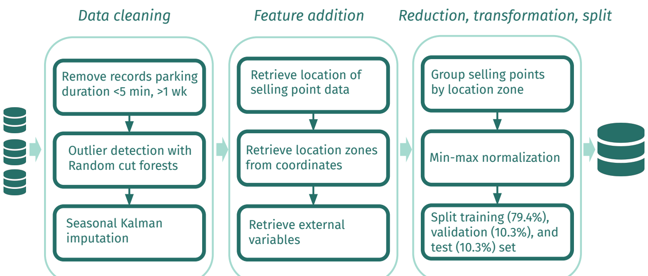

Figure 3: Data pre-processing steps.

Weather attributes. The weather attributes are provided by the Royal Netherlands Meteorological Institute (KNMI) from Schiphol weather station near Amsterdam. The variables are selected such that no correlation occurs according to the variance inflation factor [6]. Each weather variable is measured per hour.

Event attributes. The cultural, sports and meeting attributes are manually retrieved from open stage schedules, conference schedules and soccer and other sports schedules as described in previous work [11]. Two adjustments have been made to this method. First, the event variables now contain the number of visitors, instead of just 0 or 1. This empowers the model to distinguish big events from small events. Second, event attributes are obtained for each neighborhood, instead of only two venues. This way, the impact of events in the complete city of Amsterdam can be examined. Other event attributes added are black Friday and traffic closures, which are a dummies that explain whether a certain neighborhood has a traffic closure as a result of an event (e.g. during running events).

Spatial attributes. Inspired by Lu and Liao [26] spatial features are added to the models. In this paper, these are defined as the number of arrivals of the last historic measurement of all parking locations, except the location of consideration. Spatial correlation can occur in the case of searching for parking. To exemplify, if neighborhood A has many arrivals in the last hour, it might result in an increase of arrivals in neighbourhood B from motorists who could not find a parking place in neighborhood A. Additional selling points are given as dummy variables.

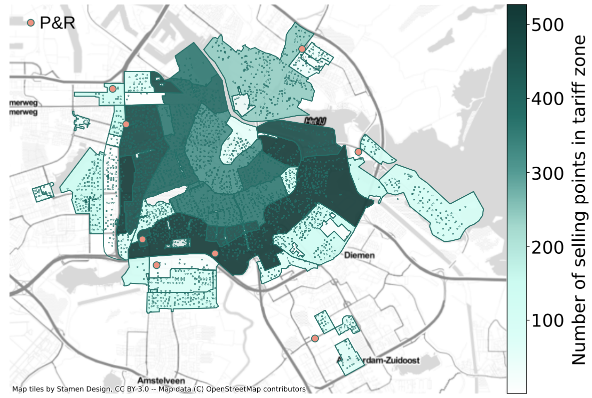

Figure 2: Spatial arrangement of selling points per tariff zone and Park and Ride locations.

Holidays and vacations. In Amsterdam a Sunday rate applies for on-street parking in most neighborhoods during some of the public holidays. In these cases, street parking is often free, resulting in less transactions and hence, less data. To investigate this effect holidays are added. Additionally, school vacations are included.

Level shift attributes. Some major events can change the parking behavior in the long term. In the measurement period analogous events are the parking tariff change, the opening of the NSL and the intelligent lockdown in the Netherlands due to the COVID-19 pandemic. The parking tariffs are added for each location, except for the locations where no tariff change occurred (i.e. Amstel III/Bullewijk and P&R locations). The period after the opening of the NSL and the lockdown has come into effect are indicated with a dummy.

3.1.3 Reduction, transformation and split. The selling points are aggregated to their corresponding location zones. This step reduces the on-street data to 1.53 million records of neighborhoods and 1.07 million records of tariff zones. In previous work [11] it is found that external variables can have different impacts on different parking locations. To investigate spatial differences between parking locations, a separate model is developed for each location zone. Afterwards, the data is scaled using Equation 1.

$$x_{scaled} = \frac{x - min(x)}{max(x) - min(x)}, \tag{1}$$

where x is the parking arrivals per hour for each location. Finally, the data is split into training, validation and test set, as visualized in Figure 4. This split is made such that there is enough training data for the model to learn post-NSL and post-parking tariff effects. The model parameters are evaluated on the validation set. The models with the best combination of parameters of each model type are then compared in the test set. Note that the start of the lockdown is not included in the test set. This is because the start of the lockdown occurs towards the end of the dataset, leaving no opportunity for the model to learn from its changes. Therefore, the final outperforming model is run on the complete dataset, including the last six weeks of measurements during the lockdown.

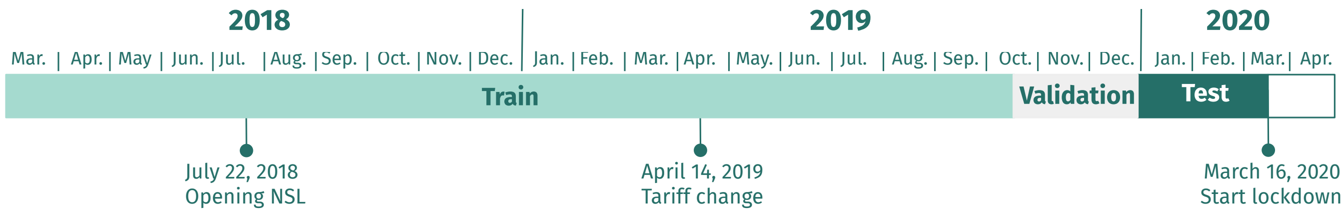

Figure 4: Timeline with the train set, validation set and test set.

Attribute	Explanation
Weather attributes	
Wind speed	Average wind speed (in 0.1 m/s)
Sunshine	Duration of sunshine (in 0.1 hrs.)
Precipitation	Sum of precipitation (in 0.1 mm)
View	Horizontal view (categorized by m)
Thunderstorm	0 = did not occur, 1 = did occur
Event attributes	
Cult	Number of visitors at a concert, festival or theatre for each location zone, 4 hrs. pre-event – 4 hrs. post-event
Sport	Number of visitors at a sports event for each location zone, 4 hrs. pre-event – 4 hrs. post-event
Meet	Number of visitors at a conference, convention or trade show, 4 hrs. pre-event – 4 hrs. post-event
Traffic closure event	0 = no traffic closure caused by event 1 = traffic closure caused by event
Black Friday	0 = no black Friday, 1 = black Friday
Spatial attributes	
Arrivals other zones	Number of arrivals in other location zones in the last hour of historic data
Parking addition	0 = pre-addition paid space in zone 1 = post-addition paid space in zone
Holidays, vacations	
Holiday	0 = no holiday, 1 = holiday
Vacation	0 = no vacation, 1 = vacation
Level shift attributes	
Parking tariff	Tariff (in €/hr.) in the location zone
North-South Line	0 = pre-NSL, 1 = post-NSL opening
COVID-19	0 = pre-lockdown, 1 = lockdown

Table 2: Attribute overview.

3.2 Data analysis

For visualization four neighborhoods and two P&R locations are highlighted. The neighborhoods are Buikslotermeer in Amsterdam North, Burgwallen Nieuwe-Zijde in Amsterdam Centre, Zuidas in Amsterdam South and Bijlmer Centre in Amsterdam South-East. The selected P&R locations are P&R Bos en Lommer and P&R Olympisch Stadion, as these are the only P&R locations with observations before the opening of the NSL with 24/7 access.

Figure 5 presents the correlograms of these locations. The values on the x-axis represent the lag $k \in (0, \dots, 336)$ where 336 equals two weeks $(24 \cdot 14)$. The values on the y-axis represent the autocorrelation value, i.e. the correlation of the time series with a shifted variant of k time steps of itself. From each of the locations a peak

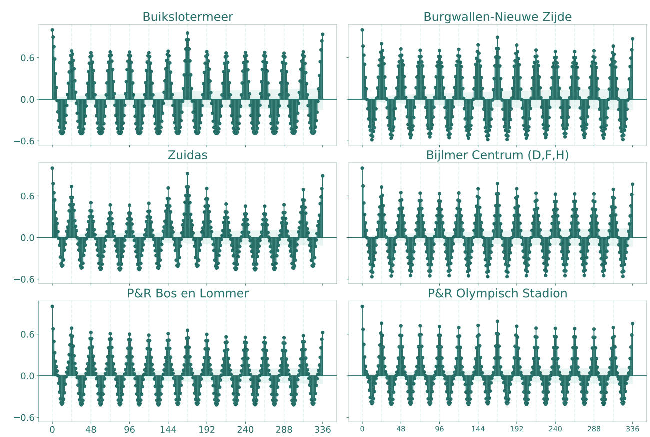

Figure 5: Correlograms of arrivals in six parking locations.

occurs every 24th lag, signifying a seasonality of 24 hours. Furthermore, a higher peak is observed at lag 168, indicating a second seasonality of 1 week. Because the highest seasonality is one week, it is chosen to take one week for both the forecast and lookback window.

4 MODEL METHODOLOGY

In this section the time series methods developed are defined, which are SARIMAX, ETSX and IMV-LSTM. To answer the first research question, it is demonstrated for each model how variable importance of the exogenous regressors is assessed with respect to the prediction of the target variable. The models are evaluated using the Root Mean Squared Error (RMSE) in Equation 2.

$$RMSE = \sqrt{\frac{\sum_{t=\tau}^{N-\tau} \sum_{i=1}^{\tau} (\hat{y}_{t+i} - y_{t+i})^2}{(N - 2\tau + 1) \cdot \tau}} \qquad (2)$$

with $\hat{y}_{t+i}$ the predicted arrivals, y_{t+i} the actual arrivals, N is the sample size and τ is the maximum time steps ahead (168 hours). The benchmark model is a Seasonal Naive model with seasonality of one week. This model does not contain exogenous regressors.

4.1 SARIMAX

A SARIMAX model combines a seasonal ARIMA model [19] with Linear Regression to include exogenous regressors. The exogenous regressors are added as time series to the seasonal ARIMA components as $\theta_1 x_{1,t} + \cdots + \theta_n x_{n,t}$ with coefficient estimates $\theta_1, \dots \theta_n$ for n exogenous regressors [29]. The value of the coefficient estimates are related to the impact of an external variable on the target. We

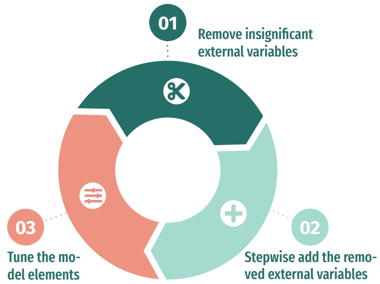

Figure 6: Three-step method for tuning SARIMAX.

propose a stepwise approach to select the model parameters and the exogenous regressors, summarized in Figure 6.

In the initial model all exogenous regressors are included. The polynomial orders of the (seasonal) ARMA processes are set to 0, of the differential processes are selected based on visual inspection of correlograms. The following steps are repeated until no improvement in RMSE is found.

Step 1. Significant exogenous regressors are selected. Considering significance level $\alpha = 0.05$, the null-hypothesis $\theta_i = 0$ is rejected if the p-value $< \alpha$ for $i = 1, \dots n$. Thus, exogenous regressors with a p-value higher than 0.05 are removed from the model.

Step 2. The removed regressors are then step-wise added to the model, which can potentially become significant when added in a different combination and order.

Step 3. The polynomial orders of the (seasonal) ARMA processes are tuned using the Hill-climbing algorithm [36]. Based on a test on 10 random locations where the model parameters are selected with the more rigorous grid search, we found both algorithms obtained the same results. However, the 3 step approach using Hill-Climbing was on average 10 times faster.

4.2 ETSX

An observed time series can be decomposed into three components: an error, a trend and a seasonality. Standard ETS models apply a different variant of exponential smoothing based on the combination of component types [18]. The type of error can be additive or multiplicative, the trend can be constant, linear, damped or exponential and the seasonality is either additive, multiplicative or non-existent. To improve the forecasting performances of these models, explanatory variables can be coupled with this method [4]. Equation 3 and 4 formulate the ETSX model for time series with an additive error and multiplicative error, respectively.

$$y_t = a_{0,t} + a_{1,t}x_{1,t} + a_{2,t}x_{2,t} + \cdots + a_{n,t}x_{n,t} + \epsilon_t, \tag{3}$$

$$\log(y_t) = \log(a_{0,t}) + a_{1,t}x_{1,t} + a_{2,t}x_{2,t} + \cdots + a_{n,t}x_{n,t} + \log(1+\epsilon_t), \tag{4}$$

where $a_{0,t}$ is the ETS model determined by the ETS components, $x_{i,t}$ is the i-th explanatory variable, $a_{i,t}$ is the parameter for that component and n is the number of external variables. The estimated parameters $\hat{a}_{i,t}$ are estimated at the optimization stage. In general, ETSX is a regression model with time varying intercept, defined by the ETS components and smoothing parameters.

Hyper-parameter	Distribution	Range
Learning rate*	Log-uniform	[1e-6, 1e-1]
Step size*	Discrete uniform	5, 20 , ... , 80, 95
Gamma*	Uniform	[0.1, 0.9]
Batch size**	Discrete uniform	24, 48, ... , 168, 192
Size hidden layer	Discrete uniform	4, 8, 16, 32, 64, 128, 256

* After each step size, learning rate = learning rate * gamma
** The number of steps for applying back-propagation

Table 3: Search space for tuning IMV-LSTM using Optuna.

Contrary to SARIMAX, ETSX does not use statistical tests to determine which external variables stay in the model, but uses the AICc. The model parameters and external variables are selected as follows. First, an empty model with only the constant and target variable is constructed. Second, the correlations between the residuals of the model and all external variables not yet in the model are calculated. A high correlation indicates that one part of the error can be explained by one of the external variables. The external variable with the highest correlation is added to the model. If this leads to a model with a higher AICc, the process is repeated from step 2. Otherwise, the external variable is not added to the model.

4.3 IMV-LSTM

Literature has shown that LSTM models are a powerful method for predicting parking behavior [2, 11, 44]. However, because LSTM models blend the information of the variables into the hidden states, the contribution of every single variable on the target is intractable. In order to investigate variable importance and variable-wise temporal importance Guo et al. [14] have explored Interpretable Multivariate LSTM (IMV-LSTM) models. We build our models from their architecture. The hidden state update is defined in Equation 5

$$\tilde{\mathbf{j}}_t = \tanh(\boldsymbol{\mathcal{W}}_j \circledast \tilde{\mathbf{h}}_{t-1} + \boldsymbol{\mathcal{U}}_j \circledast \mathbf{x}_t + \mathbf{b}_j), \tag{5}$$

where $\boldsymbol{\mathcal{W}}_j$ is the weight matrix of the activation value of the previous time step, $\tilde{\mathbf{h}}_{t-1}$ is the activation value of the previous time step, $\boldsymbol{\mathcal{U}}_j$ is the weight matrix of the new input, $\mathbf{x}_t$ is the new input and b_j is a bias vector. With the tensor-dot operation $\circledast$ the product of two tensors among the axis of the exogenous regressors is taken. In this fashion, each element of the hidden matrix covers information exclusively from a single input variable, enabling retrieval of variable-wise importance. The cells are updated based on the forget gate, input gate and output gate using tensor-dot operation, causing the gates and memory cells to be matrices as well. Afterwards, a sequence of hidden state matrices and the sequences of hidden states of a specific variable n are obtained. A mixture attention mechanism is developed to retrieve the variable and temporal relevance from the hidden state matrices. This mechanism is explained in more detail in the paper by Guo et al. [14].

In the current study external variables compared are: significant external variables according to ETSX and SARIMAX, all external variables and no external variables. The selections according to ETSX and SARIMAX obtained similar results, while the other options obtained higher RMSE values. The hyper-parameters of each model with the best selection of external variables are trained using a multivariate Tree-structured Parzen Estimator from the Optuna framework [1]. For the search spaces in Table 3 the model with the lowest RMSE for the parking location of consideration is selected.

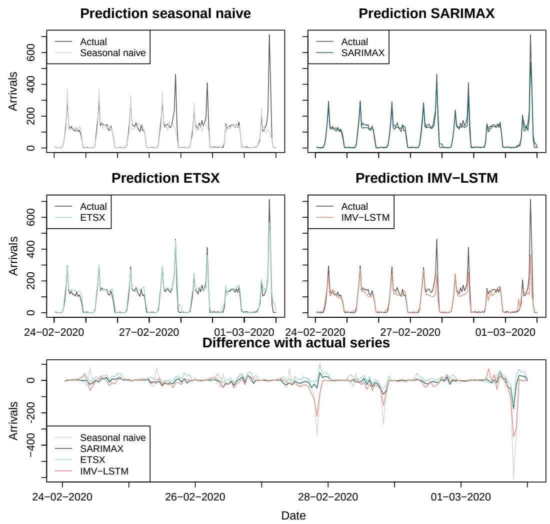

Figure 7: Comparison of predicted versus actual results in Bijlmer Centre between February 24 until March 2, 2020.

Location	SNaive	SARIMAX	ETSX	IMV-LSTM
BUI	58.139	36.311	**32.613**	42.709
BUR	9.293	6.736	**6.570**	7.945
ZUI	14.168	10.292	**9.796**	12.393
BIJ	57.771	29.261	**24.329**	42.246
PRB	4.692	3.445	**3.263**	4.125
PRO	6.714	5.743	**5.076**	5.232

Table 4: RMSE values for Buikslotermeer (BUI), Burgwallen-Nieuwe Zijde (BUR), Zuidas (ZUI), Bijlmer Centre (BIJ), P&R Bos & Lommer (PRB) and P&R Olympisch Stadion (PRO).

5 RESULTS

5.1 Comparison of models

In Figure 7 the predictive performance in Bijlmer Centre is visualized for one week with three events. All models, except seasonal naive without external variables, accurately picked up the events, Especially the predictions from the ETSX model were close to the actual values, even during the major event on Sunday. The final RMSE values are presented in Table 4. It can be observed that the ETSX model obtained the lowest error results. From Figure 5 a clear and clean seasonal pattern is observed, which is the exact type of problem ETSX and SARIMAX excel at recognizing. Meanwhile, IMV-LSTM models are more able in recognizing highly fluctuating data. When looked at the individual predictions, no clear area is found in which ETSX outperforms SARIMAX. There are enough cases where at one point SARIMAX has the best prediction and at another in the same circumstances ETSX. However, in the long run, ETSX performs better around 65% of the time. The biggest difference between SARIMAX and ETSX occurs one week after a spike that is not predicted well, e.g. due to a soccer game. Due to the large variability in number of arrivals the error is sometimes relatively large in each of the models. With this data the smoothing factor for seasonality tends to be higher by SARIMAX than for ETSX. This causes the SARIMAX model to take this error much more in account the next week, resulting in a worse prediction.

5.2 Analysis of exogenous regressors

The impact (in %) of regressor $k \in (1, \cdots, K)$ on the parking demand is defined in Equation 6

$$\delta_k = \frac{a_k \cdot N}{\sum_{t=1}^{N} \left(x_t - \sum_{i=1}^{K} a_{i,t}\right)} \cdot 100, \tag{6}$$

where a_k is the coefficient of regressor k, N is the number of data points and x_t are the arrivals at t. This indicates the change when regressor k is included, compared to the situation without any external factors.

5.2.1 *Analysis of policy changes.*

Because the lookback window of the models is one week, the estimates of the first week of a policy is built from the last week before the policy. In the second week of a policy, the model compares with the first week when no new change occurred. Thus, the coefficients only inform the impact in the first week after a policy change. Hence, analyzing the coefficient of policy changes to estimate the impact of that policy is not feasible. An alternative approach is comparing the significant difference between values before and after the policy change. Since statistical tests compare values that supposedly come from the same population, it is important that the before and after situations are comparable. Simply testing the actual values is error sensitive, because external variables add more variance to the parking arrivals, which might lead to wrong conclusions. To accurately compare two weeks, the effects of the external variables (e.g. events) are removed from the observations, since these are not part of the policy change. After removal of external variables, the values before and after a policy change are compared using the Wilcoxon rank-sum test with significance level $\alpha = 0.05$. A nonparametric test is chosen because the adjusted week values did not always show signs of normality. To the best of our knowledge, the technique with removing external factors has not been applied in previous studies.

5.2.2 *Impact of policy changes.*

Figure 8 –11 illustrate the impact of the NSL, parking tariffs and COVID-19 on the parking demand according to the ETSX model. From Figure 8 it can be noted that in most neighborhoods no significant impact of NSL was measured. However, an increase by 81% is observed near the North station of the NSL. These travelers potentially continue on the metro line. Moreover, a negative impact of −77% is detected in the east of Amsterdam and in P&R Olympisch Stadion. Possibly, commuters who previously parked at these locations found a better alternative since the opening of the NSL. Figure 9 visualizes the percentage decrease in parking demand as a result of the COVID-19 lockdown. This impact is highest at P&R locations (e.g. -99.9% in P&R RAI) and business park Sloterdijk (Amsterdam North-West). These results are expected due to the high density of businesses in these areas in combination with the advise to work from home. Figure 10 and 11 demonstrate the impact of the tariff increase per neighborhood and tariff zone. Note that the tariff change had the desired effect: significantly less motorists park in the more expensive central areas (until -22%), while an increase is found in the peripheral zones and P&R locations. A positive impact is found in the east. Here, tariff increase has been set much lower than its more central neighboring areas.

Type	Attribute	BUI*	BUR	ZUI	BIJ	PRB	PRO	Attribute	BUI	BUR	ZUI	BIJ	PRB	PRO
Weather	Wind speed	-	-0.02	-	-	-	-	Precipitation	-	-	0.02	-	-	-
	Temperture	-0.04	-	-0.10	-	-	-	Thunderstorm	-	-	-	-	-	-4.14
	Sunshine	-0.10	-0.09	-0.17	-	-0.81	-0.18	View	0.02	-	0.11	-	-	-
Events**	Cult Amstel	-	4e-5	-	-2e-4	-	-	Sport Amstel	-	-	-	1e-6	2e-4	-
	Cult Weesper.	-	5e-3	-	-	-0.02	-	Meet Jordaan	-	-	-	-	-	0.02
	Cult Zuidas	-3e-4	2e-3	-	-	-3e-3	-	Meet Zuidas	-	-1e-4	-	-	6e-4	-
	Cult IJplein.	-	-	-	-	-	-0.01	Meet IJplein.	-	-	-	-	-	-0.02
	Cult De Weter.	-	1e-4	-	-	-0.01	-0.01	Meet Burg.-O.	-	2e-3	-	-	-	-
	Dam Run	-	-	-	-	-	-	Pride Fests	-	-	25.5	-	39.2	-
	Pride Walk	-13.3	-	-	-	-	-	Canal Pride	19.4	-8.5	-	-	-	-
Holiday, vacation	Easter Mon.	-	-	-	-	-	29.7	May break	-	-	-	-	-	10.9
	King's Day	-	-	-9.09	-	-	-100	Autumn break	-	-2.5	-	-	-	-
	New Year Eve	-65.8	-	-4.19	-	-	-28.4	Christmas br.	-	-6.3	5.94	-	-	-
Spatial	Business Slo.	-	-	0.39	-	0.15	-	Prinses Irene.	-	-	-	-	0.17	-
	Buiksloterm.	-	0.03	-	-	-	-	Sloterdijk	-	-	0.36	-	-	-
	Buitenvel.-O.	-	-	-0.19	0.14	-	-	Slotermeer-N.	-	0.02	-	-	-	-
	Burg.-O.	0.10	-	-	-	-	-	Slotermeer-Z.	-	-	-	-	-	0.17
	Centrale M.	-0.02	-	-	-	-	-	Slotervaart N.	-	-	0.37	-	-	-
	Chassébuurt	-	0.19	-	-	-	-	Westelijk Ha.	-0.06	-	-0.37	-	-	-
	Dapperbuurt	-	-	-	-	-0.17	-	Westlandgra.	-	-0.19	-	-	-	-
	Grachteng.-Z.	-	-	-	0.09	-	-	Willemspark	-	-	-	-	-0.21	-
	Houthavens	-	0.40	-	-	-	-0.22	Zuidas	-	0.24	-	-	-	-
	IJburg Oost	-0.09	-	-	-	-	-	P&R Bos&L.	0.08	0.29	0.19	-	-	-
	Middenmeer	-	-	0.08	-	-	-	P&R Olymp.	-	0.23	-0.06	-0.08	0.43	-
	Nieuwmarkt.	-	-	-	-	-0.19	-	P&R ArenA	0.07	0.09	-	-	0.04	-0.05
	Noord. IJ. W.	-	-	-	-	-	0.01	P&R Sloterd.	-	-	0.52	-	0.44	0.84
	Omval/Overa.	0.02	-	-	-	-	-	P&R VUmc	-	-	8e-3	-	-	-
	Overtoomsev.	-0.02	-	-	-0.08	-	-	P&R Zeeburg	0.01	0.18	-	-	0.24	0.04
Level shift	Parking tariff	4.15	-13.1	-13.8	13.4	20.3	-11.2	COVID-19	-37.2	-59.1	-61.3	-50.5	-52.6	-61.2
	NSL	7.02	-2.47	-	-	-11.1	-15.1							

* Parking locations: Buikslotermeer (BUI), Burgwallen-Nieuwe Zijde (BUR), Zuidas (ZUI), Bijlmer Centre (BIJ), P&R Bos en Lommer (PRB) and P&R Olympisch Stadion (PRO).

** The % change is per visitor to the event for the cultural, sports and meeting events, that results in lower percentages.

Table 5: Percentage change in parking demand caused by exogenous regressors for six parking locations.

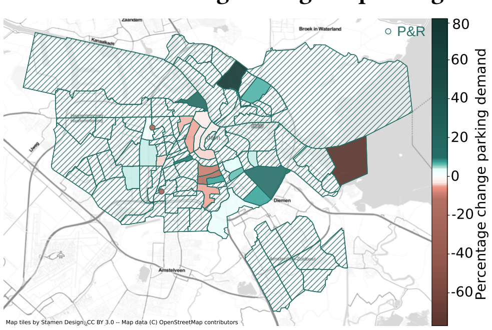

Figure 8: Change due to the North-South line.

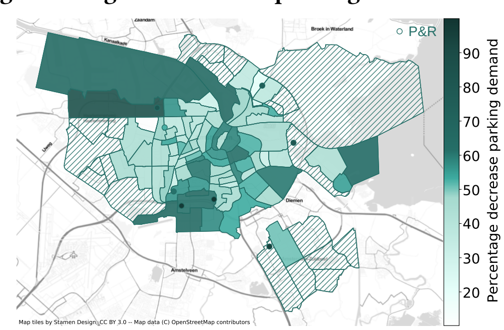

Figure 9: Decrease due to the COVID-19 measures.

Table 5 presents the impact of the exogenous regressors on the parking demand (in %) for the six locations in Section 3.2. Insignificant variables are marked with a "-". Of the weather attributes wind speed, temperature and sunshine slightly reduce parking, and thunderstorms reduced the demand by 4.14% in P&R Olympisch Stadion. Precipitation and view have a positive effect on parking.

In general, sports events result in more motorists to park on-street in the nearby locations, and slightly change demand in locations further from the event venue (e.g. P&R Bos en Lommer). More motorists tend to park in the centre during cultural events. Holidays and vacations can significantly affect parking behavior. One parks less during New Year's Eve (-65.5% in Buitenveldert), and, due to free parking, King's day (-100% in P&R Olympisch Stadion).

The spatial features are explained as follows. The value 0.39 of column Zuidas (ZUI) at Business terrain Sloterdijk (Business Slo.) means: 0.39% more travelers park in Zuidas per arrival in Business terrain Sloterdijk an hour beforehand. Arrivals in locations further

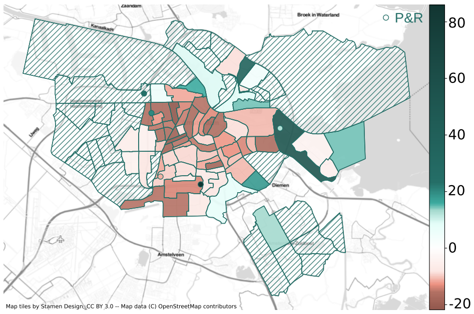

Figure 10: Change due to the tariff increase, neighborhoods.

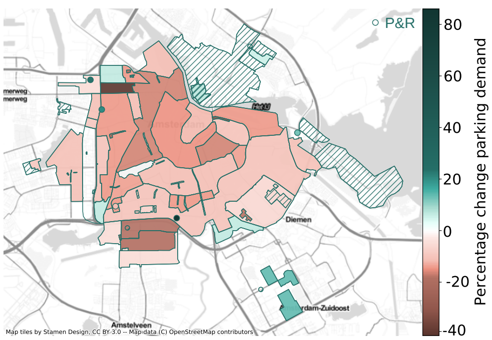

Figure 11: Change due to the tariff increase, tariff zones.

away can have a small effect on the demand in a location. For instance, an arrival in Grachtengordel Zuid in the past hour does not affect neighboring Burgwallen Nieuwe-Zijde, but increases parking in Bijlmer Centre by 0.09%.

A final observation is that the level shift attributes strongly affected the parking demand in Amsterdam. Especially the locations with a more extreme rate increase (e.g. Burgwallen-Nieuwe Zijde and Zuidas) found a sharp decline in demand due to the tariff change. Other locations (P&R Bos and Lommer and Bijlmer Centre) experienced an increase in demand. The NSL has caused less travelers to park in the centre (e.g. 2.47%) and the P&R locations (11.1% and 15.1%). In Buitenveldert demand increased by 7.02% after the opening of the NSL. In all six locations, COVID-19 resulted in significantly less (37.2% to 61.3%) parking transactions. Figure 12 presents the week averages of the time series with exogenous variables removed, retaining only the trends in demand in Burgwallen-Nieuwe Zijde (centre). It can be noted that a decrease occurred after the opening of the NSL and the parking rate increase. Finally, the COVID-19 measures have caused a huge shift. From this, we can conclude that the measures have had an effect in reducing the number of street parking in the city centre.

6 CONCLUSIONS AND FUTURE STUDIES

In this paper, time series models with external variables (SARIMAX, ETSX and IMV-LSTM) are developed to analyze changes in on-street parking and P&R demand as a result of policy measures in Amsterdam. It is found that inclusion of external variables significantly improved the forecast performance, where the ETSX model obtained the lowest RMSE values for each location. A new method

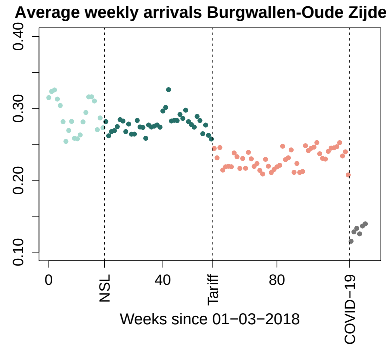

Figure 12: Impact of measures in Burgwallen-Oude Zijde.

is suggested to analyze policy changes by removing external variables from the observations. The three major measures —parking tariff increase, the opening of the metro line NSL and the intelligent lockdown —have radically changed the parking behavior in Amsterdam. As the tariff increase has led to strong decrease in more expensive central areas, more motorists tend to park in peripheral areas and P&R locations. The opening of the NSL has caused an 81% increase in the neighborhood near the northernmost station of the NSL. In the east and P%R locations further from the NSL stations a decrease of until 77% is detected. Finally, the COVID-19 measure has caused a sharp decline in all locations, especially in P&R locations such as P&R RAI (-99.9%) and business park Sloterdijk (-86%). The parking demand increases when the temperature and sunshine duration is lower and the precipitation and horizontal view are higher. Event attributes mostly have impact on locations nearby the venue. New Year's Eve and King's Day decreased parking demand, while the parking arrivals of the last hour in locations can affect the arrivals of the current hour in other locations. In future studies the performance of the IMV-LSTM model can be enhanced, for instance by convolutional neural networks in the LSTM cells. Because the model was computationally expensive, optimization of the IMV-LSTM models can provide an outcome to explore more model parameter combinations in more detail. This paper showed how external variables are useful in time series models: these do not only enhance the forecast performance, but allow to assess its impact (in %) on the target. Interpretable time series models with external variables are therefore well-suitable to provide empirical evidence for more intelligent policy making.

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