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Short-term time series forecasting for multi-site municipal solid waste management

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Abstract

Smart containers equipped with ultrasonic sensors at waste and recycle facilities allow waste and recycling companies to build a more efficient and data-driven approach for the collection of municipal solid waste (MSW). In this paper, we propose three time series algorithms that predict the MSW generation of six waste types, using data obtained from smart sensors placed inside 3,640 containers at facilities in six municipalities in the Netherlands. Per neighborhood and per waste type, three models are developed: a Seasonal Naïve Benchmark model, ensemble models of Error, trend, seasonality models with external variables (ETSX), and Quantile Regression models with external variables. According to the RMSE, the ETSX model is the outperforming model for 74% of the time. It is also found that poor weather conditions such as precipitation, wind gusts and thunderstorms result in less waste disposal. The proposed prediction models can be used for more efficient waste collection, in order to collect waste before the fill rate percentage exceeds 100%. In future studies the inclusion of spatial variables and clustering of the containers can be considered.

Keywords: solid waste management; time series; etsx; quantile regression; sensor data; smart cities; prediction models; external variables

1. Introduction

With the rapid economic development and urbanization, the urban well-being has improved substantially for large proportions of the world population [1]. Yet, the increased resource consumption and release result in large amounts of waste generation. Therefore, Municipal Solid Waste (MSW) generation is becoming an serious challenge to urban local authorities around the globe [3]. To illustrate, the current waste production is about 3.3 million tons per day, and is expected to grow to 11 million tons per day by 2100 [4]. In the Netherlands, household waste had grown by 6.8 percent in one year in 2020, which is the largest increase in almost 25 years [5]. In order to ensure an urban

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environment that contributes to the well-being and productivity of the residents, MSW management is a demanding, yet challenging task. For the development of a successful planning for the collection and recycling of MSW, accurate MSW forecasts are essential. However, data collection from silent containers (not fitted with monitoring devices) is performed manually, which is time-consuming and labour-intensive, prone to error and can be fraudulent or incomplete.

The advent of Internet of Things (IoT) applications in the waste collection industry makes it possible to equip every waste container with ultrasonic sensors that can measure the fill rate percentage. The *fill rate percentage* is defined as the percentage of the volume that the container is filled with household waste. To illustrate, a completely empty container is signified with 0%, while a completely filled container is equal to 100%. The data from these sensors allows planners to create more efficient routes to empty containers just in time before they overflow, reducing the number of overflowing containers and minimizing the number of vehicle miles traveled.

In this paper we propose a framework for the collection waste, and present how three forecasting algorithms perform on real-world sensor data to forecast the fill rate percentage. We also look at influence of external factors such seasonality, weather data and the schedule of events such as soccer matches.

The following contributions have been made throughout this research:

- A framework is presented for the development of MSW collection using sensor-equipped containers
- With a Seasonal Naïve method as a benchmark model, Error, trend and seasonality models with external variables (ETSX) and Quantile Regression models with external variables are developed to accurately predict the fill percentage increase of one week ahead of time for six types of waste.

This paper is structured as follows. First, the relevant literature is discussed. Subsequently, the framework and methodology is proposed. After presenting the results, this paper is finalized with a conclusion.

2. Background

Due to the pressing demand for urban environmental protection [15] [14], prediction models are increasingly prominent in waste-management literature. A major field within this literature is the prediction of MSW to use for waste collection planning services with statistical and machine learning techniques. An example of a statistical application is developed by Navarro-Esbrı et al. [8], who compared a prediction technique based on non-linear dynamics using the embedding theorem of Takens [13] with a SARIMA methodology. The authors tested their models on a dataset of MSW collected in three cities in Spain and Greece and obtained comparable results from both models. Another time series application in this context is developed by Kumar and Samadder [18]. The authors developed a Multiple linear regression model using personal and fuel waste data from a questionnaire survey and personal interviews in over 100 selected households in Dhanbad, India.

Alternatively, MSW can be predicted using machine learning applications. For example, Abbasi and El Hanandeh [2] compared four machine learning techniques —support vector machine (SVM), adaptive neuro-fuzzy inference system (ANFIS), artificial neural network (ANN) and k-nearest neighbours (kNN) —to predict monthly waste generation in Queensland, Australia. Based on their test results, the authors concluded that the ANFIS model outperformed the other models. In a similar research, Johnson et al. [3] built a Gradient Boosting Regression Model to forecast weekly MSW in 232 sites in New York City, using MSW data collected from a single truck. Their model was able to capture external variables, derived from both spatial datasets (e.g. employer household dynamics data) and temporal datasets (e.g. historical weather data). From the model results, the authors concluded that external variables, such as weather patterns, are crucial to accurately predict MSW generation.

While above-mentioned machine learning methods do not encounter sequential data (e.g. time series data), Cubillos [12] applied a multi-site Long Short-Term Memory (LSTM) Neural Network, which can be used for time series data. Tested on waste generation rates of approximately 1000 households in Herning, Denmark, the author found that this model can improve the results by 85% on average compared with the traditional ARIMA model.

Only little research has been done into the prediction of MSW using time series techniques [17]. Moreover, multiple studies [16] suggest to use smart containers with sensors equipped, but only few studies actually use sensory data. More occasionally, we see daily, weekly or monthly MSW averages, obtained from e.g. municipal datasets, which is less granular than hourly sensory data. In this work, we focus on the usage of 4-hourly sensory data obtained from smart containers equipped with ultrasonic sensors in predicting MSW using time series algorithms. As suggested by Johnson et al., we experiment with the impact of external datasets on MSW by including historic weather data.

3. Methodology

3.1. Dataset

We have tested our methodology on a dataset of over 15 million hourly observations of historic fill rate percentages between the 27th of May, 2021 and the 6th of December, 2021. These observations are obtained from ultrasonic sensors placed inside 7,659 unique drop bottom containers located at 1,814 waste and recycle facilities, which can either be above ground or underground. These containers are located in seven municipalities in the province of South Holland, the Netherlands (i.e., Delft, Den Haag, Leidschendam-Voorburg, Midden-Delfland, Pijnacker-Nootdorp, Rijswijk, and Wassenaar). In order to keep each waste type separate, we assume that a vehicle only collects waste of one specific waste type. Therefore, the prediction models are developed for six types of waste separately: Residual, Organic, Plastics, metal, and drink packaging (PMD), Glass, Paper, and Textile. Because the data contains random drops to 0% between unequal, unpredictable time intervals (which are the moments when the container is emptied), we use the deviation in fill rate percentage at time t with respect to the previous time step $t - \Delta t$, where Δt denotes the step size.

3.2. Framework

The framework towards our approach and methodology is presented in Figure 1. For the sake of explanation, only two waste types are assumed in the figure, which are Paper and Organic waste. The process consists of the following five steps:

1. **Data Collection:** The hourly fill rate percentage values and measurement times are obtained from the with sensors equipped containers at 1814 facilities. Additionally, external variables are retrieved from holiday and event schedules and historic weather data is obtained from the Royal Netherlands Meteorological Institute (KNMI).
2. **Data preparation:** First, the containers with sufficient amount of records are selected and aggregated per area. Second, anomalies are detected and imputed if these are most likely errors. Afterwards, the data is transformed into four-hourly observations. Finally, the external variables are prepared to use in the modeling stage.
3. **Predictive Modeling:** For each waste type and area, a separate model is developed to predict the deviation of the MSW for one week in advance. For the sake of demonstration, each area is assumed to be one municipality. The models compared are a Seasonal Naïve forecasting model as a benchmark approach, ETSX models and a Quantile Regression model with external variables.
4. **Vehicle Routing Modeling:** In future work, the forecasts can be used to develop a vehicle routing optimization model to collect the waste of each waste type before the fill rate percentage exceeds 100%. Examples of analogous models are a Mixed Integer Linear Programming (MILP) model to solve the Vehicle Routing Problem (VRP) and other VRP-based algorithms. After this process, every waste type gets assigned a series of trips.
5. **MSW Collection:** These trips can finally be presented in an interactive GPS application, which provides the MSW collector with routes for the collection of the specified waste type.

Since the scope of this paper are step 2 and 3, these are covered in more detail in paragraph 3.3 and 3.4, respectively.

3.3. Data Preparation

The dataset is prepared in four steps, which are (1) Selection and aggregation, (2) Anomaly detection and imputation, (3) Granularity transformation, and (4) Preparation of external variables.

3.3.1. Selection and aggregation

Multiple containers may be located in a waste and recycling facility. Since each type of waste is collected with a separate vehicle, containers of the same waste type at the same facility are combined into a cluster by aggregating these respective waste volume observations. To ensure that the models have enough records to learn seasonal and off-seasonal patterns, the containers and clusters of containers that contain at least one month of observations have been selected. This step reduced the number of containers by 24%. Additionally, the dataset contains measures from an experimental waste type during the final month of the measurement period. Likewise, because the observations

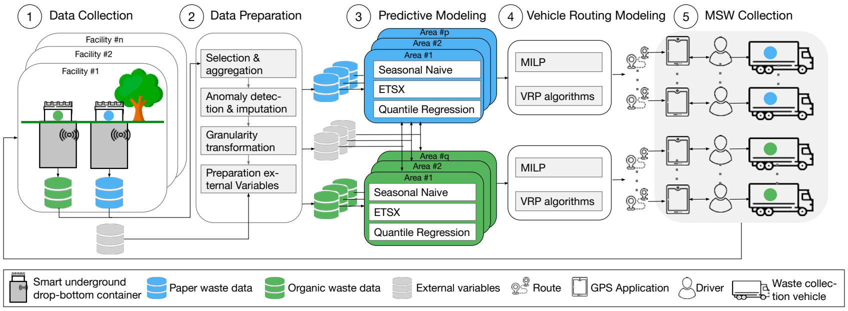

Fig. 1. Framework of the waste collection model

from these containers is in a very short time span, these containers are excluded as well. After this step, another 22% of the containers (including the few facilities inside Den Haag) is excluded. The resulting dataset consists of 3,640 containers at 1,289 facilities, retaining 75% of the MSW observations. Finally, we calculated the weighted mean of the deviation of the fill rate percentage per waste type, per municipality. Here, larger clusters of containers are given more weight than smaller clusters or single containers.

3.3.2. Anomaly detection and imputation

Sometimes a failure can occur in the mechanical or electrical system of the ultrasonic sensor. This may lead to unrealistic values of the fill rate percentage deviation, such as a volume decrease of 50% while the container is not being emptied. If analogous observations are kept in the dataset, the error variance can be increased, reducing the prediction power of the models. Therefore, the observations which diverge from otherwise well-structured or patterned data, defined as *anomalies*, are detected and removed if these are most likely caused by failure. The algorithm chosen is the *Amazon Sagemaker Random Cut Forests* algorithm [19]. This is an unsupervised algorithm that assigns an anomaly score to each data point based on a forest of trees. The following steps are taken for each data point:

1. A bounding box is created for each dimension by taking the minimum and maximum of the dimension;
2. For each dimension a cut is taken randomly inside the bounding box of the dimension, creating new bounding boxes and new branches in the tree model;
3. Step 2 is repeated until the data point is isolated from the other points;
4. This point gets assigned an anomaly score based on the location of the tree, where the closer to the root of the tree, the greater the anomaly score.

An anomaly score of three standard deviations from the mean score is considered to be anomalous. Intuitively, if a data point is an outlier there would be a very high probability that this point would be close to the root of the tree, because it becomes cut and isolated early in the process. This algorithm is especially suitable for time series data, since this allows to include multiple dimensions (here, the dimension of time and the dimension of the MSW observations). In order to obtain robust results, we have selected anomalies using 2,500 trees. Subsequently, the anomalies most likely caused by measurement errors are removed and imputed with the Seasonal Naïve method.

3.3.3. Granularity Transformation

Next, a granularity level is chosen for the fill rate percentage observations. This is determined based on visual analysis, for example of the autocorrelation function for aggregation levels Δt = 1 hour, Δt = 4 hours, Δt = 6 hours and Δt = 24 hours. These aggregation levels are chosen because these allow the daily patterns to be neatly distributed. Figure 2 visualizes the autocorrelation function of the four granularity levels. This function represents the degree of similarity between a given time series and a shifted version of itself over successive time intervals. It allows us to analyze the data structure, such as white noise processes, trends and seasonal components.

For a one-hourly granularity a peak can be observed every 24th lag (i.e., 24 hours), and every 168th lag (i.e., one week). This implies that the time series is correlated with a shifted version of itself of one day and one week, respectively. In other words, the MSW observations contain a daily and a weekly seasonal component. However, after

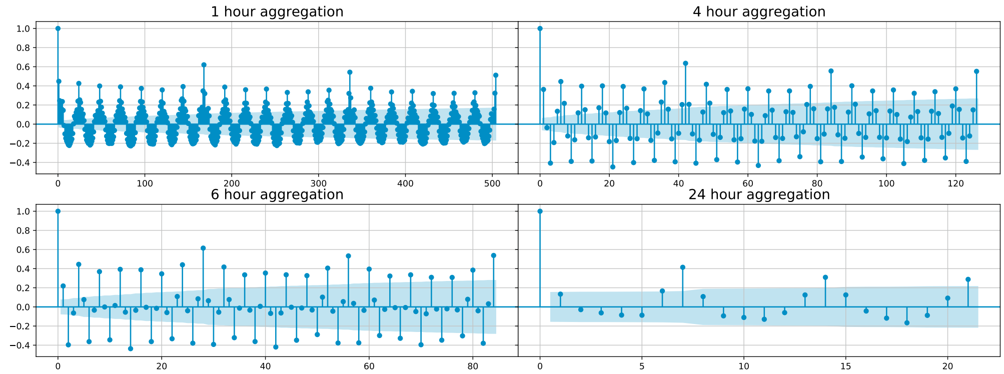

Fig. 2. Autocorrelation functions to compare four levels of granularity (Δt = 1, Δt = 4, Δt = 6, and Δt = 24) for Paper waste in Midden-Delfland.

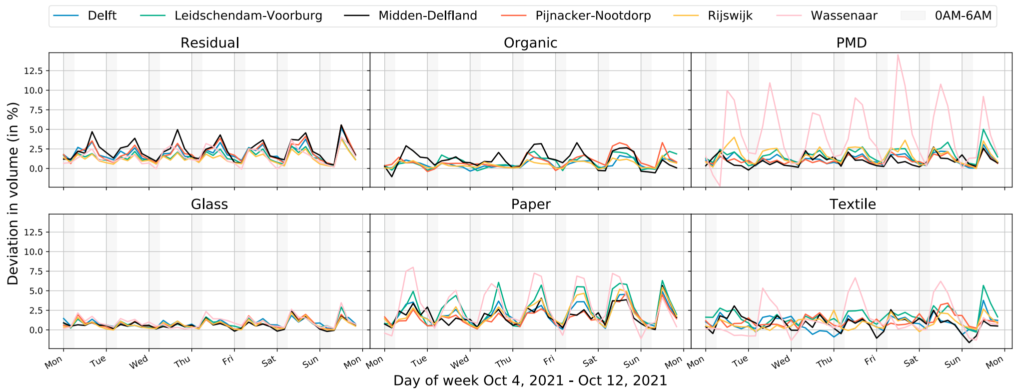

Fig. 3. Percentage of deviation in waste volume, per waste type

visualizing the MSW at 1-hourly time intervals, excessive fluctuation has been noted. This would prevent the models from capturing the general trend of the MSW observations.

On the other hand, a time step of one day (Δt = 24) (a commonly chosen aggregation level in waste collection literature) is too smooth, preventing the model to capture seasonal time patterns. From the figure, it can be noted that the daily seasonality has disappeared.

Similar to the one-hourly granularity, a daily and weekly seasonality is observed for Δt = 4 hours and Δt = 6 hours. However, note from the six-hourly autocorrelation function that the points in between the lags of one day are all insignificant, which indicates that less intra-daily patterns are preserved. Since the four-hourly granularity has more significant observations in between every 24 hours, the observations are aggregated to a granularity of four hours.

The resulting deviation of the fill rate volume (in %) per waste type is presented in Figure 3. From the figure, three observations can be made: (1) the fill rate deviation has a day-night pattern as the values drop down at night (indicated by shaded areas), (2) the time series are similar for each waste type, except for textile and PMD waste, which contains more extreme values in Wassenaar, (3) occasionally, the deviation of the fill rate has two peaks, i.e., in the morning and in the afternoon. The autocorrelation function of the observations in Midden-Delfland is presented in Figure 4. For each waste type a peak can be observed every 6th lag (i.e., 24 hours). Moreover, a higher peak can noted every 42th lag (i.e., a week). This implies that the MSW observations of each waste type contain a daily and weekly seasonal component.

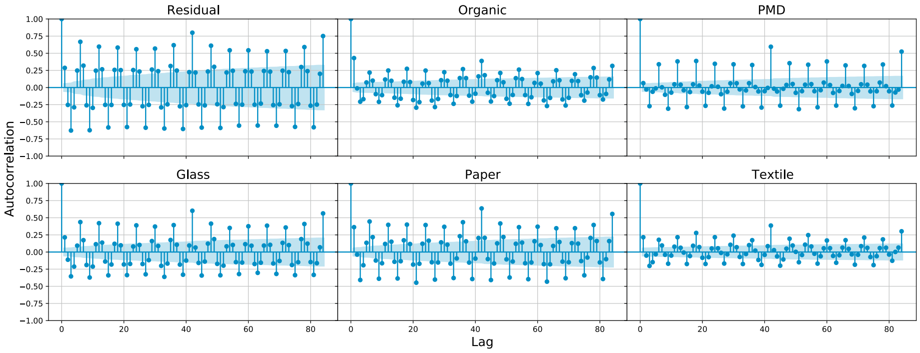

Fig. 4. Autocorrelation function per waste type in Midden-Delfland.

3.3.4. Preparation of external variables

Finally, the external variables are prepared for the predictive modeling step. Since containers might be added, placed or removed, a variable is created that indicates the moments of these changes. Moreover, the external variables are selected that are significantly correlated with the deviation of the fill rate percentage. Based on the Variance inflation factor no significant correlation was found between the holidays and event variables and the target variable. However, since weather variables and addition of new containers seemed to be slightly correlated with the target variable, these are included.

3.4. Predictive Modeling

Accurate MSW forecasts are essential for waste collection planning, since these indicate the expected moments that the container is full, which are the latest moments when a container need to be emptied. While over-estimation can lead to too early collection times, which costs vehicle kilometers, time and money, under-estimation can result in littering. For each municipality and for each waste type three models are developed: a Seasonal Naïve Forecasting model as a benchmark model, an ETSX model, and a Quantile Regression model. These models provide predictions for one week ahead. In the following, the process and methodology is described.

3.4.1. Train and validation approach

Because the measuring period is only 6 months, a larger training set is taken to allow the models to learn patterns from the historic fill-rate percentages. The validation set is used for the selection of the model hyper-parameters, and the test set is used to compare the final model predictions with unseen fill rate percentage. Both sets consist of a period of 2 weeks, resulting in a train-validation-test split of about 80/10/10.

3.4.2. Evaluation metric

The evaluation metric used for the model selection is the Root Mean Squared Error (RMSE). This model is chosen, since it penalizes errors with larger absolute values more than with smaller absolute values. With this metric, we aim to reduce more extreme overprediction and underprediction. Its equation is given by

$$\mathrm{RMSE} = \sqrt{\sum_{i=1}^{n} \frac{(\hat{y}_i - y_i)^2}{n}}, \tag{1}$$

where $\{\hat{y}_1, \ldots, \hat{y}_n\}$ are the predicted values, $\{y_1, \ldots, y_n\}$ are the observed values and n is the number of observations. A downside of this metric is that it is less interpretable—there is a need to compare with other RMSE values to check the model quality. For this reason, the more interpretable metric Mean Absolute Scaled Error (MASE) is used in addition to the RMSE. This metric is proposed by Hyndman and Koehler [24]. For prediction $\hat{y}_i$ and corresponding observed value y_i as well as training data z_t with seasonality p the metric is given by:

$$\mathrm{MASE} = \frac{\sum_{i=1}^{n} |\hat{y}_i - y_i|/n}{\sum_{t=p+1}^{T} |z_t - z_{t-p}|/(T-p)}. \tag{2}$$

Generally, the MASE calculated the mean absolute error of the forecast values and divides this by the mean absolute error of the in-sample one-step naive forecast method (here the Seasonal Naïve model). The scaled error can be easily interpreted, as values smaller than one indicate that the forecast values are better than the average one-step, naïve method. Conversely, values greater than one indicate that in-sample one-step forecasts from the naïve method perform better than the forecast values under consideration.

3.4.3. Seasonal Naïve forecasting model

Because a clear seasonal component has been observed in the time series data (see Figure 4) we chose the Seasonal Naïve model as a benchmark model. This model requires minimum amount of data manipulation and effort to provide predictions, while including the seasonal components of 1 day and 1 week. In this model, a forecast value equals the last observed value of the same season of this data point. The h-step ahead forecast is given in the following equation

$$\hat{y}_{t+h|t} = y_{t+h-s(k+1)}, \tag{3}$$

where h denotes the step size, s denotes the seasonal period and k denotes the number of complete time steps in the forecast period prior to time t + h [21].

3.4.4. Error, Trend, Seasonality models with external variables

Usually, a time series can be decomposed into the components of trend and cyclical, seasonal and irregular [22]. Error, Trend, Seasonality (ETS) models apply a different variant of exponential smoothing based on the structure of these components, which can for instance be additive, multiplicative or nonexistent. The state space equations for each of the models in the ETS framework can be found in the book by Hyndman et al., Table 7.7 [23]. An ETSX model combines the ETS model with external variables. Technically, an ETSX model is a regression model with time varying intercept, defined by the ETS components and smoothing parameters. Its equation for the additive and multiplicative error type can be found in Equation 4 and 5, respectively.

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

$$\log y_t = \log a_{0,t} + a_{1,t}x_{1,t} + a_{2,t}x_{2,t} + \cdots + a_{n,t}x_{n,t} + \log(1 + \epsilon_t), \tag{5}$$

where $a_{0,t}$ is the point value 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 using the branch and bound algorithm. In order to generate more accurate forecasts, we propose an ensemble model that combines the best performing ETSX models for each waste type and municipality.

3.4.5. Quantile Regression model

Quantile regression is an extension of linear regression that is used when the assumptions of linear regression (i.e., linearity, homoscedasticity, independence, or normality) are not met. Unlike regular linear regression which uses the method of least squares to calculate the conditional mean of the target across different values of the features, quantile regression estimates the conditional median of the target. With this model, one is not limited to finding the median, but any quantile (percentage) can be calculated for a particular value in our target variables [20]. Given that we aim to forecast the fill rate percentage and we need to ensure that it will not exceed the 100%, quantile regression can be very useful in our analysis.

One drawback of standard quantile regression models is that these only predict one step ahead, whereas we aim to predict a full week ahead (which are $1, \ldots, 42$ time steps ahead). In order to solve this, we built 42 models instead of one model: one model to predict at $t + \Delta t$, one to predict at $t + 2\Delta t$, until $t + 42\Delta t$, where Δt is the time step of 4 hours. These models are fed with the most recent 2 weeks, and enhanced by including external variables at the time of the prediction to the input variable.

4. Results

The RMSE and MASE values of the three models per waste type, per municipality are presented in Table 4. The best and worst performing model results are highlighted in green and red, respectively.

From the table, it can be noted that the ETSX model outperforms the other models for 74% of the time based on the RMSE values and 71% of the time based on the MASE values. In the case of Residual waste and Paper waste, the

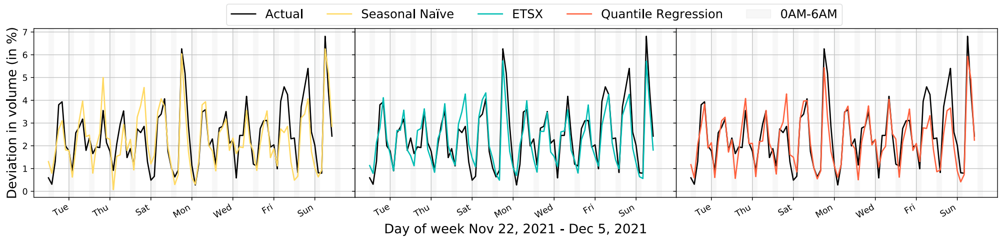

Fig. 5. Model comparison for the residual waste generation in Midden-Delfland.

ETSX model provides the most accurate results for each municipality. Regarding Organic and PMD waste, the ETSX model and Quantile Regression model alternate as the best model, depending on the municipality. Apart from three cases where Quantile regression performs the worst, the Seasonal Naïve model results obtain the highest errors for every municipality and waste type combination according to the RMSE. This can be caused by the fact that neither external variables nor the trend are included. When looking at the MASE values, it can be noted that most of the time the ETSX and Quantile model error is lower than the Seasonal Naïve model error, especially for Organic and Textile waste. An explanation is that the time series of these waste types are less predictable if only the seasonal pattern is considered, and require more complex computation. This can also be seen in Figure 4, where the autocorrelation values are generally lower compared to the other waste types. Moreover, the MASE value is greater than 1 in four cases, indicating that these models perform worse than the baseline model. Contradictory, the RMSE value of three of these models is lower than the Seasonal Naïve RMSE value. This can happen, since the MASE divides by the MAE of the training set (which can be rather unpredictable).

Since we decided to ensemble the ETSX models to enhance the prediction results, the impact of the external variables cannot be interpreted —these models blindly blend the information of all variables. However, based on first single model development, we saw a that higher precipitation, higher wind speed and the event of a thunderstorm result in less waste being thrown away.

In Figure 5 the actual residual waste deviation is compared with the model predictions for Midden-Delfland. We can see that the predictions are close to the actual values, especially from the ETSX model and the Quantile Regression model. The ensemble model that uses ETSX models seems to provide the most promising results and is for example the only model that accurately predicts the peaks on Friday December 3rd and Saturday December 4th.

5. Conclusion

In this project, time series models are developed to predict the deviation of the waste volume (in %) for one week ahead in six municipalities in the Netherlands. These models use real world data obtained from ultrasonic sensors placed inside 3,640 underground containers. For each distinctive waste type and for each municipality, three models have been developed: a Seasonal Naïve model as a benchmark method, and two advanced models, i.e. an ensemble model built from ETSX models and a Quantile Regression model, which is adjusted to predict multiple steps ahead. The advanced models incorporate external variables, which are the addition of new containers at the waste facilities and weather variables. The ETSX ensemble model obtained the lowest RMSE values for 74% of the time. The second best model is the Quantile Regression model, which performs better than the benchmark model for 89% of the time. From the MASE results it is observed that these two models especially outperform the benchmark model when predicting Paper waste and Textile waste.

Based on a comparison with the actual values, we found that the proposed advanced models provide promising results. Besides the structural time patterns, these models are able to capture less predictable peaks, for example due to the addition of new containers at facilities and weather variables. Regarding the latter, less waste disposal has been noticed during rainfall, higher wind speed and thunderstorm.

Based on the analysis up to now, we propose the next steps to further enhance the model results and increase the prediction accuracy. First, spatial variables can be added to these models to improve the predictions per facility location. In this work, the weighted average of each waste type *per municipality* is taken. However, the distinctive waste facilities can differ in one municipality. To illustrate, at a facility located in an area with a high population density in a municipality, more waste can be disposed compared to a more remotely located facility in the same municipality.

Table 1. RMSE and MASE values of the ETSX model and Quantile Regression model and RMSE values of the Seasonal Naïve model.

Waste Type	Municipality	ETSX		Quantile Regression		Seasonal Naïve
		RMSE	MASE	RMSE	MASE	RMSE
Residual	Delft	0.360	0.981	0.361	1.091	0.361
	Leidschendam-Voorburg	0.261	0.849	0.306	0.937	0.383
	Midden-Delfland	0.589	0.926	0.659	0.931	0.732
	Pijnacker-Nootdorp	0.328	0.793	0.341	0.859	0.341
	Rijswijk	0.241	0.920	0.315	0.989	0.357
	Wassenaar	0.547	0.796	0.671	0.963	0.730
Organic	Delft	0.277	0.789	0.277	0.791	0.278
	Leidschendam-Voorburg	0.432	0.634	0.485	0.715	0.628
	Midden-Delfland	0.792	0.776	0.771	0.758	0.970
	Pijnacker-Nootdorp	0.443	0.833	0.443	0.832	0.547
	Rijswijk	0.228	0.734	0.212	0.684	0.241
PMD	Delft	0.255	0.872	0.242	0.826	0.285
	Leidschendam-Voorburg	0.347	0.719	0.352	0.764	0.477
	Midden-Delfland	0.490	0.922	0.487	0.920	0.498
	Pijnacker-Nootdorp	0.275	0.874	0.320	0.988	0.304
	Rijswijk	0.477	0.844	0.456	0.870	0.534
	Wassenaar	1.408	0.669	1.455	0.764	1.420
Glass	Delft	0.264	0.968	0.274	0.955	0.327
	Leidschendam-Voorburg	0.253	0.974	0.262	0.991	0.281
	Midden-Delfland	0.297	0.717	0.316	0.756	0.416
	Pijnacker-Nootdorp	0.269	0.917	0.283	0.957	0.309
	Rijswijk	0.336	1.035	0.308	1.020	0.347
	Wassenaar	0.383	0.867	0.411	0.935	0.441
Paper	Delft	0.491	0.985	0.498	0.993	0.53
	Leidschendam-Voorburg	0.794	0.896	0.914	1.009	0.963
	Midden-Delfland	0.983	0.989	1.112	1.006	1.116
	Pijnacker-Nootdorp	0.467	0.905	0.495	0.978	0.512
	Rijswijk	0.694	0.912	0.768	0.947	0.811
	Wassenaar	1.401	0.906	1.630	0.977	1.882
Textile	Delft	0.449	0.662	0.524	0.812	0.676
	Leidschendam-Voorburg	0.707	0.846	0.821	0.906	0.955
	Midden-Delfland	0.739	0.686	0.790	0.754	1.076
	Pijnacker-Nootdorp	0.855	0.998	0.725	0.976	0.870
	Rijswijk	0.669	0.836	0.765	0.900	0.923
	Wassenaar	1.224	0.702	1.132	0.581	1.253
Best model		74%	71%	26%	26%	0%

This can be improved by performing a new segmentation using unsupervised machine learning techniques, such as the k-means algorithm. With this method the single containers and clusters of containers that show similar patterns in their MSW volume deviation, would be routed to these destinations and enable to make most use of their fleet. Finally, future studies can focus on bridging the gap between the model results and providing the routes, where important detailes are taken into account, such as the work schedules of the MSW collectors, the varying speeds on the roads based on time and location, and the total capacity of both the vehicle and the containers.

With this work, we demonstrate how smart city sensors can be used to predict the MSW for a more efficient waste collection. If more smart sensors are equipped inside containers, Information and Communication Technology systems can be designed such that less vehicle miles need to be traveled without the risk of littering, reducing the carbon footprint and hence, providing a more sustainable solution for the future.

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