Hierarchical Optimisation Model for Waste Management Forecasting in EU

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Abstract

The level of waste management varies significantly from one EU state to another and therefore they have different starting position regarding reaching defined EU targets. The forecast of waste production and treatment is essential information for the expected future EU targets fulfilment. If waste treatment does not meet the targets under the current conditions, it is necessary to change waste management strategies. This contribution presents a universal approach for forecasting waste production and treatment using optimisation models. The approach is based on the trend analysis with the subsequent data reconciliation (quadratic programming). The presented methodology also provides recommendations to include the quality of trend estimate and significance of territory in form of weights in objective function. The developed approach also allows to put into context different methods of waste handling and production. The variability of forecast is described by prediction and confidence intervals. Within the EU forecast, the expected demographic development is taken into account. The results show that most states will not meet EU targets with current trend of waste management in time. Presented methodology is developed at a general level and it is a suitable basis for strategic planning at the national and transnational level.

Keywords

Waste forecasting, Circular Economy Package, quadratic programming, trend modelling, data reconciliation, confidence intervals

1 Nomenclature

Sets

$j, \bar{j} \in J$	All territories, i.e. individual states and the EU as a whole
$h, \bar{h} \in H$	Waste handling /production, incineration, recycling, landfilling, treatment/
$t \in T$	Time period of historical data and forecast
$\beta \in B$	Bootstrap resampling

Mathematical symbols

a, b, c	Regression coefficients for trend estimate
$A_{j,\bar{j}}$	Membership matrix for territory hierarchy
$\tilde{k}_{ii}$	Diagonal element of regression matrix
$l_{t,j,h}$	Binary parameter taking into account results from data pre-processing
$m_{t,j,h}$	Forecasted result of waste production or handling after data reconciliation
$\widetilde{m}_{t,\beta}^{j,h}$	Forecasted result of bootstrap generated data β
n	Number of points in time series used for trend estimate
$p_{t,j,h}$	Trend value for territorial unit j and waste handling h
q	Number of parameters in regression used for trend estimates
$\tilde{t}$	Order of predicting year
$t_{\mathrm{n}-q}(1-\alpha/2)$	$(1-\alpha/2)$-quantile of Student's t-distribution with $n-q$ degree of freedom
$T_{j,h}$	Total number of available points in time series after data pre-processing
$U_{h,\bar{h}}$	Membership matrix for waste production and handling hierarchy
$v_{j,h}$	Weight characterising the size of the producent
$w_{j,h}$	Weight characterising the quality of data fitting
$x_{i,j,h}$	Historical data point in time series
$\tilde{x}_{t,\beta}^{j,h}$	Generated data for confidence interval bootstrap construction
$\epsilon_t^{j,h}$	Data residuals from evaluated trend
$\epsilon_{t,\beta}^{j,h}$	Selected residual from the set of data residuals in bootstrap
$\tilde{\epsilon}_t^{j,h}$	Scaled data residuals from evaluated trend
σ_t^2	Variance estimate of prognosis based on bootstrap repetition
$\tilde{\sigma}^2$	Variance estimate of residual component
$\varepsilon_{t,j,h}$	Error included into trend to maintain links in the system
$\varepsilon_{t,j,h}^{+}$	Positive part of error
$\varepsilon_{t,j,h}^{-}$	Negative part of error
$\delta_{t,j,h}$	Multiplier of trend in data reconciliation

Abbreviations

BE	Belgium
CEP	Circular economy package
CZ	Czechia
DK	Denmark
ES	Spain
EU	European Union
FI	Finland
IT	Italy
LR	Linear regression
LT	Lithuania

LV	Latvia
MSW	Municipal solid waste
RO	Romania
SE	Sweden
TSA	Time-series analysis
WM	Waste management

1 Introduction

Waste management (WM) in the EU is currently undergoing a transition from a linear economy to a circular economy (Morseletto 2020). The WM modification is motivated by the need to treat large amounts of waste and save the environment. Appropriate waste treatment could also replace and save some limited primary resources (Gai et al. 2021). The smooth and sustainable transition to the circular economy and the transformation of WM is enshrined in legislation by Circular economy package (CEP), essential for municipal solid waste (MSW) are directives: Directive (EU) 2018/850, Directive (EU) 2018/851, Directive (EU) 2018/852. The goal of CEP is to maintain the value of the product as long as possible based on Waste management Hierarchy, Directive 2008/98/EC. The key years for CEP are the years 2025, 2030 and 2035. The major milestones contained in CEP are recycling targets and landfilling target, see Fig. 1.

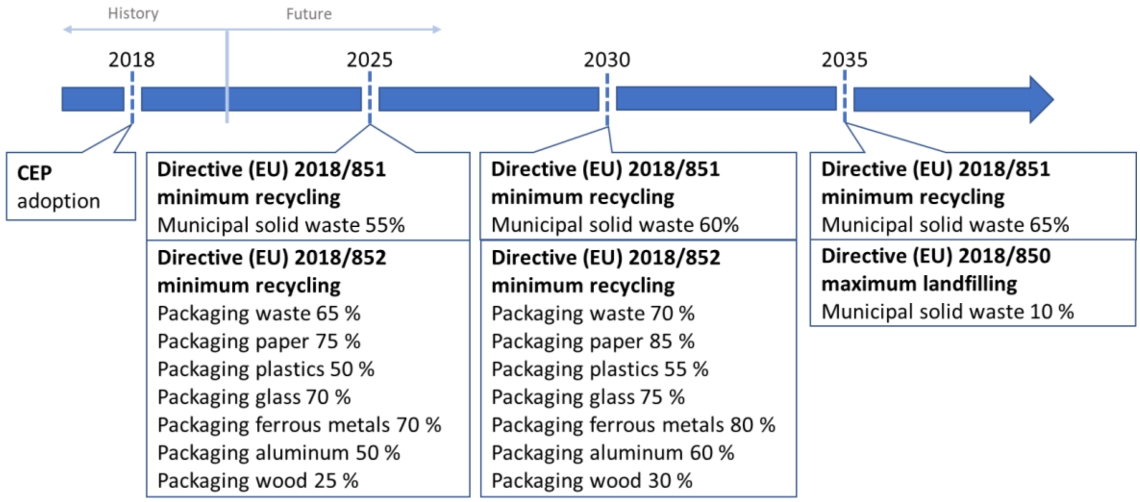

Fig. 1. Targets of Circular Economy Package

The EU's goals are set at state level, but each EU country has a different starting position for meeting the CEP targets. Significant differences are observed in terms of MSW generation and ways of treatment. The level of waste generation is coupled with economic development (Wilson et al. 2015). As a key information can be considered the waste composition, which shapes future WM development (Šramková et al. 2021). The Fig. 2 illustrates the time evolution of EU MSW treatment in the period 1995–2018. The construction of the ternary graph is based on principle presented by Pomberger et al. (2017) and shows the ways of MSW treatment in percentage. An obvious trend of reduction of landfilling and increase in material recovery can be seen. A slight increase in incineration of waste can be observed. The incineration, in other words energy recovery, of waste in Waste-to-Energy plants represents efficient method, how to deal with non-recyclable components, and thus constitutes an important countermeasure against global warming (Maki et al. 2021). The area where the goals in 2035 are met (the last monitored year in CEP) is marked in green. The right part of the Fig. 2 shows the percentage change in waste production related to the initial year 1995.The historical development of WM at the state level and also at the EU level as a whole the initial information for estimating future development in this article. It can be stated that there are considerable differences between individual states. Most states already show a gradual development to reduce landfilling and increase material recovery, thus approaching the CEP target. The question is whether this gradual development will reach the required goal in time, i.e., in 2035. This information will be provided by the forecast of the expected development of waste treatment on the basis of the current trend. A complete visualisation of historical data with a follow-up forecast at the state level is available in Section 5 and Appendix B.

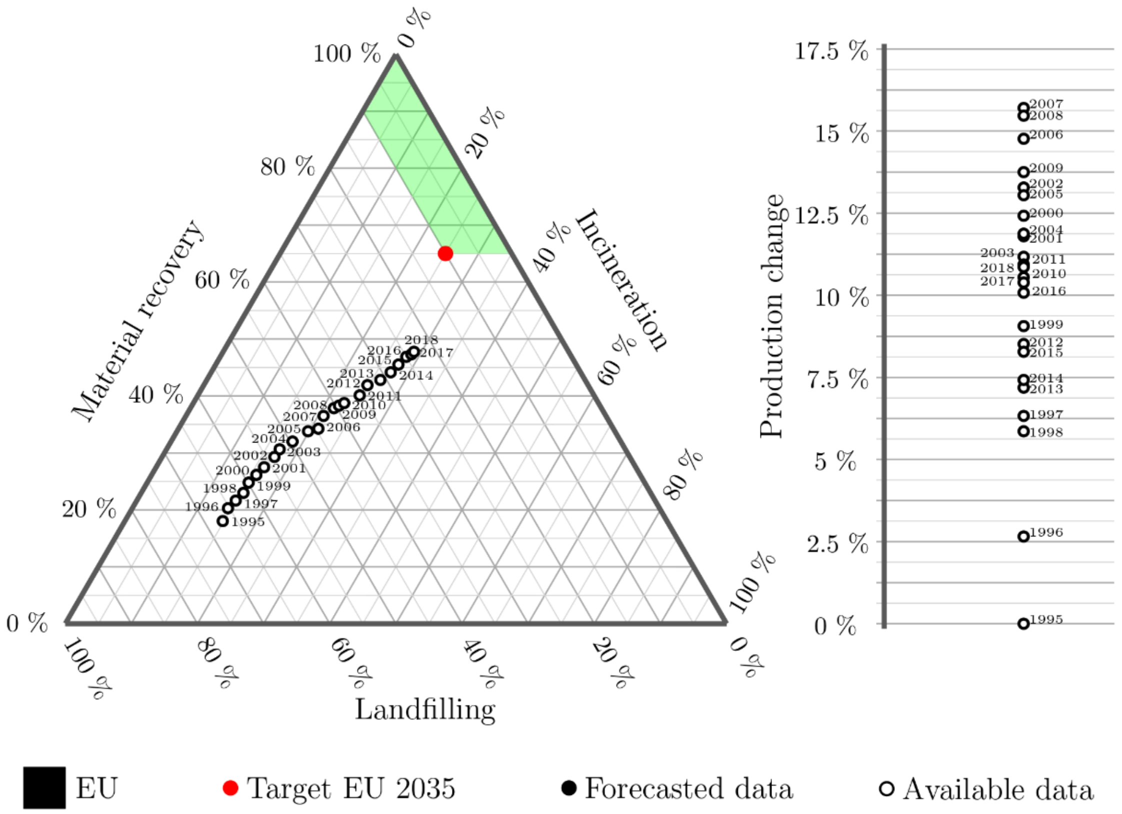

Fig. 2. Waste production and processing in the EU, data 1995–2018 (Eurostat 2020)

This contribution presents a methodology for forecasting waste production and treatment at the state level in EU. Input information is historical data on WM. The methodology uses trend analysis of historical data with subsequent data reconciliation to maintain the link between waste production and treatment. At the same time, the expected demographic development of individual states is considered. Demography is a factor that is well predictable and at the same time has a significant impact on the absolute amount of produced waste (Smejkalová et al. 2020b). The knowledge of expected future MSW production and treatment is valuable information for WM planning. In addition, the forecasting of baseline scenario identifies countries, which need the systematic change to achieve the defined targets.

2 Literature review

Waste production and treatment forecasting is an essential input for planning in WM. The waste treatment models rarely appear, see Table *1*. The waste production models can be distinguished into prediction models and forecasting models. Prediction models deal with description of current or future waste production using factors influencing it. In this way, it is possible to estimate the waste production for example in the locality without available data according to influencing factors. Simultaneously it is possible to model expected development in future. In contrast, forecasting models focus on estimates for the future waste production using only historical data without external intervation. The difference between prediction and forecasting models is if the estimation is modelled using links in the system (prediction) or using historical development (forecasting). There is currently no comprehensive review for forecasting models. Quality review for prediction models was provided by Beigl et al. (2008). A subsequent article (Lebersorger and Beigl 2011) by the same authors follows up on the mentioned shortcomings in the review by creating a regression model, which desribes links between WM and socio-economic factors. These links can be valuable for forecasts in a field of WM. As another way for forecasting is time series analysis (TSA) and its combination with other methods. An interesting example, how to obtain value in unmeasured point, can be the use of surrounding values (Lanzi et al. 2009). Further in Table 1 is a summary of articles that have dealt with the forecasts in the EU during recent years.

Table 1: Literature review – MSW forecasting for EU member states

State	Source	Treatment (yes/no)	Territory level	Data detail	Number of historical data	Forecast length	Confidence intervals	Method
EU	Andersen et al. (2007)	no	state	year	-	15	no	General regression
BE	Peeters et al. (2017)	no	region	year	18	25	scenarios	distribution delay forecasting
CZ	Pavlas et al. (2017)	no	micro-region	year	6	6	no	TSA – trend analysis, data reconciliation*
	Pavlas et al. (2020)	no	micro-region	year	6	10	no	TSA – trend analysis, data reconciliation*
	Hřebíček et al. (2017)	no	state	year	6	6	yes	LR
	Smejkalová et al. (2020a)	no	micro-region	year	9	14	no	TSA – trend analysis, credibility model
DK	Andersen and Larsen (2012)	yes	state	year	15	12	no	LR
FI	Sokka et al. (2007)	no	state	year	43	18	scenarios	IPAT equation
IT	Bramati (2016)	no	region	year	10	13	scenarios	SEM = Simultaneous equations model
LV	Klavenieks and Blumberga (2016)	no	state	year	10	7	scenarios	LR
LT	Denafas et al. (2014)	no	municipality	month	24	12	yes	TSA
	Karpušenkaitė et al. (2018)	no	state	year	10	7,14	no	TSA
	Rimaitytė et al. (2012)	no	municipality	week	416	10	no	LR, TSA
RO	Ghinea et al. (2016)	no	municipality	year	16	15	no	TSA

State	Source	Treatment (yes/no)	Territory level	Data detail	Number of historical data	Forecast length	Confidence intervals	Method
ES	Estay-Ossandon and Mena-Nieto (2018)	yes	region	year	16	16	scenarios	SD
	Oribe-Garcia et al. (2015)	no	municipality	year	15	13	no	CA, LR, factor models
SE	Sjöström and Östblom (2010)	no	state	year	13	24	no	computable general equilibrium analysis

*Remark: * methods involving optimisation*

The waste forecasts listed in the Table 1 deal with production of MSW as a whole and also its fractions (paper, plastic, glass, etc.). However, only Andersen and Larsen (2012) and Estay-Ossandon and Mena-Nieto (2018) also provided a forecast of waste treatment, see column "Treatment". Lack of forecasts of waste treatment methods are considered a significant shortcoming and research gap. Territorial level ranges from the municipal to the state level, so data are in various details. Only at the level of municipalities the data are available in greater detail than on the annual basis (month, week). Forecasts are usually targeted at a long prediction horizon compared to the number of historical data used.

In most cases, the forecast is modeled using statistical approaches which vary through contributions, but LR and TSA are applied repeatedly. Therefore, these two are classical approaches. LR describes the links between waste production and influential factors from various fields (economics, sociology, demography and others). TSA has different forecasting approach, it uses historical data to describe development over time, which is then extrapolated to the future. Optimization methods are marked * in Table 1, these are just two papers. Both of them use data reconciliation to ensure links in the hierarchical structure of territorial units (Pavlas et al. 2017) and links between waste fractions (Pavlas et al. 2020). Forecasts for states outside Europe include the use of optimisation only exceptionally. Usually the optimisation is used for estimated suitable parameters in the model, as was the case study of e- waste forecasting production in Australia (Islam and Huda 2019). A study presented by (Dai et al. 2020) described the links between influencing factors and waste production in China. These links involving nonlinear dependencies were estimated using SVM, coefficients for the model were found by minimizing risk function using a genetic algorithm. The regression risk and the loss function were minimized by solving the quadratic optimization problem in the study for USA presented by (Song et al. 2014). Simulated annealing was used by (Song et al. 2014) for combine three models.

Estimate of variability or expected deviations from forecasted data are an important additional information about all predictions. It can be expressed by confidence intervals. As literature review shows, the variability evaluation and modelling is usually omitted. Some publications tried to desribe potential future development using many scenarios. Only two papers presented construction of confidence intervals, but they aproach only waste production. To maintain links between production and treatment, advanced statistical and optimisation methods are needed.

Many publications have shown that there is a link between waste production and some factors, such as population size, income, education etc. The methods for searching links between waste production (treatment) and economic or demoghraphic data presume sufficient quality of explanatory parameters, which is not usually available. It represents significant limitations for these approaches for prediction of WM, especially for long-term prediction. Quality forecasts of influential factors are therefore needed. In addition, most contributions are presented for only one EU state. As an exception, Andersen et al. (2007) applied a model of dependence on economic and demographic factors for the 25 EU states. The inclusion of influential factors in the forecast (economics, sociology, demography) will be discussed further in Section 4.

TSA has a significant representation among the approaches used for forecasting waste production. The choice of method for time series analysis depends on many factors, but the length of the time series is crucial. WM usually offers only short-time series of data. In this case, it is possible to successfully model the trend component in the historical data by mathematical curves. It may be advantageous to use S-curves, as a logistic trend or a Gompertz curve Ghinea et al. (2016). These types of S-curves are asymptotically limited and it is therefore necessary to determine in advance the potential that the modelled quantity can reach. Sometimes the development of a time-series is disrupted by an external factor that changes its trend (legislation, change in waste collection, new materials etc.). Smejkalová et al. (2020a) introduced an approach correcting the S-curve trend in data using credibility theory. With this approach, it is possible to take into account a change in the trend even if the individual territories react to the intervention with different intensity. TSA models generally do not include hierarchy, which is ensured by approach presented by Pavlas et al. (2020). On the other hand, there were no criteria, which take into account the model quality. The explanatory predictor like demoghraphic development was also not considered.

In most cases, WM plans are available in the national language of the country, making it difficult to study. The summarized forecasts within selected WM plans are available in Appendix A, which can help readers with analysis of approaches in other countries. Based on the study of selected WM plans it is clear that the forecast are often modelled on very short time-series of historical data. The definition of MSW is not the same for all EU member states. The inconsistent definition may cause also differences in the fulfilment of EU targets. The existence of non-uniform definition of MSW can be also substantiated by the fact that MSW production varies greatly among countries (Eurostat 2020). The different definitions do not represent significant limitation if they are consistent within historical data. The MSW treatment will be assessed according to the national definition at EU level. Even in WM plans, there is often no MSW treatment forecast. However, this is an essential information for planning of MSW treatment infrastructure to ensure proper waste management. This contribution presents a uniform methodology for production and waste treatment forecasts using data from the Eurostat database (Eurostat 2020).

3 Contribution and Novelty

In order to achieve the CEP targets, it is necessary to react in time to the changes. EU member states have currently different levels of WM. Some of them are already on track to meet targets with their current form of WM. In other cases, changes in WM will be needed to meet the CEP targets in a timely manner. It is essential to identify the appropriate form of WM for each individual state. Key information will be provided by the forecast of MSW production and treatment. Based on the results of the forecast it is possible to assess whether it is necessary to change the current form of WM.

This contribution presents an approach for forecasting the MSW production and treatment. The input data is information on the annual amount of MSW in the history. The available data set plays a crucial part of successful forecast. The methodology uses TSA and trend evaluating, individual time series are solved on basis of available data and its properties. Therefore, more regression functions are introduced in this paper, which should take into account different development in the history more precisely. It also enables finding the trend in different units measures and unify them afterwards in data reconciliation. The methodology is based on the assumption of maintaining the link between production and treatment of waste – all produced waste must be treated in some way. This link is crucial from a planning point of view but has not been considered in previous publications.

The data reconciliation is based on the method by Pavlas et al. (2020) using the principles of quadratic programming. But the methodology is significantly extended. Due to different nature of the task, two approaches for errors, and thus the form of the objective function to minimize, are introduced to keep mass balance in the system. The additive and multiplicative approaches are presented with individual advantages and recommendations in specific situations based on experience with optimisation models and solvers on real data sets. In addition to data reconciliation, the weights are newly addressed, which are developed to consider the quality of trend estimate and the significance of individual territory. Another novelty is the description of uncertain development by the construction of confidence and prediction intervals, which provide additional information about variability of collected data and parameters estimate in regression-based trend evaluation. With respect to the forecast methodology, standard statistics cannot be used for confidence interval and its construction is based on random sampling – the bootstrap method. The intervals also reflect the result from data reconciliation (deviation from trend) and the length of forecast.

Literature review has shown that optimization is used only rarely for forecasting in waste management. This contribution presents approach based on non-linear regression, quadratic optimisation and experience with real data sets is used for EU forecasting. The expected demographic development of the state is taken into account. The methodology is a comprehensive approach to forecasting that is applicable to all EU member states and makes it possible to compare developments in individual EU member states. Part of the case study is a summary of the results and expected developments for EU member states and it also evaluates the recommendations for intervention in the way of MSW treatment for individual countries. The results can serve as a basis for adequate WM plans at national and EU level.

4 Time series analysis

The forecast of waste production and treatment carries several challenges. As review has shown, WM data are often available only annually. Unfortunately, the annual data do not provide a sufficiently long time series. In addition, the relatively long prediction horizon, which is usually modelled in the field of WM, must be considered. The reason is that infrastructure modification is a long-term issue that needs to be covered by a forecast already in the planning phase. The text in this section describes the proposed methodology for forecasting waste production and treatment. In this paper, waste treatment is also newly included in the model. The approach allows the inclusion of significant influencing factors where relevant data can be provided. However, the main idea is the analysis of time series with subsequent data reconciliation taking into account the links in the system.

4.1 Available data and influencing factors

Waste production and treatment methods have been shown to be influenced factors, see Smejkalová et al. (2020b). According to regression models, waste production is specifically influenced by some economic variables, education and age composition of the population. The same is true for the method of waste treatment (Smejkalová et al. 2020b). In order to be able to use these links for the forecast of waste production and treatment, it is necessary to have forecasts of all important factors.

Demographic forecasts are published for all EU member states in databases at European level (Eurostat 2020). In other areas (economics, sociology), mostly forecasts created by national institutions for specific countries are available. Economic forecasts are made only for short periods due to dynamic and unpredictable changes. For example, GDP is forecasted in German to 2023 (Deutsche Bundesbank Eurosystem 2021), in Austria to 2024 (Federal Ministry of Republic of Austria 2021) and in Czechia to 2023 (Czech National Bank 2021) and due to the current turbulent economic development the forecasts are probably not accurate. The basic precondition for the use of any factors is that their forecast covers the entire forecasting horizon, at least until 2035 with regard to the CEP. In the sufficient prediction horizon, only demographic forecasts are available. Another feature of economic and social forecasts are very wide confidence intervals if the uncertainty in the forecast is expressed at all. Therefore, it is not eligible to consider them in WM forecast.

Historical data, period 1995–2018, annual detail (Eurostat 2020):

- MSW production [kt],
- MSW treatment [kt],
- MSW material recycling [kt],
- MSW composting [kt],
- MSW energy recovery [kt],
- MSW incineration [kt],
- MSW landfilling [kt],
- Population [person].

Forecast, period 2019–2035, annual detail:

- Population [person].

MSW treatment considers all treatment methods in aggregated form. The approach to forecasting consists of five steps: data pre-processing, extrapolation of trend in historical data, inclusion of expected demographic development, data reconciliation to maintain the links in the system and confidence intervals.

4.2 Data pre-processing

The available datasets were aggregated, if desired, to allow comparison with EU targets. Specifically, it is waste recycling, which includes material recycling and composting. Furthermore, incineration will generally be referred to as incineration and energy recovery of waste. From the point of view of the targets, information on the energy production of waste incineration is not essential at this time. Although, according to the Waste management hierarchy (Directive 2008/98/EC) this is the preferred treatment method. Furthermore, the term incineration will be understood as MSW energy recovery + MSW incineration, similarly recycling will be understood as MSW material recycling + MSW composting. Other datasets were not aggregated.

Diverse algorithms on data pre-processing were developed and published in the past to identify significant deflections and changes in the data. The review was provided on outlier detection by Blázquez-García et al. (2020), and changepoint detection by Aminikhanghahi and Cook (2017). Individual methods are suitable for a certain type of data and there is no known general method. Individual time series for waste production and treatment were expertly analysed to identify outliers and changepoints. There are outliers in the WM data that are not significant at the state level. This is an advantage for this application and outlier was detected only for treatment in Finland in the year 2015. This point was omitted for following steps of the calculation. At the state level, changes in the system can be evident, which will be reflected in changepoints. As part of pre-processing, it is desirable to reveal these points in time series.

This EU state-level application includes a total of 145 time series from WM field, 5 variables (after the required aggregations) for 29 territories (28 states and EU as a whole). The case study is being carried out for the current 27 Member States of the European Union and the United Kingdom. These 145 time series were gradually assessed individually by experts. On the basis of a visual assessment, it was decided whether a changepoint occurs. Experience in waste management has been taken into account. This is especially the energy recovery, when new facilities are gradually built and there are step changes. However, these changes were not considered as anomalies in the data, but the trend of this series is modelled. The changepoints was identified for landfilling in 3 time series (Germany, Netherland, Austria) and for recycling in 2 time series (Bulgaria, Romania). For the next part of the calculation, the time series before the changepoint was neglected and the time series analysis was applied only to the part of the time series after the change. If there is a missing point in the data, it is considered an unavailable value and is not replaced in any way.

4.3 Extrapolation of trend in historical data

Every citizen produces waste, so MSW production and overall treatment is affected by demographic trends. For this reason, historical data on MSW production and overall treatment are converted from absolute quantities to kg / capita, so these values are extrapolated per capita. The specific treatment method is extrapolated as a rate of the total amount of waste treatment and the interconnection between methods is already included in trend estimate. This adjustment ensures the positive impact on trend quality, because any data oscillations can be smoothed out.

The approach draws on the idea that the development of the observed variables in history will continue in the future, provided that the current conditions are maintained. It is therefore a forecast of the so-called scenario business-as-usual. Historical data are modelled by a suitable curve. Three trend functions are considered for historical data fitting: power function, logistic function and average. Primarily a trend in the form of a power function was considered (Eq. (1)).

$$p_t = a + bt^c, \tag{1}$$

where, p is a dependent variable. Trend p is fitted for the following dependent variables: production [kg / cap], treatment [kg / cap], recycling [%], incineration [%] and landfilling [%]. The symbol t denotes the year, which is an independent variable. The regression coefficients sought are a, b, c. The nonnegativity of trend is ensured only after regression because this constrain represents difficulties. Any negative value of evaluated trend is set to zero.

If the coefficient $c > 1$ applies, an exponential increase (or decrease) in the trend can be expected. In order to avoid the development of a too growing (or shrinking) trend and thus an unrealistic estimate of the development, in the case of $c > 1$, the model was approached by a logistic function, see Eq. (2). To use this function, it is necessary to normalise the input data to 0 – 1 range. The historical data should be normalised by minimum and maximum values that can be reached on the basis of the estimate. If such values are not available, it is recommended to use 1.5 times the maximum value of historical data for the upper limit and 0.5 times the minimum value of historical data for the lower limit.

$$p_t = \frac{1}{1 + e^{-(a+bt)}}. \tag{2}$$

The notation remains the same as for Eq. (1). The regression coefficients are a, b.

The non-linear regression was solved by non-linear optimisation, where finding a global solution is not guaranteed and therefore a suitable setting of the initial points is essential (e.g. by linearisation of equations). The choice of solver also plays key role (Chu et al. 2013). In the case, that there is no way to model the trend quality, the trend is modelled as an average in historical data. The average is modelled in the three following cases:
1. If a small amount of data remains after pre-processing, so the trend cannot be modelled by a curve. The authors recommend modelling the trend only by an average in the case of less than five points of historical data.
2. The trend model using above functions (1) or (2) has low quality. The criterion for this approach was the coefficient of determination $R^2 < 0.1$.
3. Trend is modelled by average to avoid using a complicated model if the change from a simple model (average in the data) is very small. The criterion for the average model is as follows:

$$\frac{|p_{\bar{t}} - \bar{x}|}{\bar{x}} < 0.05, \tag{3}$$

where $\bar{t}$ is the last year of the forecasting horizon and $\bar{x}$ is the average of historical data. Subsequently, the trend model p_t is recalculated back to the absolute amount of waste produced in order to apply the data reconciliation model.

5 Data reconciliation to maintain the links in the system

Historical data on WM includes hierarchical links that result from the nature of the data. The idea of data reconciliation comes from the fact that the trend estimates p are not in logical compliance (i.e., the sum of estimated production of states is not equal to estimated production of EU). Models based on this idea are commonly used for systems, where the values are measured with some errors and at the same time laws of physics applied (Galan et al. 2019). The goal of this paper is to obtain high-quality estimate of future waste production and treatment with respect to links in the system and at the same time, with minimal deviations from already estimated values obtained from trend extrapolation.

5.1 Mathematical model

The mathematical model for data reconciliation is based on quadratic optimisation and it is defined by objective function and set of boundaries. The objective function minimises the square of errors, which are influenced by weights. These errors represent the deflection from evaluated trends. The minimisation is done with condition of fulfilment mass balance, which ensure the hierarchy. To evaluate the error $\varepsilon_{j,h}$, it can be based on the additive (A) or multiplicative (B) approach. In the case of additive approach (A), some problems may occur due to disproportion of input data (i.e. orders of magnitude different values). Multiplicative approach (B) is more complicated due to its solvability caused by non-linear dependencies. In some cases, the suitable chosen solver (KNITRO, Conopt or lpopt) can figure out this problem. Another solution is reducing the scale of task for considered links in balance conditions. The constraint conditions and objective function for the data balancing model are presented below. The time index is omitted in all equations because the model is developed for one period. Individual periods are balanced independently of each other.

The Eq. (4) reflects the territorial hierarchy. It means in practise that the sum of production in countries is equal to EU production. The relationship between territories is defined by hierarchy matrix $A_{j,\bar{j}}$.

$$m_{j,h} = \sum_{\bar{j} \in J} A_{j,\bar{j}} m_{\bar{j},h}, \qquad \forall j \in J, \forall h \in H. \tag{4}$$

The hierarchy from the point of view of WM respects the links between MSW production and treatment. This means that the MSW production is equal to the waste treatment and at the same time the individual methods of waste treatment (recycling, incineration, landfilling) are equal to the total amount of MSW treatment. The Eq. (5) ensures the required relationships by using matrix $U_{h,\bar{h}}$, which defines specific links.

$$m_{j,h} = \sum_{\bar{h} \in H} U_{h,\bar{h}} m_{j,\bar{h}}, \qquad \forall j \in J, \forall h \in H. \tag{5}$$

As a next part, the data errors must be defined. Below are two options for introducing model errors: additive (A) and multiplicative (B) form. The use of an additive or multiplicative form of the model depends on the specific task. The additive model (A) is unsuitable for tasks with a large difference in the size of input values. However, its advantage is that it is less computationally intensive and, in addition, it copes well with zero trends. The multiplicative model (B) works with a percentage change, thus eliminating the problem of different data sizes. On the other hand, it is a more computationally intensive variant. Moreover, it is unsuitable in the case of zero trend values, because the percentage change from zero still remains at zero.

Conditions (9) and (10) are valid for both methods (A) and (B). The Eq. (6) connects the estimated amounts of waste $p_{j,h}$ with variables $m_{j,h}$ and errors $\varepsilon_{j,h}$ in additive form. The Eq. (7) states link between amounts of waste $p_{j,h}$ and variables $m_{j,h}$ using multiplier $\delta_{j,h}$. The Eq. (8) describes the deflection from trend function. The logarithm ensures symmetry of multiplier used, i.e. $\delta_{j,h} = 0.5$ has the same impact on objective function as $\delta_{j,h} = 2$. However, the logarithm function can make the model implementation more difficult and significantly influence the computing time, even the solvability. The formula $\delta_{j,h} + \varepsilon_{j,h} = 1$ can be used instead of the logarithm, however the change of bigger amount is preferred (the same percentage change has bigger impact to satisfy mass balance). It can be partially maintained by appropriate weight (see Eq. (14)). Another limitation of multiplicative approach (B) is input zero values in production or waste handling. Such cases should be solved by additive approach (A). The Eq. (9) describes the division of error into positive and negative parts. This division of the error enables to implement other criteria, such as the sum of absolute error values, but can also be used to add additional constrains or process the results. The formulas in Eq. (10) represent the nonnegativity of specific variables.

$$\text{(A)} \qquad m_{j,h} = p_{j,h} + \varepsilon_{j,h}, \qquad \forall j \in J, \forall h \in H, \tag{6}$$

$$\text{(B)} \qquad m_{j,h} = p_{j,h}\delta_{j,h}, \qquad \forall j \in J, \forall h \in H, \tag{7}$$

$$\text{(B)} \qquad \varepsilon_{j,h} \ = \ log\ \delta_{j,h}, \qquad \forall j \in J, \forall h \in H, \tag{8}$$

$$\varepsilon_{j,h} = \varepsilon_{j,h}^{+} - \varepsilon_{j,h}^{-}, \qquad \forall j \in J, \forall h \in H, \tag{9}$$

$$\varepsilon_{j,h}^{+}, \varepsilon_{j,h}^{-}, \delta_{j,h}, m_{j,h} \geq 0, \qquad \forall j \in J, \forall h \in H. \tag{10}$$

The aim of the forecast is to maintain these links. Compliance with constraints is required with the smallest possible change from the trend in the historical data. This is achieved by the minimisation task of mathematical programming. The formula Eq. (11) represents the objective function with weights $v_{j,h}$ and $w_{j,h}$.

$$\sum_{j \in J} \sum_{h \in H} \left(v_{j,h} w_{j,h}\right)^2 \left[\left(\varepsilon_{j,h}^{+}\right)^2 + \left(\varepsilon_{j,h}^{-}\right)^2\right]. \tag{11}$$

The goal is to minimise the sum of squared errors related to each territorial unit and type of handling. The individual time-series are influenced by the weights $v_{j,h}$ and $w_{j,h}$, which are described below. This correction achieves the final forecast of production and WM for the-business-as usual scenario. Presented model is further used for every forecasted year. It can be beneficial to limit the maximal change from the trend $p_{j,h}$, these are mainly cases that do not have a clear trend. For this condition, the estimation of waste production resp. treatment potential, if available, can be used. However, it is necessary to monitor the solvability of the model

5.2 Ensuring the significance of input data

The goal of the first weight $v_{j,h}$ is to ensure the significance of all input parameters. In the system of hierarchical arrangement, orders of magnitude of different values naturally occur. The same problem can be observed in the case of two countries of different sizes. The weights incorporation ensures that the error is minimised for each country with same rate, in other words, it is a kind of data normalisation. The weights are therefore defined as inverse value for each input data, see following formula Eq. (12), where $\bar{t}$ is the last year of historical data. The reason is to ensure equal weight for all modelled years. This measure will be particularly important for declining trend, so as not to put too little weight on trends approaching zero. In the case where the trend is zero in year $\bar{t}$, the weight $v_{j,h}$ is set to big M. This ensures that if the trend has reached zero in the historical data, a restart is not expected in the forecast.

$$\text{(A)} \qquad v_{j,h} = \begin{cases} \dfrac{1}{p_{j,h,\bar{t}}}, & \text{for } p_{j,h,,\bar{t}} > 0, \forall h \in H, \forall j \in J, \\ M, & \text{for } p_{j,h,,\bar{t}} = 0, \forall h \in H, \forall j \in J. \end{cases} \tag{12}$$

Thanks to this system of weights, each value in the model has the same significant level. The recommendation for some cases, where the big difference between hierarchical levels is observed, is to consider the possibility of preference on higher territorial division. It can be achieved for additive approach (A) by using weights in the form defined by Eq. (13).

$$\text{(A)} \qquad v_{j,h} = \begin{cases} \dfrac{1}{\sqrt{p_{j,h,\bar{t}}}}, & \text{for } p_{j,h,,\bar{t}} > 0, \forall h \in H, \forall j \in J, \\ M, & \text{for } p_{j,h,,\bar{t}} = 0, \forall h \in H, \forall j \in J. \end{cases} \qquad (13)$$

In the case of multiplicative approach (B), it is recommended to implement weights in the form defined by Eq. (14), which also makes preference on bigger amounts. However, there is no goal to normalise data, because the essence of the multiplicative approach is already a percentage change.

$$\text{(B)} \qquad v_{j,h} = \sqrt{\frac{p_{j,h,\bar{t}}}{\max_j p_{j,h,\bar{t}}}}, \qquad \forall h \in H, \forall j \in J. \qquad (14)$$

These modified weights are very useful in that cases when more different models are used for forecasting estimate. Due to specific links in the system, some territory or waste handling must be modelled by diverse procedure or individual approach and this weight can help to maintain all dependencies with reasonable error from trend in every partial territory. Otherwise, there could be the tendency to modify region with greater values or higher territory division because it is more favourable in context of relative change in objective function.

5.3 The quality of trend estimate

The weight $w_{j,h}$ considers the quality of historical data fitting. Individual time series of historical data show different variability. The more reliable estimate of a trend can be observed in the case of stable and clear development in the history. It is desirable to preserve the set trend also in the future. In the case of more variable development, the trend is more difficult to be estimated and such time series are considered as less trustworthy in the process of data reconciliation. The weight $w_{j,h}$ quantify the quality of the data fitting and implement this information into the model. The weight is defined by Eq. (15) and Eq. (16) with range of values from 0.5 to 1.

$$w_{j,h} = \frac{1 - \frac{SMAPE_{j,h}}{\max\left(SMAPE_h^{0,9}; SMAPE_{j,h}\right)}}{2} + 0.5\,, \qquad (15)$$

$$SMAPE_{j,h} = \frac{1}{T_{j,h}} \sum_{i=1}^{T_{j,h}} \frac{\left|p_{i,j,h} - x_{i,j,h}\right| l_{i,j,h}}{\left(\left|x_{i,j,h}\right| + \left|p_{i,j,h}\right|\right)/2}. \qquad (16)$$

The symbol $x_{i,j,h}$ represents real data related to waste handling in year i for time series in territory j a waste handling h. Index i means years with available historical data. Next, the $p_{i,j,h}$ represents the trend for the point $x_{i,j,h}$ and the symbol $l_{i,j,h}$ in a binary parameter taking into account results from data pre-processing. If the parameter $l_{i,j,h}$ is equal to 0, the point was removed and has no impact on $SMAPE_{j,h}$. Otherwise, the parameter $l_{t,j,h}$ is equal to 1. The symbol $T_{j,h}$ is defined as total number of available points in time series after data pre-processing. $SMAPE_h^{0,9}$ means 90. percentile of set of values of $SMAPE_{j,h}$. The weight $w_{j,h} = 0.5$ is set for the time series with higher value of $SMAPE_{j,h}$ than 90. percentile. The same value of the weight ($w_{j,h} = 0.5$) is defined for these time series, where no trend is modelled, and historical data was fitted by mean. The key requirement for weight calculation is to have same units for each time series in the model.

With respect to the nature of the data reconciliation, it cannot be expected that the overall error for approach with weight $w_{j,h}$ is better than without it. Necessary adjustments for ensuring the mass balance are in sum the same. The difference lies in which time series are adjusted to maintain links in the system. The goal is to modify those time series, which show more variability. On the contrary, it is not suitable to change data, which shows long-term and obvious trend.

5.4 Confidence and prediction intervals

The important additional information is variability of estimated values. The confidence interval represents the uncertainty of parameters estimate. It provides an insight into likely future direction of the trend. On the other hand, it does not provide the variability of specific values around the trend. These values can deviate from the trend, especially for data set with big variability. The prediction interval determines the uncertainty for individual data sample. It is usually significantly wider and shows the variability around the trend. This additional information reflects bigger variability in future estimated value. The construction of intervals estimates is complicated due to territory hierarchy and data reconciliation. Thanks to implemented errors, which preserve the links in the system, the standard methods are not directly usable. Therefore, the construction is based on scenarios, which are calculated by model-based bootstrap with resampling errors. The error from data reconciliation and the length of prediction are implemented. The wider intervals can be expected in the case of bigger deviations and longer forecast. The procedure is as follows, where t denoted forecasted years:

- Step 1: The above-mentioned methodology is performed to get the estimate $m_{t,j,h}$ for each period t, which is based on base scenario, i.e. point estimate.
- Step 2: The data residuals $\epsilon_t^{j,h}$ from evaluated trend are determined. These residuals form a set, from which the values are selected for parametric bootstrap. The residuals should be centred by subtracting the average of residuals from each residual of a time series. It is also recommended to take into account the number of parameters in regression used for trend estimates and apply scaled residuals defined by Eq. (17).

$$\tilde{\epsilon}_t = \frac{\epsilon_t}{\sqrt{1 - \frac{q}{n}}}. \tag{17}$$

The symbol n is number of points in time series used for trend estimate and q is number of parameters in regression used for trend estimates. As another way based on non-linear regression is to use standardised residuals, which are defined by Eq. (18).

$$\tilde{\epsilon}_t = \frac{\epsilon_t}{\sqrt{1 - \tilde{k}_{ii}}}. \tag{18}$$

The element $\tilde{k}_{ii}$ is diagonal element of regression matrix, which rows contain gradients of the trend function with respect to a specific parameter in the point estimate of this parameter. This formulation can lead to unfavourable results if historical data represents short time series much more than Eq. (17). Therefore, it is recommended to use previous formula, because available data represents one of the biggest problems of forecasting.

- Step 3: The generation of new random sample is performed for β bootstrap. The residuals are selected from the set defined in previous step for each point of time series. It is selection with repetition. The data for β bootstrap is defined as $\tilde{x}_{t,\beta}^{j,h} = p_{t,j,h} + \tilde{\epsilon}_{t,\beta}^{j,h}$,where $p_{t,j,h}$ is trend and $\tilde{\epsilon}_{t,\beta}^{j,h}$ is a residual from range defined in step 2.
- Step 4: The methodology for trend analysis and data reconciliation is performed for each generated scenario β. The result is future development estimate $\widetilde{m}_{t,\beta}^{j,h}$ for bootstrap β. The recommendation is to perform at least 30 bootstrap repetitions.
- Step 5: The correction $\frac{n+\tilde{t}}{n}$ is introduced to take into account the fact, that the methodology is based on TSA, which is neglected in bootstrap principle. It can be expected that the residuals are positively corelated, which leads to greater variance. It represents caution in the cases, where long prediction is performed with short available time series. The symbol $\tilde{t}$ is order of predicting year. Thanks to this correction, longer prediction has wider interval as well as fewer available points in historical data.
- Step 6: Based on the newly obtained values of $\widetilde{m}_{t,\beta}^{j,h}$, confidence intervals for the obtained estimates are constructed. The approximate confidence interval for the trend in the data is determined by Eq. (19).

$$\left(m_t - t_{n-q}\left(1 - \frac{\alpha}{2}\right)\sqrt{\frac{n+\tilde{t}}{n}\sigma_t^2}, m_t + t_{n-q}\left(1 - \frac{\alpha}{2}\right)\sqrt{\frac{n+\tilde{t}}{n}\sigma_t^2}\right), \tag{19}$$

where $t_{n-q}\left(1-\frac{\alpha}{2}\right)$ is $\left(1-\frac{\alpha}{2}\right)$-quantile of Student's t-distribution with $n-q$ degree of freedom. The symbol σ_t^2 represents the variance estimate of prognosis $\widetilde{m}_{t,\beta}^{j,f}$ based on bootstrap repetition. The prediction interval is defined by Eq. (20), where $\tilde{\sigma}^2$ is variance estimate of residual component. Both variance estimates should consider the number of degrees of freedom equal to $n-q$.

$$\left(m_t - t_{n-q}\left(1 - \frac{\alpha}{2}\right)\sqrt{\frac{n+\tilde{t}}{n}(\sigma_t^2 + \tilde{\sigma}^2)}, m_t + t_{n-q}\left(1 - \frac{\alpha}{2}\right)\sqrt{\frac{n+\tilde{t}}{n}(\sigma_t^2 + \tilde{\sigma}^2)}\right). \tag{20}$$

For EU countries, the authors do not have a sufficient dataset to validate the approach. There are 145 time series and only 29 time series for waste production or particular waste treatment. Therefore, it is not possible to statistically evaluate the quality of the model on such a small data set. For this reason, the computation of the prediction intervals was tested with WM data of Czech Republic (ISOH 2021), where the authors could obtain relevant number of time series. Unfortunately, the length of time series is too short for long-term assessment and the principle was evaluated only for one-year forecast. Overall dataset contains 206 regions and 17 waste types, which results to 3502 time series. The 90 % prediction intervals cover 85 % of data points. The value was obtained by median from results of individual waste types. The median approach is less sensitive to waste types outliers, which can occur in cases with unexpected legislative intervention or inaccuracies in available data set. Similar underestimated results were obtained for intervals with different value of significance. The 70 % intervals cover 62% of data points and the 50 % intervals cover 49 %. The intervals should be wider from the essence of it, on the other hand, it can be considered satisfactory because the deviance is not great. The testing of this approach confirms the benefit of data reconciliation when real data is on average closer to reconciled data than the trend. The future research related to confidence and prediction intervals is needed to reveal improvements and the diagnostic of this approach should be repeated with additional data.

6 Results

The forecast of MSW production and treatment at the state level showed the expected development of WM for the so-called business as usual scenario. The Fig. 3 shows the waste production and treatment forecast for the EU. The results were obtained by additive approach (A) of data reconciliation due to occurrence of zero values. The additive approach works well because time series trend differences are commensurate with the size of the task. For each time-series (production, recycling, incineration, landfilling), four data series are displayed in a given colour. The first of these is historical data, these are the input data for the forecasting approach. The trend in this data is modelled by a curve, which is shown by a solid line in each time-series. Trend in data for MSW recycling and landfilling were modelled by power function (Eq. (1)). Data on MSW incineration show a slightly exponential character, so trend was modelled by logistic function (Eq. (2)). Production data oscillate around the average value, so value of R^2 is very low. Thus, the trend was modelled by the average in the data per capita. The Fig. 3 shows the absolute amount predicted for the EU, where the demographic forecast is already included. The trend model enters the data reconciliation. The Fig. 3 is shown at the EU level, so data reconciliation is also influenced by the trends of lower territorial units - states. The sum of trends at the national level is shown by the dashed line.

The resulting forecast after data reconciliation is shown in solid dots. It is obvious that the results of data reconciliation for recycling and incineration are concentrated around two trends: on the basis of EU data (trend) and on the basis of the sum of trends for EU states (sum of trend). Limiting the decline in landfilling due to non-negativity needs to limit changes in other series. The approach due to landfilling accelerated MSW production in forecast. The landfilling deceleration should affect other types of MSW treatment rather than production. In the further research, it would be appropriate to modify the model in step-by-step data reconciliation or to implement correlations between time series.

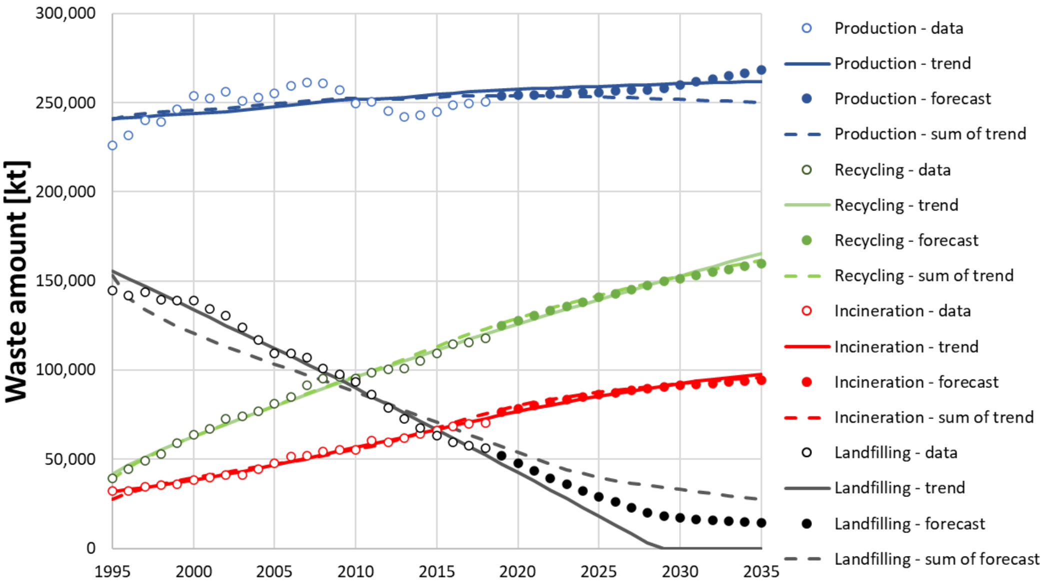

Figure 3. Waste production and treatment forecast for EU

The resulting forecast is supplemented by prediction intervals. They provide a necessary information about variability and show the credibility of forecasted data. If in any series the confidence or prediction interval reached a value lower than zero, it was limited to zero. The intervals for waste production and each type of waste treatment are shown for EU level in Fig. 4. It is obvious that intervals for waste treatment are relatively narrower in context of waste production. It supports the explanation of principle of data reconciliation described in Fig. 3, where production has the bigger deviation from trend.

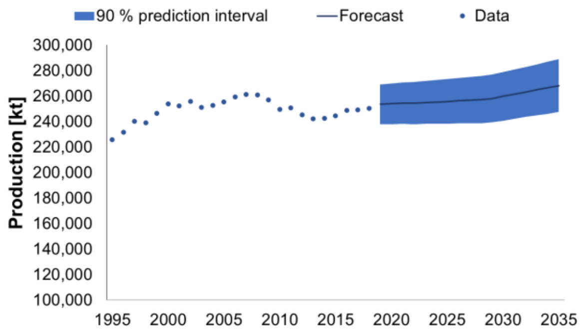

Figure 4a. Waste production forecast

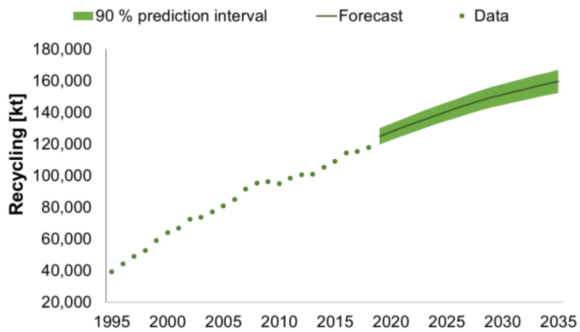

Figure 4b. Waste recycling forecast

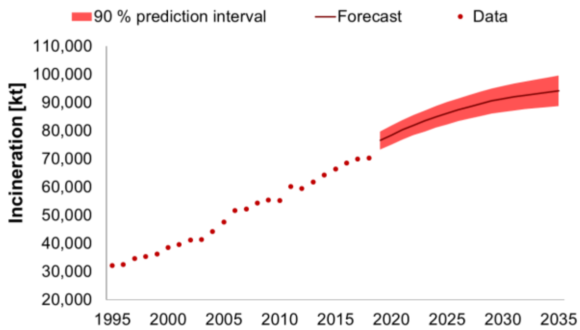

Figure 4c. Waste incineration forecast

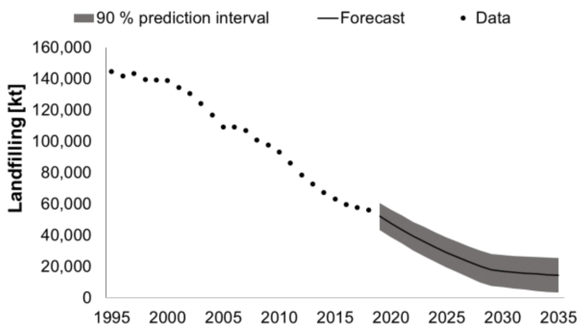

Figure 4d. Waste landfilling forecast

Figure 4. WM development for EU in selected historical and forecasted years with confidence and prediction intervals

The step increase in the incineration is caused by historical development. The incineration is usually affected by the construction of new plant with large capacity, which is also projected into forecast. In the case of recycling, the growth slowdown can be observed around the year 2008. It can be affected by bad economic situation in the world caused by the global economic crisis. In the subsequent research, it could be beneficial to focus on data cleansing based on social and economic factors. These are difficult to forecast, but their influence could be found in a historical context.

The results of the forecast are compared with the EU's targets. The outputs of the forecast at state level were divided into three categories for individual countries, see Table 4, and marked with symbols defined in the Table 3. The Table 4 shows the numerical results of the forecast. Percentage recovery of recycling and landfilling of MSW is available in the last year with historical data from 2018 and the EU targets key years 2025, 2030, 2035. The last column „Meeting EU targets“ uses the symbols if the country will meet the EU's targets according to the legend in the Table 3.

Table 3: Indication of forecast results

Symbol	Explanation
	The EU's targets are met based on forecast (year 2035) of the current situation – there are no necessary interventions.
	The EU's targets are met based on the positive scenario (upper 90 % prediction interval (PI) of recycling and lower 90 % PI incineration and landfilling) of the forecast. The better values to meet EU goals are presented.
	The EU's targets will not be met with the current form of WM, not even within prediction intervals. Necessary interventions in the system.

It is clear that only one country, Germany, in 2018 met the EU targets set for 2035 contained in the CEP, see Table 4. If the current trend of WM in the EU states is maintained in the future, based on the results, other 7 countries are expected to meet the EU's recycling targets for the key years. The question is whether these states can continue the established trend into the future until 2035. Limited equipment capacities, waste separation efficiency, etc. may be an obstacle to maintain the historical trend also to the future. With respect to the uncertainty and presented prediction intervals, there is probability that 18 countries will meet 65 % recycling rate and 10 % landfilling rate for positive scenario. Of course, prediction intervals apply also to opposite side and therefore the number of countries can be smaller. Historical and forecasted data in selected years are visualised in Appendix B for the EU and its members.

A lot of EU states face a situation where their current state of WM is failing to meet given milestones, especially in context of recycling. However, a relative diversion from landfilling can be observed, which is replaced mostly by incineration. If the targets set out in the CEP are not met, the EU states will be subjected to sanctions. Nevertheless, there are tools that can influence the way waste is handled and redirect waste in the desired direction. It is the responsibility of the state to ensure suitable conditions for the desired waste treatment, in particular, build the necessary equipment. As introduced by Smejkalová et al. (2020b), MSW production and treatment is affected by some economic, sociological and demographic variables. Focusing on these influencing factors can contribute to the transformation of WM. It is highly recommended to update results each year and flexibly respond to actual development and prediction.

Table 4: Results of MSW production and treatment forecast for EU states, comparison with EU targets

	Recycling			Landfilling			Meeting EU targets	
Locality	2018	2035	PI 2035	2018	2035	PI 2035	Recycling	Landfilling
EU	48 %	60 %	64 %	23 %	5 %	1 %	✗	✓
Austria	59 %	47 %	63 %	2 %	0 %	0 %	✗	✓
Belgium	55 %	55 %	67 %	1 %	0 %	0 %	✓	✓
Bulgaria	37 %	51 %	93 %	60 %	40 %	0 %	✓	✓
Croatia	28 %	66 %	100 %	72 %	33 %	0 %	✓	✓
Cyprus	17 %	41 %	81 %	82 %	57 %	19 %	✓	✗
Czechia	35 %	75 %	92 %	49 %	0 %	0 %	✓	✓
Denmark	48 %	48 %	68 %	1 %	0 %	0 %	✓	✓
Estonia	31 %	40 %	89 %	24 %	0 %	0 %	✓	✓
Finland	42 %	30 %	43 %	1 %	0 %	0 %	✗	✓
France	44 %	63 %	67 %	21 %	0 %	0 %	✓	✓
Germany	68 %	67 %	76 %	0 %	0 %	0 %	✓	✓
Greece	19 %	34 %	77 %	80 %	64 %	23 %	✓	✗
Hungary	37 %	77 %	93 %	49 %	0 %	0 %	✓	✓
Ireland	43 %	63 %	86 %	24 %	0 %	0 %	✓	✓
Italy	55 %	70 %	74 %	24 %	0 %	0 %	✓	✓
Latvia	29 %	65 %	87 %	68 %	31 %	11 %	✓	✗
Lithuania	59 %	76 %	84 %	27 %	0 %	0 %	✓	✓
Luxembourg	50 %	59 %	65 %	6 %	0 %	0 %	✓	✓
Malta	7 %	9 %	16 %	93 %	91 %	84 %	✗	✗
Netherlands	56 %	52 %	64 %	1 %	0 %	0 %	✗	✓
Poland	34 %	61 %	78 %	42 %	0 %	0 %	✓	✓
Portugal	30 %	61 %	82 %	51 %	2 %	0 %	✓	✓
Romania	12 %	45 %	90 %	82 %	42 %	0 %	✓	✓
Slovakia	36 %	52 %	85 %	55 %	37 %	15 %	✓	✗
Slovenia	75 %	77 %	100 %	12 %	0 %	0 %	✓	✓
Spain	36 %	48 %	76 %	51 %	32 %	13 %	✓	✗
Sweden	46 %	43 %	53 %	1 %	0 %	0 %	✗	✓
United Kingdom	45 %	57 %	71 %	15 %	0 %	0 %	✓	✓

7 Conclusion

In order to meet the EU's strict targets, it is necessary to make the adjustments in WM in a timely manner. The need to intervene in the current system can be revealed by a forecast of expected development. This article presented a methodology for the forecast of MSW production and treatment. It is based on non-linear regression, quadratic optimisation and experience with real data sets, which leads to building a comprehensive tool with wide range of uses. The methodology is a generally applicable approach that can be applied to all EU member states. As results show, it is possible to estimate the expected way of waste treatment and thus the fulfilment of EU targets. The forecast revealed that with current developments in WM, most EU member states are not on track to meet EU targets in time. Even under a positive scenario, not all states are expected to meet the EU targets. This crucial information should help to initiate efforts to modernize WM.

In the follow-up, it would be appropriate to make forecasts also on greater detail of individual states (e.g., regions or municipalities). Modification of WM can then take place with a link to a specific area. The influence of demographic development and other influencing factors on specific treatment methods is another challenge that should be addressed in this area in the future. In addition, it would be beneficial to consider correlations between different waste treatment methods and production for data reconciliation model. Then it is possible to model scenarios that lead to the achievement of goals. Scenarios can identify regions that have the potential to improve WM and thus help national assessment. The cornerstone of the model is also the data availability, so future work will be focused on data collection related to specific waste treatment and territory detail. Construction of prediction intervals should take into account residuals variance depending on time. From the optimisation point of view, the future research can improve the model performance, solvability and starting points with respect to other solvers. The verification of the presented approaches could be evaluated with respect to data heteroskedasticity and other characteristics. Of course, the application of this approach on real data can reveal another links and dependencies, which can lead to extensions of the methodology and recommendations originating from the experience.

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Data Availability

The demographic data and data about municipal solid waste used in the case study are available from the database of the Eurostat – European statistical office and Waste Management Information System of Czech Republic called ISOH (ISOH 2021).

Author contributions

All authors contributed to the presented study. Conceptualisation was provided by Radovan Šomplák. The data collection and formal analysis was performed by Veronika Smejkalová and Kristýna Rybová. Development of methodology and creation of models were performed by Veronika Smejkalová and Radovan Šomplák. Validation of results was performed by Veronika Smejkalová, Radovan Šomplák and Jaroslav Pluskal. The figures and overall visualisation were performed by Veronika Smejkalová and Jaroslav Pluskal. The first draft of the manuscript was written by Veronika Smejkalová, Radovan Šomplák and Jaroslav Pluskal. All authors read and approved the final manuscript.

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APPENDIX A: The summarized forecasts within selected waste management plans

Czech Republic (Ministry of the Environment of Czech Republic 2014)

- MSW definition: Group 20 from all producers and 15 01 from citizens based on Waste catalogue (ANION CS, 2021)
- Treatment: yes
- Territory level: state
- Data detail: year
- Number of data: 4
- Forecast length: 12
- Method: Design of 3 models: 1. linear regression, 2. exponential trend, 3. multidimensional linear model.

Austria (Federal Ministry for Climate Protection, Environment, Energy, Mobility, Innovation and Technology 2017)

- MSW definition: Municipal waste is waste from private households and other types of waste which, on account of its nature or composition, is similar to domestic waste. This includes fractions such as mixed municipal waste (residual waste), bulky waste or biogenic waste collected separately.
  There is no reference to the waste catalogue in the document.
- Treatment: no
- Territory level: state
- Data detail: end state
- Number of data: no information
- Forecast length: 6
- Method: No information

Germany (LAGA 2021)

There is no national waste management planning in Germany. Instead, each Federal State develops a waste management plan for its area.

a) Berlin (Senate Department for Environment, traffic and climate protection 2011)

- MSW definition: MSW is waste that, based on its origin, can be allocated to private households and is collected as part of public waste collection. MSW also includes waste from commercial industry and wastewater treatment plants
- Treatment: no
- Territory level: Federal state
- Data detail: 2 milestones (2015, 2020)
- Number of data: 1
- Forecast length: 9
- Method: Setting progressive targets to be met and will have an impact on waste production. Inclusion of demographic projection.

b) Nordrhein-Westfalen (Ministry for Climate Protection, Environment, Agriculture, Nature and Consumer Protection of the State of North Rhine-Westphalia 2015)

- MSW definition: Household waste is waste and packaging that is usually produced predominantly in private households and collected as part of public waste collection or from Take-back systems according to the Packaging Ordinance or Packaging Act, the so-called dual system. This typical household waste includes household and bulky waste, organic and green waste, separately collected valuable waste or packaging (including paper, light packaging, glass) as well as waste that is collected as part of municipal pollutant collections.

- Treatment: no
- Territory level: District, administrative districts and municipalities
- Data detail: year
- Data detail: End state
- Number of data: 1
- Forecast length: 14
- Method: Population projection combined with assumption about per capita waste production.

c) **Baden-Württemberg** (Ministry of Environment Climate and Energy, 2015)

- MSW definition: The document does not directly contain a definition of MSW, but the federal states have usually the same definition of MSW, see Nordrhein-Westfalen.
- Treatment: no
- Territory level: Federal state
- Data detail: year
- Number of data: 19
- Forecast length: 10
- Method: Determination of two scenarios for each type of waste. Scenarios are based on the expansion of the involved part of the population, the use of more efficient methods of collection, greater promotion, etc. Involvement of the demographic projection, the percentage decrease in the number of inhabitants is considered.

d) **Hesse** (Hessian Ministry for the Environment, Climate Protection, Agriculture and Consumer Protection 2015)

- MSW definition: See Nordrhein-Westfalen.
- Treatment: no
- Territory level: Federal state
- Data detail: 5 years
- Number of data: 3
- Forecast length: 12
- Method: Population forecast and assumption of economic growth and fulfillment of goals in waste management.

Poland (Ministry Climate and Environment of Poland 2021)

- MSW definition: Municipal waste is waste generated in households and waste generated in retail trade, enterprises, office buildings and educational institutions as well as health care and public administration institutions, and the nature and composition of this waste is similar to that of waste generated in households.
  There is no reference to the waste catalogue in the document.
- Treatment: no
- Territory level: Region, state
- Data detail: 2 milestones (2025, 2030)
- Number of data: 1
- Forecast length: 16

- Method: Based on population forecast and two waste generation indexes – it is still assumed the same year-on-year growth in production (0.6% or 1.0%) and a decrease in population.

Slovakia (Ministry of the Environment of Slovakia 2015)
Waste management plan does not include any forecast

- MSW definition: Code 20 in Waste catalogue

Finland (Launonen 2019)

- MSW definition: Municipal waste means waste generated in permanent dwellings, holiday homes, residential homes and other forms of dwelling, including sludge in cess pools and septic tanks, as well as waste comparable in its nature to household waste generated by administrative, service, business and industrial activities.
- Treatment: yes
- Territory level: state
- Data detail: End state
- Number of data: 1
- Forecast length: 8
- Method: The first scenario makes use of the waste volumes in 2015 as indicated in the waste statistics. The scenario presumes that the generation of waste has been successfully halted at the level of 2015. The second scenario makes use of the moderate waste quantity growth forecast to 2023 of the Forecasting waste volumes -project, in which future municipal waste quantities were modelled.

Switzerland – Canton Zürich (Kanton Zürich 2021)

- MSW definition: waste from households, commercial and service companies with less than 250 full time employees.
- Treatment: no
- Territory level: Canton
- Data detail: year
- Number of data: 6
- Forecast length: 18
- Method: No information

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APPENDIX B: The waste management development for EU and its members

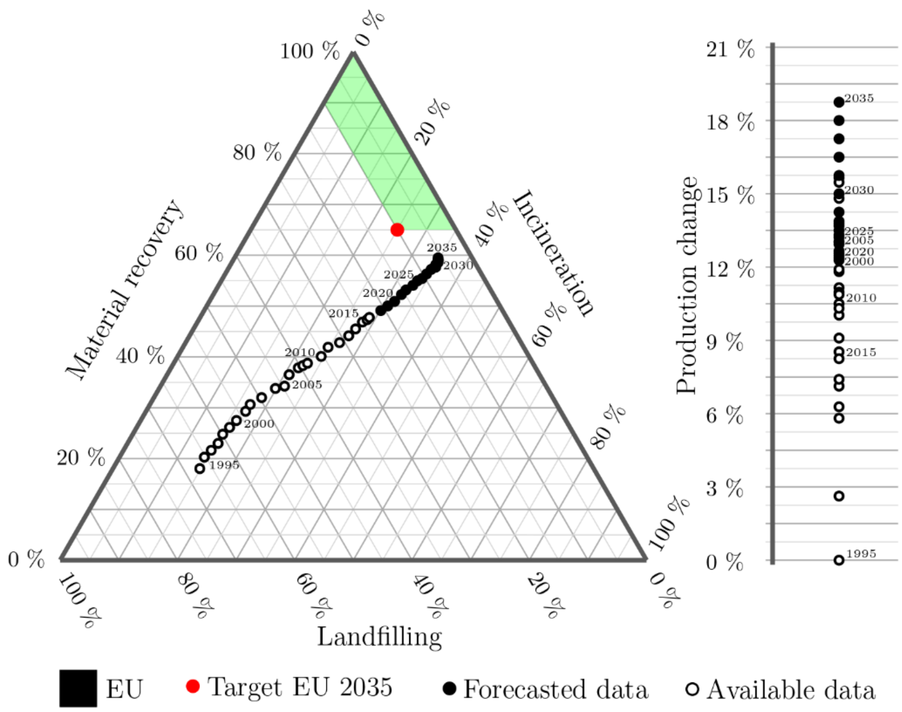

Fig. 5. Waste management development for EU

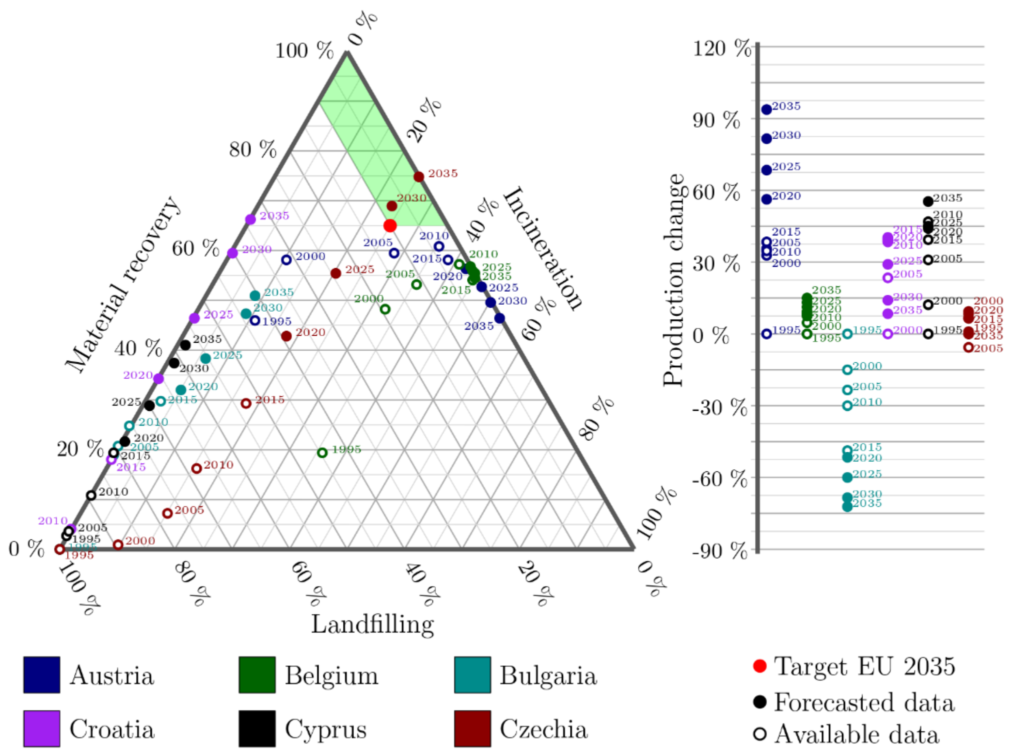

Fig. 6. Waste management development for Austria, Belgium, Bulgaria, Croatia, Cyprus and Czechia

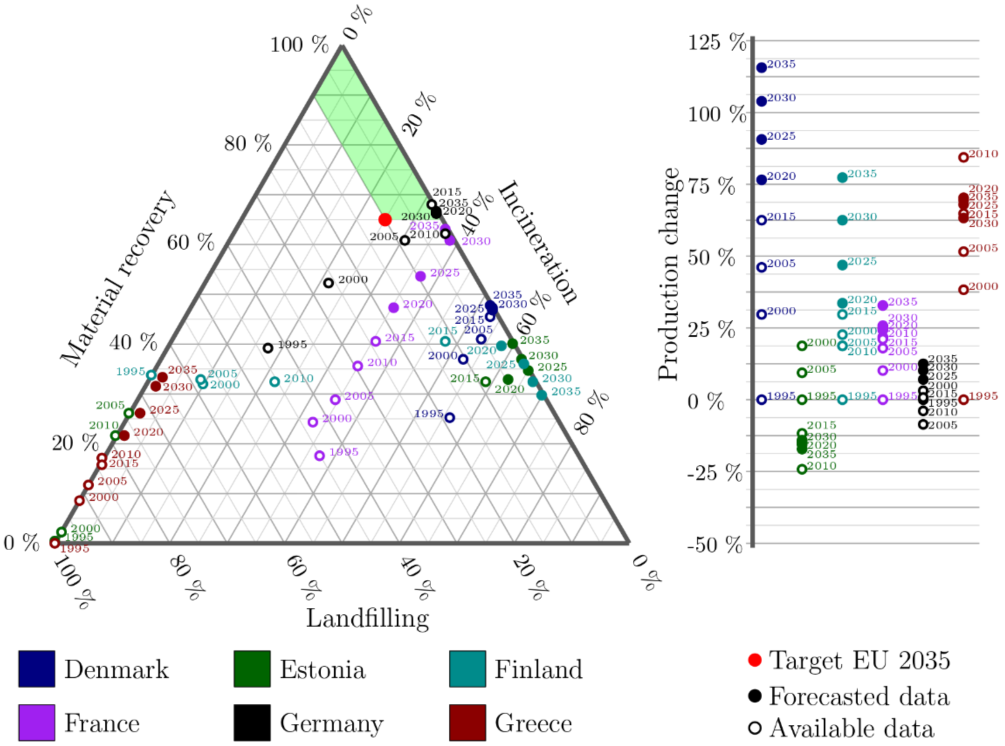

Fig. 7. Waste management development for Denmark, Estonia, Finland, France, Germany and Greece

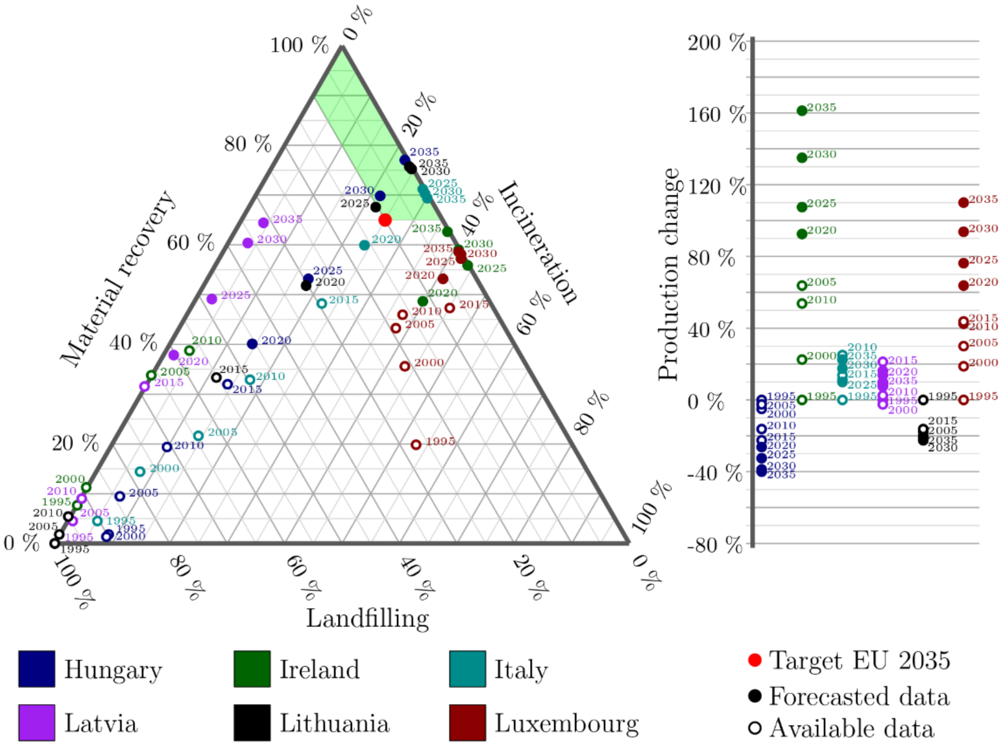

Fig. 8. Waste management development for Hungary, Ireland, Italy, Latvia, Lithuania and Luxembourg

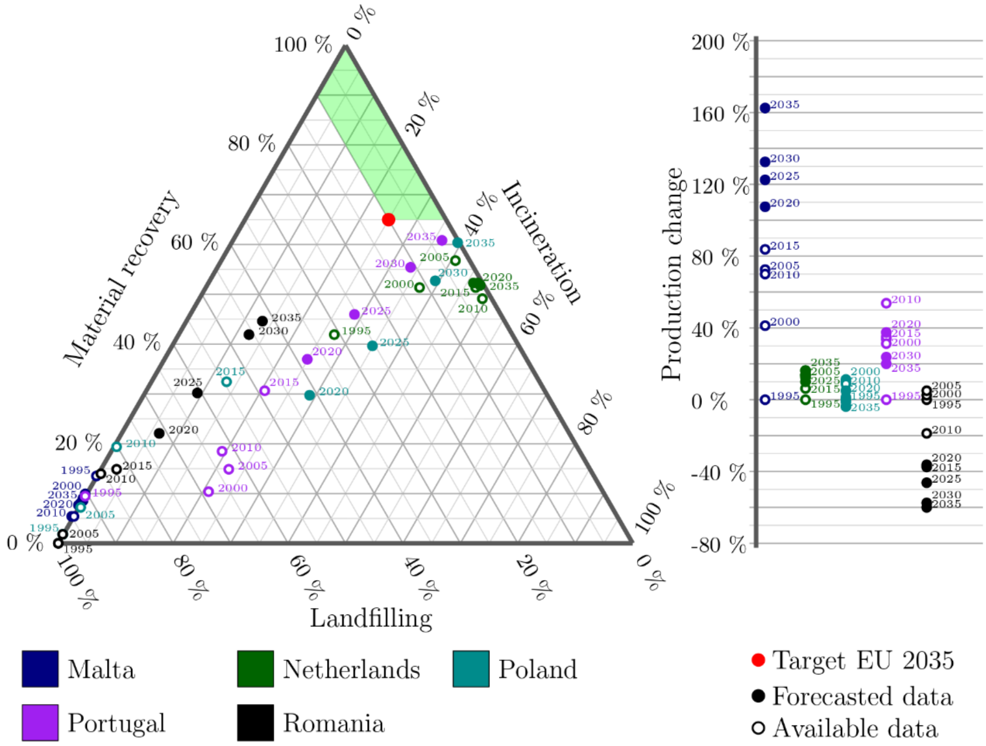

Fig. 9. Waste management development for Malta, Netherlands, Poland, Portugal and Romania

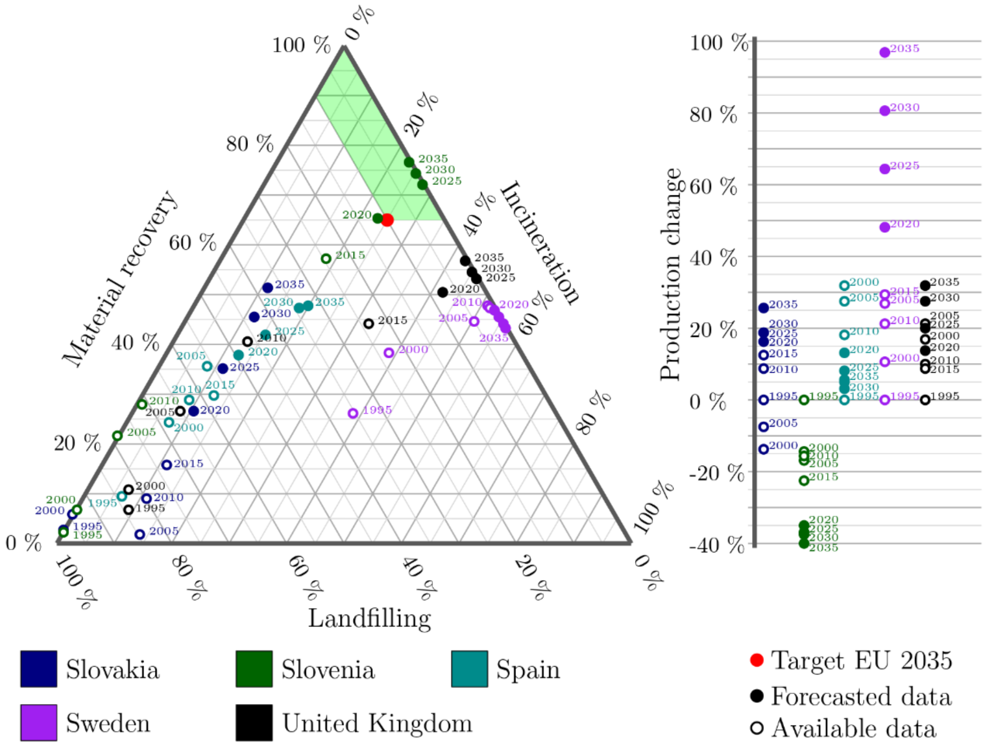

Fig. 10. Waste management development for Slovakia, Slovenia, Spain, Sweden and United Kingdom