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The Forecasting Waste Generation Model based on Linked Open Data and the DPSIR Framework.

Case study concerning municipal waste in the Czech Republic

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### **Abstract**

Current waste generation forecasting models provide tools to assess the efficiency of waste management plans (WMP) of the European Union (EU) Member States (MS) implementing the EU action plan for the Circular Economy (CE). These tools are based on environmental as well as economic and social perspectives, and thus will enable making the appropriate decisions to improve the national WMP performance. The paper presents developed multi-linear regression models for waste streams through linked open data of the Czech Republic and sets of indicators (predictors) integrated into forecasting models that measure the effectiveness in which WMPs operate in waste management to fulfil the CE vision. The methodology consisted in adjusting predictors of the forecasting models into a Driving Force-Pressure-State-Impact-Response (DPSIR) framework developed by the European Environment Agency in 1999. The most relevant predictors were chosen through a selection process that included experts' opinions and a literature review based on relevance and applicability to different waste streams setting. The appropriate predictors were selected and fitted into the DPSIR framework. The construction of the forecasting model consisted of construction and definition of the predictors based on the DPSIR framework; integration of the predictors into the forecasting models; a sensitivity analysis of the models; implementation of the forecasting models in open source software and its verification using appropriate data, and choosing prevention scenarios to follow the EU action plan for the Circular Economy. The four-step outputs of the developed forecasting model are presented for municipal waste of the Czech Republic.

### **Keywords**

waste generation, forecasting, modelling, DPSIR, waste management plan, circular economy.

## Introduction

Forecasting waste generation on the national, regional or local levels is very important for planning of the efficient waste management system. Future estimations of waste generation serve as a basis in development of the existing waste management infrastructure as well as its further sustainable development and optimization. Imprecise forecasts may lead to widespread problems, such as inadequate or excessive waste treatment infrastructure (e.g. collection, material recycling, energy recovery, landfilling or other disposal). For decision-making public authorities (PA), waste management planning is the cornerstone of any national, regional or local waste management policy.

Establishment of a Waste Management Plan (WMP) within the basic European Union (EU) framework allows taking stock of the existing situation, defining the objectives that need to be met, formulating appropriate strategies, and identifying the necessary implementation means. The drawing up of WMPs is an obligation of the EU Member States (MS) and it is also required by Article 28 of the Waste Framework Directive (WFD) [1]. In order to assist national, regional and local competent authorities in preparing WMPs in line with the WFD requirements, the European Commission (EC) has published a methodological Guidance Note [2] where a framework for the decision making PA is specified. In order to move up the waste hierarchy, the WFD requires that the MSs establish Waste Prevention Programs (WPP) as a part of the WMP.

Making decisions in waste management is not only very capital-intensive, but also difficult from the environmental, economic and social points of view. There is a need to develop, master and implement simple but reliable models that will help decision-makers at PA to analyze waste management processes, follow the national legislation and WFD implementation, further the WMP, WPP for the respective PA level and to consider the EU Circular Economy tasks [3-4]. The deeper analysis of waste management in the Czech Republic required to develop forecasting models of prescribed waste streams generation on the national level of the Czech Republic. These models could measure the effectiveness in which the WMP of the Czech Republic operates in the national waste management to fulfil the CE vision.

Therefore we developed forecasting models of prescribed waste streams generation on the national level of the Czech Republic through linked open data of the eGovernment system and a set of indicators (predictors). This methodology consisted in adjusting predictors of the forecasting models into the Driving Force-Pressure-State-Impact-Response (DPSIR) framework developed by the European Environment Agency in 1999. The most relevant predictors were chosen through a selection process that included experts' opinions and literature review based on relevance and applicability to different waste streams settings. Appropriate predictors were selected and fitted into the DPSIR framework. The models include appropriate predictors for drivers (causes), state (amount of waste), pressure, impact and response, where the status of each criterion is evaluated.

The analysis of the DPSIR framework dealt with [5-6] and its support to decision-making [7]. Integrating ecosystem services into the DPSIR framework is implemented in [8]. Here we find the general procedures of the DPSIR framework, which, however, focus on areas other than waste management. Armijo et al. [9] and Puma et al. [10] selected fifteen general indicators with respect to the DPSIR framework for Mexican waste management and identified specific predictors, i.e. prevention, generation, treatment, resources, efficiency and composition of municipal solid waste.

In the DPSIR framework, important predictors concern driving forces (D). We therefore analyzed other papers where: the driving force is discussed in research in the field of building materials [11]; an analysis is made of the barriers and factors affecting successful sustainable waste management in Nigeria [12]; driving forces of waste generation are identified using a waste-flow analyzing model based on the interdependence between trade and industry and waste treatment; six general groups of driving forces for waste management economy are identified [13]. Other articles were considered dealing with the DPSIR models for biodiversity [15-16], construction industry [17-20] and municipal solid waste [21-26]. However, the waste generation forecasting process is often challenging and limited by rapidly changing and uncontrollable parameters [22]. Forecasting methods can be broadly classified into five main categories [27]: descriptive statistical methods; regression analysis; material flow models; time series analysis; and artificial intelligence models. However, all the modelling approaches have their own strengths and weaknesses. We will focus on a combination of multi-regression methods and time series analysis with material flow models in the DPSIR framework.

The paper introduces the developed models to forecast prescribed waste stream generation in the Czech Republic within the period 2015–2024 using linked open data of the period 2009–2014 and following research results [21-31]. These models allow the PA on the national level of the EU Member States to make sustainable environmental decisions, focusing on waste management data requirements, national strategies for waste data acquisition, management and processing in a similar way as it was done earlier

[13, 28, 32, 33]. They will assist in identifying alternative waste management strategies of the Czech Republic and support the national WMP and WPP that meet the objectives of the EU WFD and Circular Economy principles.

## Material and Methods

Our developed forecasting model of waste stream generation includes the following consequent modelling steps [31]:

1. Identification of the required waste streams using waste codes of the European List of Waste (ELW) [34] and computation formulas for their amounts.
2. Processing of the historical annual waste streams generation and treatment reports (2009–2013) provided by waste generators and facilities and creating of their data sets.
3. Identification and development of socioeconomic and demographic predictors based on the DPSIR framework (which have influence on waste streams generation) using linked open government data (eGovernment systems) of the Czech Republic.
4. Construction of a multi-linear regression model of waste streams generation with predictors from the DPSIR framework analyses.
5. Forecasting of predictors from the DPSIR framework and calculation of waste stream forecasts.
6. Processing of sensitivity analyses of predictors of waste stream generation models and scenarios for decision makers.

## Identification of waste streams

In Table 1, there are defined waste streams for which we developed appropriate models to forecast their generation in the period 2015-2024.

**Table 1** The list of waste streams and the list of the ELW waste codes of each waste stream [34]. Digits of hazardous waste codes are finished by \*. Source: Authors

Waste stream number	Waste stream	ELW waste codes
1	All wastes	010101-200399
2	All waste of other category	Codes from 010101-200399 without *
3	All waste of hazardous category	Codes from 010101-200399 with *
4	Municipal solid waste	200101, 200102, 200108, 200110, 200111, 200113*, 200114*, 200115*, 200117*, 200119*, 200121*, 200123*, 200125, 200126*, 200127*, 200128, 200129*, 200130, 200131*, 200132*, 200133*, 200134, 200135*, 200136, 200137*, 200138, 200139, 200140, 200141, 200199, 200201, 200202, 200203, 200301, 200302, 200303, 200306, 200307, 200399, 150101, 150102, 150103, 150104, 150105, 150106, 150107, 150109, 150110*, 150111*
5	Mixed municipal waste	200301
6	Biodegradable wastes	020101, 020103, 020106, 020107, 020201, 020203, 020204, 020301, 020304, 020399, 020305, 020401, 020403, 020501, 020502, 020601, 020603, 020701, 020702, 020704, 020705, 030101, 030105, 030301, 030307, 030308, 030309, 030310, 030311, 040101, 040107, 040210, 040220, 040221, 040222, 150101, 150103, 160306, 170201, 190503, 190603, 190604, 190605, 190606, 190805, 190809, 190812, 190814, 190901, 190902, 190903, 191201, 191207, 200101, 200108, 200110, 200111, 200125, 200138, 200201, 200301, 200302, 200303, 200307
7	Biodegradable municipal wastes	150101, 200101, 200108, 200110, 200111, 200138, 200201, 200301, 200302, 200303, 200307
8	Construction and demolition wastes	170101, 170102, 170103, 170106*, 170107, 170201, 170202, 170203, 170204*, 170301*, 170302, 170303*, 170401, 170402, 170403, 170404, 170405, 170406, 170407, 170409*, 170410*, 170411, 170503*, 170504, 170505*, 170506, 170507*, 170508, 170601*, 170603*, 170604, 170605*, 170801*, 170802, 170901*,

9	Wastes from electrical and electronic equipment	170902*, 170903*, 170904 160211*, 160212*, 160213*, 160214, 160215*, 160216, 200123*, 200135*, 200136, 200121*
10	Wastes from batteries and accumulators	160601*, 160602*, 160603*, 160604, 160605, 200133*, 200134
11	Waste of end-of-life vehicles	160104*
12	Waste of end-of-life tyres	160103
13	Hazardous oils	120106*, 120107*, 120110*, 120119*, 130109*, 130110*, 130111*, 130112*, 130113*, 130204*, 130205*, 130206*, 130207*, 130208*, 130306*, 130307*, 130308*, 130309*, 130310*, 130401*, 130403*, 130506*, 200126*
14	Sludge from urban waste water treatment	190805
15	Wastes from human or animal health care and/or related research	180101, 180102, 180103*, 180104, 180106*, 180107, 180108*, 180109*, 180110*, 180201, 180202*, 180203, 180205*, 180206, 180207*, 180208*
16	Hazardous wastes with asbestos	060701*, 061304*, 101309*, 160111*, 160212*, 170601*, 170605*

### Processing of the historical annual waste streams generation and treatment reports

Environmental legislation of the Czech Republic requires organizations, companies, enterprises, municipalities etc. (i.e. environmental reporters) to provide public administration (PA) on the regional level with annual data and information on their waste management activities (waste report). They insert them into ISPOP - Integrated System of Reporting [35] of the Ministry of the Environment (MoE) in prescribed annual standards [36] according to the Czech waste legislation. These waste reports are processed by the Czech Environmental Information Agency (CENIA) using the ISPOP system which was developed in the collaboration with IBM between 2008 and 2013 [37].

ISOH - Waste management information system [38] of the MoE is a comprehensive environmental information system built according to the principles of SOA architecture. Environmental reporters send their annual waste reports into ISPOP and the data are imported to ISOH which processes them. Each annual report is verified by the PA with respect to its administrative region and sent to the ISOH central database which then generates a publicly accessible aggregated annual database. The data are available in a detailed form to the PA and in an aggregated form to the public [39].

ISOH contains data concerning waste generation and treatment by generators and data concerning facilities to treat, recover and dispose of waste. Every year, it records more than 70,000 different generators' reports in all 6,500 municipalities of the Czech Republic and more than 3,000 facilities' reports. The annual ISOH database contains more than 50,000 records of municipal waste generation and 10,000 records concerning their treatment [39]. The database was available to us in 2009-2014 and we calculated waste streams from Table 1 for these years.

### Linked open government data of the Czech Republic for models

The current state of several national environmental, socio-demographic, economic, financial data facilities and services based on eGovernment implementation in the Czech Republic was introduced by Soukopová et al. [39]. These eGovernment systems provide sources of necessary input data for the DPSIR framework predictors for different waste streams. The related linked open data for the DPSIR framework predictors are often available on the PA web sites, such as those of the MoE, CENIA, the Ministry of Finance (MoF), the Ministry of Regional Development (MoRD), and the Czech Statistical Office (CZSO).

For example, the MoF provides a specialized web information portal MONITOR [40] that allows open public access to budget and accounting information from all PA levels including every municipality in the Czech Republic. The presented information is updated quarterly. The primary version of MONITOR was released in May 2013. It replaced the previous web information portals ARIS [41] and

ÚFIS [42] (database of municipalities' accounting from 2000 to 2012) of the MoF. The analytical part of MONITOR portal allows dynamic data analysis using advanced tools for financial analyses.

Data on the national economy, industry, health, municipal areas and population are also publicly accessible on the web site of the Czech Statistical Office [43] and in the web information system RIS [43] of the MoRD, where there are data and information from the all regions, districts, municipalities with extended competence (MEC) and municipalities of the Czech Republic.

It was necessary to parse these data (DPSIR framework predictors) to the forecasting models from the linked open data of MONITOR, ISOH, RIS and CZSO. These parsers were developed in similar ways and we will not describe them because of the limit of pages of the paper.

The process of parsing the linked open data of MONITOR can be divided into five phases: definition of the appropriate data; data export; data processing; data import and optimization.

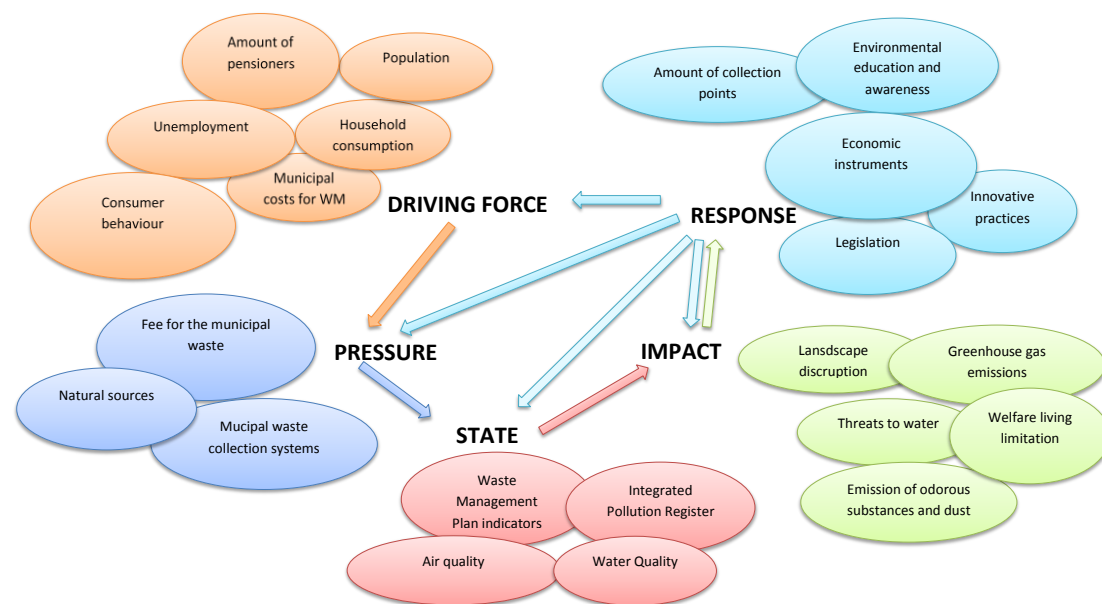
We have used the MONITOR analytical part to define the appropriate data; after entering the parameters which identify the appropriate data (e.g. year, paragraph, given value), they were exported to Windows XLS format and stored in a single CSV file which could be exported to the MySQL database of the forecasting software. The annual data downloaded from MONITOR were subsequently modified to the desired format and uploaded by parser to the MySQL database which had to be optimized. It includes entities of data concerning all municipalities connected with their municipality with extended competence (MEC), district and region geographic identification.

### Identification and development of socioeconomic and demographic predictors based on the DPSIR framework

Together with experts for every waste stream [45], we analyzed and identified socioeconomic and demographic factors based on the DPSIR framework. Below we introduce the DPSIR analysis for only two waste streams: municipal solid waste (MSW) and construction and demolition waste (CDW).

#### Municipal solid waste

Our expert team identified the following main factors in the DPSIR framework for MSW, see Figure 1.



**Fig. 1** Factors in the DPSIR framework for municipal wastes. Source: authors

#### *D – Driving force*

The basic *driving force* of MSW is *population*. Development of the population, together with relocation of residents with higher purchasing power to cities and agglomerations, also reduce its own waste treatment options (e.g. composting) and create demand for faster replacement of goods, which affects household consumption. The number of *pensioners* and the level of *unemployment* are also driving forces for the amount of MSW, as families with small children, some students, pensioners and the unemployed remain near their residence throughout the day where their activities generate waste. Workers and children in kindergartens and schools and some students carry out their daily activities at the place of employment or school where they generate MSW, etc. A major driving force behind the

MSW production is also *consumer behaviour*, including ways of packaging, driven by consumer demand and legal regulations, e.g. hygienic and health protection requirements. Generation of MSW is also driven by *municipal costs of MW* of citizens. We are able to download driving forces data from linked open government data of the Czech Republic.

#### *P – Pressures*

The main pressures affecting the amount of generated MSW include the fees for MSW that may motivate residents to produce less waste, especially in smaller communities where the fee is determined directly by the owner of the house for a garbage collection container. In larger settlements, this effect is suppressed due to a greater number of residents using a single collection site. The fundamental pressure consists in setting of the MSW collection system. When the system is set effectively, it can motivate residents to minimize MW generation and achieve lower waste treatment costs. Waste treatment and disposal cause pressures on natural sources. Availability of collection centers or waste assembly points reduces the amount of illegal waste dumps and necessary removal costs.

#### *S – State*

Data and information on MSW generation are collected annually through ISPOP [35] and processed by ISOH. We are able to download the MSW data from ISOH [38]. They enter the indicators evaluation of the Waste Management Plan of the Czech Republic [49] and other sources of information (e-PRTR register, etc.) and evaluation reports (air quality, water quality, etc.).

**Table 2** Municipal solid waste generation 2009 – 2014. Source: ISOH [38]

<i>year</i>	2009	2010	2011	2012	2013	2014
amount [tonnes]	5 325 179	5 361 883	5 388 058	5 192 784	5 167 805	5 323 947

#### *I – Impact*

Environmental impacts of the MSW generation are still seen primarily in landscape disruption, especially by landfills, waste incinerators and industrial areas with waste treatment facilities. Generation and treatment of MSW also poses a potential threat to groundwater and surface water, landfilling and incineration of waste lead to emissions of greenhouse gases, which, especially for small landfills, are poorly constrained. The entire life cycle of MSW is also accompanied by significant emissions of odorous and particulate matter. There are also restrictions on welfare of the population which consist in having to endure regular waste removal, placement of collection containers, waste disposal facilities, etc.

#### *R- Response*

In response to MSW generated by the population, the number of places for waste separation (collection centers) is increasing and the system of MSW collection and disposal is being streamlined. Along with improving the MSW management, there are also systems to educate the population in the context of environmental education and awareness. The population starts learning to separate waste as early as in pre-school institutions. The system permeates all levels of education and advertising and it ends at educational events for adults and raising awareness in the society. Along with education, legislative measures are taken which cover both the municipality as the originator of MSW and the entire system of waste collection and treatment, i.e. the entire life cycle of municipal waste. Legislative measures are accompanied by economic tools, especially in the form of fees (waste disposal in a landfill) and the level of tax rates and subsidies directed to the development of MSW management systems. MSW generation also brings a response in the form of innovative approaches (e.g. measures to minimize packaging of retailed goods, etc.).

#### **Construction and Demolition waste**

Our expert team identified the main factors in the DPSIR framework for CDW, see Fig. 2.

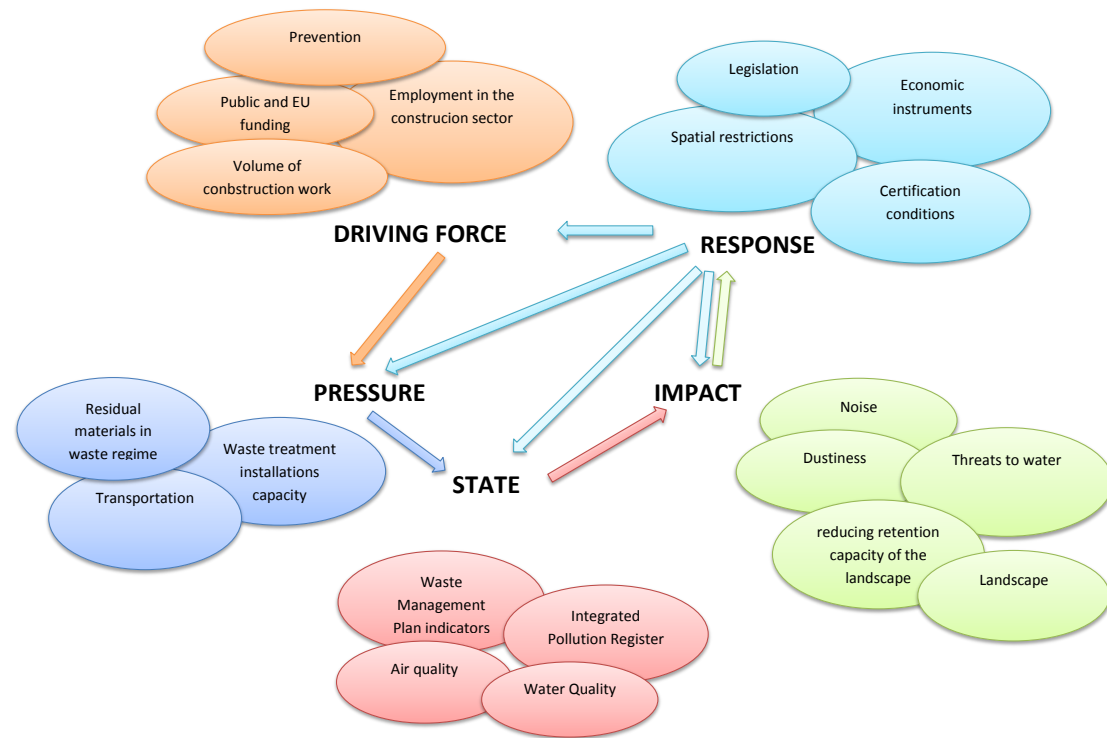
#### *D – Driving force*

Construction and demolition waste (CDW) is mostly generated during major infrastructure projects, especially in construction of highways and urban areas or demolition of large industrial complexes. In CDW generation, the *amount of construction work* is essential. In the framework of linear constructions (roads, railways), significant quantities of bulk waste are produced. Prevention of CDW generation plays an important role. These constructions are usually organized on the basis of *public and EU*

*funding*. Other drivers of CDW production are *the number of people employed* in construction and prevention programs also have an indispensable role.

*P – Pressures*

The basic operating pressure concerning CDW generation is transport infrastructure, which has high demands on the capacity of mobile and stationary installations when moving large volume of waste generated. Significant pressures are connected with the conditions for assigning materials to the waste regime, which often leads to a purposeful spool of construction materials generated, or demolition activities only for economic reasons.



**Fig. 2** Factors in the DPSIR framework for construction and demolition waste. Source: authors

*S – State*

Data and information on CDW generation are collected annually through ISPOP [35] and processed by ISOH. We are able to download the CDW data from ISOH [38]. They enter the indicators evaluation of the Waste Management Plan of the Czech Republic [49] and other sources of information (e-PRTR register, etc.) and evaluation reports (air quality, water quality, etc.).

Table 3. Construction and demolition waste generation 2009 – 2014. Source: ISOH [38]

year	2009	2010	2011	2012	2013	2014
Amount [tonnes]	18 520 614	18 480 355	17 387 158	17 318 625	17 904 590	19 124 592

*I – Impact*

The main impacts of CDW, which is generated during construction and demolition works, are especially increase of noise near buildings, raising dustiness, threat to groundwater and surface water. Other influences include the potential reduction of the landscape retention capacity as the landscape captures much worse and increasingly frequent short downpours. CDW generation has significant impacts on the landscape through landfills of inert waste.

*R- Response*

The answer to the demands of continued growth in the construction sector, expansion of settlements, and construction of commercial and industrial sites induces a response which modifies spatial restrictions in new land administration. Constant pressure on agricultural and forest land is hampered

by economic instruments and legislation, especially in the form of fee exemption. Other responses to the development in CDW generation related to the development in the construction sector include requirements and conditions for certification of building products on the basis of the EU Regulation no. 305/2011 laying down harmonized conditions for the marketing of construction products.

## Construction and analysis of a multi-linear regression model of waste streams generation

In this chapter we describe the construction and analysis of the multi-linear regression model of waste streams generation with predictors from the DPSIR framework analyses. We predict the amount of waste generated on the national level of the Czech Republic for the given year  $t$  and the chosen waste stream  $w^f(t)$ ,  $f = 1, \dots, 16$  (consisting of chosen ELW codes, see Table 1). We have developed mathematical forecast models based on the DPSIR (Driving forces-Pressures-State-Impacts-Responses) framework predictors by Horáková et al. [45] following models [46-48]. It uses available linked open data on DPSIR predictors from eGovernment systems [39, 45] and past waste generation from ISOH (from the period 2009 - 2014).

Let us assume that for every waste stream  $f = 1, \dots, 16$  (see Table 1), the amount of waste  $\hat{w}_t^f$  and predictors  $\hat{A}_{i,t}^f$ ,  $i=1, \dots, K^f$ ; in years  $t=2009, \dots, 2014$  are known, where  $K^f$  is the number of predictors for the waste stream  $f$ . Let waste stream generation  $w^f(t)$  at the given year  $t$  fulfils the equation

$$\log(w^f(t)) = a_0^f + \sum_{i=1}^{K^f} a_i^f \cdot \log(A_i^f(t)) + \varepsilon_t^f, \quad (1)$$

where

$A_i^f(t)$ ,  $i=1, \dots, K^f$  are predictors in the given year  $t$  derived from the DPSIR analysis [45] of the waste stream  $f$ ,

$\varepsilon_t^f = \log(w^f(t)) - \log(\hat{w}_t^f)$ , for  $t=2009, \dots, 2014$  are approximation errors.

Coefficients  $a_0^f, \dots, a_{K^f}^f$  in (1) for each waste stream  $f$  are calculated using multiple regression on the basis of the values of waste generation  $\hat{w}_t^f$  and predictors  $\hat{A}_{i,t}^f$ ,  $i=1, \dots, K^f$ ;  $t=2009, \dots, 2014$ . Approximation errors  $\varepsilon_t^f$ ,  $t=2009, \dots, 2014$ , have the mean equal to 0 and the normal distribution.

If we want to establish the confidence interval of predictors  $A_i^f(t)$ , it will be necessary to restrict their number to  $K^f \leq 4$ , since we only have a time series of six past known values. If we have the values of  $\hat{w}_t^f$  and  $\hat{A}_{i,t}^f$  for the next years  $t=2015, \dots$ , the model (1) will be more accurate and an approximation error  $\varepsilon_t^{f,ps}$  will be smaller.

Furthermore, we assume that the predictors  $A_i^f(t)$ ,  $i=1, \dots, K^f$ , for  $t=2015, \dots, 2024$  have either known values (GDP, population, household consumption, etc.) from the eGovernment systems or are determined by an appropriate extrapolation method or are chosen by decision makers.

These models are implemented in application of the software FORECAST written in language R and they use predefined predictors  $\hat{A}_{i,t}^f$  [45], which were parsed from linked open data. The outputs  $w^f(t)$  are time series of the amount of waste generated for the years  $t=2015, \dots, 2024$  of waste stream  $f$ .

An estimate of the waste stream generation  $w^f(t)$  can be expressed the after treatment (1) as

$$w^f(t) = A_0^f \cdot \prod_{i=1}^{K^f} A_i^f(t)^{a_i^f}, \quad (2)$$

where  $A_0^f = e^{-\varepsilon_t^f}$ , while we have neglected the error  $\varepsilon_t^f$ .

### The sensitivity of estimate of waste generation with respect to statistical significance of predictors

The local sensitivity of the model (1), (2) for the  $i^{\text{th}}$  predictor  $A_i^f(t)$ , in the year  $t$  and waste stream  $f$  can be estimated using the partial derivatives of the waste stream  $w^f(t)$  in (2) according to the  $i^{\text{th}}$  predictor  $A_i^f(t)$ :

$$a_i^f \cdot \frac{w^f(t)}{A_i^f(t)}. \quad (3)$$

It follows from (3) that if the value of predictor  $A_i^f(t)$  is increased by 1 percent then the amount of waste  $w^f(t)$  in waste stream  $f$  will increase or decrease by  $a_i^f$  percent, if  $a_i^f > 0$  or  $a_i^f < 0$ , for  $i=1, \dots, K^f$ . This knowledge is important for users of the model. We continue in the further analysis of the developed model, i.e. assessment of the statistical significance of predictors.

The predictors  $A_i^f(t)$ ,  $i=1, \dots, K^f$  in (1), (2) were determined for each waste stream  $f$  on the basis of the analysis of the DPSIR framework [45] and expert's assessment. Therefore, we will conduct an assessment of their statistical significance in the multiple linear model (1) depending on the input



values of the predictors in the years 2009 to 2014. First, we are considering in the model (1) all predictors  $A_j^f(t), j=1, \dots, K^f$  in (1), in the waste stream  $f$  where we calculate its sample variance, i.e.:

$$s^2 = (\sum_{t=2009}^{2014} (\varepsilon_t^f)^2) / (K^f - 1). \quad (4)$$

Statistical significance of each predictor  $A_i^f(t)$  is calculated using the F-test of the difference of two sample variances, i.e. the sample variance  $s$  of the model (1) with all predictors and sample variance  $s_i$  of the model (1) where the  $i^{\text{th}}$  predictor  $A_i^f(t)$  is excluded and the rest of the predictors, i.e.  $K^f-1$ , are recalculated and its sample variance is calculated

$$s_i^2 = (\sum_{t=2009}^{2014} (\varepsilon_{t,i}^f)^2) / (K^f - 2), \quad (5)$$

Where  $\varepsilon_{t,i}^f$  is approximation error of multiple linear regression of the model (1), where the  $i^{\text{th}}$  predictor was excluded.

Then we set the number of degrees of freedom for both samples:  $n_1 = K^f - 1$  (for  $s^2$ ) and  $n_2 = K^f - 2$  (for  $s_i^2$ ) and compute the value of the test criteria (statistics)  $F_i$ :

$$F_i = \text{the greater of } (s^2, s_i^2) / \text{the smaller of } (s^2, s_i^2), \quad (6)$$

that has the Fischer probability density distribution

$$H(x) = \frac{\Gamma(\frac{n_1+n_2}{2})}{\Gamma(\frac{n_1}{2}) \cdot \Gamma(\frac{n_2}{2})} \cdot n_1^{\frac{n_1}{2}} \cdot n_2^{\frac{n_2}{2}} \cdot \frac{x^{\frac{n_1-2}{2}}}{(n_2+n_1x)^{\frac{n_1+n_2}{2}}}, \quad (7)$$

for  $x > 0$  and is equal to 0 for  $x \leq 0$ .

We use statistical software where it is more common to calculate the test  $p$ -value, which we denote  $p_i$ . This is the smallest level of the F-test in which we would reject the hypothesis  $H_0: \{s^2 = s_i^2\}$ . We set this value as  $p_i = 1 - H(F_i)$ .

This procedure is repeated gradually for other predictors  $A_i^f(t)$ , for which we calculate  $F_i$  statistics and the test  $p$ -values  $p_i, i = 2, \dots, K^f$ .

Denote  $V = \{F_i, p_i, s_i\}_{i=1}^{K^f}$  the set of predictors significance. We can now simplify the model (1) and exclude non-significant predictors.

Let us choose the level of significance  $\alpha$  (values 0.05 or 0.1 are usually selected) of the predictors. We calculate  $p$ -values  $p_i, i = 1, \dots, K^f$  and compare them with this level of significance  $\alpha$ :

- If  $p_i > \alpha \Rightarrow$  the null hypothesis  $H_0: s^2 = s_i^2$  is rejected. Conclusion: the variances of different models are statistically significant and the  $i^{\text{th}}$  predictor  $A_i^f(t)$  is significant.
- If  $p_i < \alpha \Rightarrow$  we cannot reject the hypothesis  $H_0$ . Conclusion: the variances of both models are not statistically significantly different (i.e., the selections originated from the same basic model with the common variance  $s^2$ ) and the  $i^{\text{th}}$  predictor is not significant.

In this way, we can simplify the model (1), (2) if we exclude insignificant predictors  $A_i^f(t)$ , which we originally selected on the basis of the DPSIR analysis [45]. In the developed model, only the statistically significant predictors  $A_i^f(t)$  will then remain. For some waste streams  $f$ , however, it may happen that of the original proposed predictors based on the DPSIR analysis will not remain in any model (1). The resulting forecast  $p$  of waste stream generation is then constant and independent of the predicted values of the predictors of the future. In this case, we can only reduce the statistical significance level  $\alpha$ , i.e. reliability of the developed model and accept a greater risk of erroneous predictions.

### Extrapolation of the predictors

Let us suppose that for each waste stream  $f$  the amount of waste stream generation  $\hat{w}_t^f$  and predictors  $\hat{A}_{i,t}^f, i=1, \dots, K^f; t=2009, \dots, 2014$  are known and we have calculated for each waste stream  $f$  the coefficients  $a_0^f, \dots, a_{K^f}^f$  in the model (1) by using multiple regression.

For the calculation of the forecast waste stream generation  $w^f(t)$  in the years  $t=2015, \dots, 2024$  it is necessary to know the values of predictors  $A_i^f(t), i=1, \dots, K^f, t=2015, \dots, 2024$ . These values, however, may not always be listed in the sources (linked open data in the eGovernment systems) from which we draw the data predictors  $\hat{A}_{i,t}^f, i=1, \dots, K^f; t=2009, \dots, 2014$ . In this case, the procedure is the following:

- Enter the values of the predictors based on expert's estimates or other appropriate sources;
- On the basis of the values of the predictors  $\hat{A}_{i,t}^f, i=1, \dots, K^f; t=2009, \dots, 2014$  the values of predictors  $A_i^f(t), i=1, \dots, K^f, t=2015, \dots, 2024$  are calculated using either linear or exponential extrapolation.

## Modelling measures in waste management and scenarios

The developed models (1), (2) of forecast waste generation  $w^f(t)$  for the waste stream  $f$  should also reflect the trends in changes in this waste stream as a result of the anticipated  $N$  measures  $o_j, j = 1, \dots, N$  (WMP, WPP, EU and national legislative changes etc.), which will have an impact on the given waste stream  $f$  in the year  $t$ . Therefore, we introduce the function  $P^f(t, o_1, o_2, \dots, o_N)$  in the form:

$$P^f(t, o_1, o_2, \dots, o_N) = \prod_{j=1}^N \left(1 - \frac{P_j^f(t)}{100}\right), \quad (8)$$

where functions  $P_j^f(t)$  are time-dependent functions of the impact of given measures (e.g. prevention, kind of collection, permitted treatment, delivery distance to waste facilities, etc.) on the waste stream  $f$  in the given year  $t$  (generally in the whole waste management of the Czech Republic) and for simplicity, we assume that

$$0 \leq P_j^f(t) < 100, j = 1, \dots, N; t = 2015, \dots, 2024. \quad (9)$$

The functions  $P_j^f(t)$  for the year  $t$  will set as a percentage which should be achieved in years  $t = 2015, \dots, 2024$ , as a result of the measures  $o_j$  (on the basis of the WMP, WPP or other strategic documents). For the period  $t = 2009, \dots, 2014$ , zero values of these functions are considered. In most of the waste streams  $f$  simple function values  $P_j^f(t)$  for the given year  $t = 2015, 2016, \dots, 2024$  will not be provided, therefore, they will be estimated on the basis of the expert's assessment. If it is not possible to set them realistically, we consider them to be equal to 0.

The forecast of the waste generation  $w_{prognosis}^f(t)$  for the given waste stream  $f$  let us consider now as the product of the function  $P^f(t, o_1, o_2, \dots, o_N)$  and estimated waste stream generation  $w^f(t)$  of (2):

$$w_{prognosis}^f(t) = \prod_{j=1}^N \left(1 - \frac{P_j^f(t)}{100}\right) \cdot A_0^f \cdot \prod_{i=1}^{K^f} A_i^f(t) a_i^f \quad (10)$$

To compute logarithms (10) we receive the resulting equation of our developed model for the forecast of the waste stream generation  $f$  in the year  $t = 2015, \dots, 2024$ :

$$\log(w_{prognosis}^f(t)) = a_0^f + \sum_{i=1}^{K^f} a_i^f \log(A_i^f(t)) + \sum_{j=1}^N \log\left(1 - \frac{P_j^f(t)}{100}\right). \quad (11)$$

The values of the waste stream generation  $\hat{w}_t^f$  and the values of predictors  $\hat{A}_{i,t}^f$  are known for each waste stream  $f$  and  $P^f(t, o_1, o_2, \dots, o_N) = 0$  in the years  $t = 2009, \dots, 2014$  and the coefficients  $a_0^f, \dots, a_{K^f}^f$  from (1), (2) are calculated using the method of multiple regression. The forecast of the amount of waste stream generation  $w_{prognosis}^f(t)$  in the years  $t = 2015, 2016, \dots, 2024$  depends on the values of the predictors  $A_i^f(t)$  and functions  $P_j^f(t), i=1, \dots, K^f; j=1, \dots, N$  for each waste stream  $f$ .

Using the functions  $P_j^f(t)$ , the decision makers at the MoE could simulate different scenarios for anticipated impact of the individual measures  $o_j, j = 1, \dots, N$  on the total waste generation in the given waste stream  $f$  and year  $t$ .

They could choose for example the value of  $P_j^f(t)$ , which was achieved for the year 2024 and the values of the function  $P_j^f(t)$  in the previous years from 2015 to 2023, until the year 2014, where they choose this equal to zero and examine what is the impact of the forecast value on the waste stream generation  $w_{prognosis}^f(t)$ .

## Results and Discussion

We developed open source software [50] where in its current version there are the outputs of forecasting models for 18 waste streams of Table 1 (MSW, CDW, bio-waste, car wrecks, hazardous waste, WEEE and other streams). The outputs of the forecasting model consist of four basic output steps for every waste stream generation. The outputs for the MSW forecasting are presented in the following figures.

### Municipal solid waste forecast generation analysis outputs

### Step 1: Input data for MSW prediction model

**Initial year:**  
(first year in which the generation will be modelled).

**Statistical significance:**  
(probability in % of not being wrong when estimating significant predictors).

**Previous MSW generation:**  
(values in tons/year with decimal dot separator, split by comma separator, NA for not available value).

**Previous household expenditures for food, clothes and shoes:**  
(values in billions (10<sup>9</sup>) CZK, with decimal dot separator, split by comma separator, NA for not available value).

**Previous mid-year population:**  
(values in thousand of inhabitants, with decimal dot separator, split by comma separator, NA for not available value).

**Previous number of retired:**  
(values in thousand of retired persons, with decimal dot separator, split by comma separator, NA for not available value).

**Previous unemployment:**  
(values in %, with decimal dot separator, split by comma separator, NA for not available value).

**Fig.3** Step 1. Input data for MSW generation. Source: authors.

1. In the first step, Fig. 3, there are boxes of basic data inputs over the time  $t=2009, \dots, 2014$  for modelling: previous MSW generation and time series of the known values of the relevant DPSIR analysis predictors (implicit values are parsed from linked open data) and forecasting model outputs.
2. In the second step, Fig. 4, users can specify the values of the predictors (pre-filled values are available with hyperlinks to the linked open data sources) expected in the model (1), (2) or choose their possible linear/exponential extrapolation. Users can also input expected prevention measures (three possible scenarios of MSW prevention are available).

### Step 2: Expectations of future development 2024

Household expenditures for food, clothes and shoes [bil. CZK]	2015:	2016:	2017:	2018:	2019:	2020:	2021:	2022:	2023:	2024:	Source:
	589.9733	595.4104	600.8475	606.2846	611.7216	617.1550	622.5920	628.0291	633.4662	638.9033	<a href="https://vdb.czso.cz/vdbvo2/faces/cs/index.jspx?_af=statistiky#katalog=30847">https://vdb.czso.cz/vdbvo2/faces/cs/index.jspx?_af=statistiky#katalog=30847</a>
Mid-year population [thousand of inhabitants]	2015:	2016:	2017:	2018:	2019:	2020:	2021:	2022:	2023:	2024:	Source:
	10538	10534	10531	10527	10524	10520	10507	10493	10480	10467	<a href="https://www.czso.cz/csu/czso/obyvateilstvo_hu">https://www.czso.cz/csu/czso/obyvateilstvo_hu</a>
Number of retired [thousand of inhabitants]	2015:	2016:	2017:	2018:	2019:	2020:	2021:	2022:	2023:	2024:	Source:
	2884	2848	2843	2838	2833	2828	2823	2818	2813	2808	<a href="http://www.cssz.cz/cz/o-cssz/informace/informacni-materialy/statisticke-rocenky.htm">http://www.cssz.cz/cz/o-cssz/informace/informacni-materialy/statisticke-rocenky.htm</a>
Unemployment [%]	2015:	2016:	2017:	2018:	2019:	2020:	2021:	2022:	2023:	2024:	Source:
	6.6	5.9	5.8	5.8	5.8	5.8	5.8	5.8	5.8	5.8	<a href="https://vdb.czso.cz/vdbvo2/faces/cs/index.jspx?_af=statistiky#katalog=30853&amp;str=v95&amp;c=v3_RP2014">https://vdb.czso.cz/vdbvo2/faces/cs/index.jspx?_af=statistiky#katalog=30853&amp;str=v95&amp;c=v3_RP2014</a>
1st prevention measure (effect) [% of MSW generated]	2015:	2016:	2017:	2018:	2019:	2020:	2021:	2022:	2023:	2024:	
	0.5	1	1.5	2	2.5	3	3.5	4	4.5	5	
2nd prevention measure (effect) [% of MSW generated]	2015:	2016:	2017:	2018:	2019:	2020:	2021:	2022:	2023:	2024:	
	0	2	5	9	14	20	27	35	44	9	
3rd prevention measure (effect) [% of MSW generated]	2015:	2016:	2017:	2018:	2019:	2020:	2021:	2022:	2023:	2024:	
	0	3	6	9	12	15	18	21	24	27	

**Fig.4** Step 2. Scenario of forecasting future development in MSW generation in 2015-2024 with expected prevention measures. Source: authors.

3. In the third step, Fig. 5, results are shown in a form of a table, mathematical expression of (1) and a time-plot, showing the future MSW generation development and effects of the prevention measures taken (the curves representing the prediction interval and shaded areas showing the confidence intervals).
4. In the fourth step, Fig. 6, a sensitivity analysis is presented, showing decision makers an estimated effect of the individual predictors from the model (1) and the quality of forecasting.

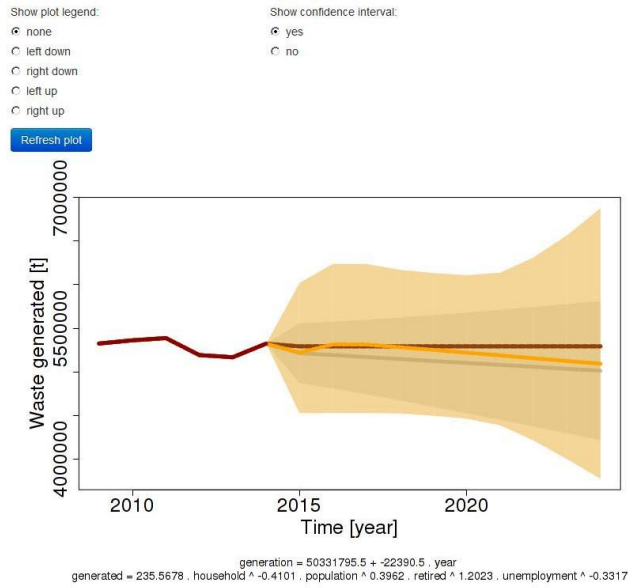
## Conclusion

The predictors of the forecasting models (1), (2) were chosen through a selection process that included opinions from experts, literature review based on relevance and applicability to different waste streams settings. Appropriate predictors were selected and fitted into the DPSIR framework, which is presented for MSW and CDW. The construction of the forecasting models consisted of construction and definition of the predictors based on the DPSIR framework, integration of the predictors into the forecasting model and analysis of sensitivity of the predictors. The forecasting model was implemented as open source software and it was verified using appropriate data. The outputs of the developed forecasting model are presented for MSW of the Czech Republic with scenarios to follow the EU action plan for the circular economy.

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### Step 3: Final prediction and model equation



[Download table](#)

generation = 50331795.5 -22390.5 . year

generation = 5292619.2353

Table of modelled values:

	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024
<b>Modelled values</b>	5292619	5292619	5292619	5292619	5292619	5292619	5292619	5292619	5292619	5292619
<b>Lower threshold</b>	5044674	5044674	5044674	5044674	5044674	5044674	5044674	5044674	5044674	5044674
<b>Upper threshold</b>	5552751	5552751	5552751	5552751	5552751	5552751	5552751	5552751	5552751	5552751
<b>Linear extrapolation</b>	5325179	5361883	5388058	5192784	5167805	5323947	5214909	5192519	5170128	5147738
<b>Lower threshold</b>	5325179	5361883	5388058	5192784	5167805	5323947	4871640	4809740	4742870	4672570
<b>Upper threshold</b>	5325179	5361883	5388058	5192784	5167805	5323947	5557978	5575298	5597386	5622906

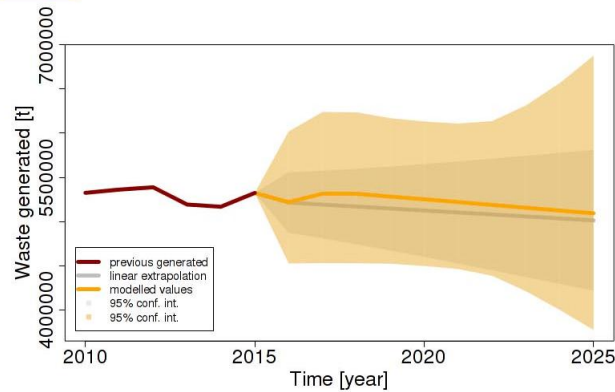
Fig. 5 Step 3. Final prediction of MSW generation. Source: authors.

#### Step 4: Sensitivity analysis

Show plot legend:

- none
- left down
- right down
- left up
- right up

Refresh plot



generation = 50331795.5 + -22390.5 . year  
 generation = 235.5678 . household ^ -0.4101 . population ^ 0.3962 . retired ^ 1.2023 . unemployment ^ -0.3317

Table of model outputs (in logarithmic form):

Predictor	Degrees of freedom	Sum of squared residuals	F statistics	p value
Variable: household	1	0.000324	6.3	0.241
Variable: population	1	5.3e-05	1	0.494
Variable: retired	1	2.6e-05	0.5	0.606
Variable: unemployment	1	0.001039	20.3	0.139
Residuals	1	5.1e-05		

**Fig. 6** Step 4. Sensitivity analysis of forecasting MSW generation. Source: authors.

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