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Computational System for Simulation and Forecasting in Waste Management Incomplete Data Problems

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Nowadays, shift towards an effective waste management is a big issue as well as a necessity for many countries. Infrastructural projects in waste management (e.g. new waste-to-energy plants, WTE) have long-term implementation phase (up to 10 y). WTE, processing residual waste, represent keystone of sustainable concepts. In this context, information on waste availability and incinerated waste properties, especially calorific value, are vital for successful design and operation of these plants. However, hardly predictable future changes in these parameters make the design process challenging.
In this contribution, we present a tool for verification and forecasting of current and future production of residual municipal waste and its lower heating value (LHV) to support WTE design process. Newly developed tool JUSTINE is introduced. From the principal point of view it is a wait-and-see optimization model recursively applied to region divided into several sub regions and also their parts.
It processes variety of spatially distributed statistical data bound together through equations and constraints. This data is supposed to be incomplete (some local information might be unavailable) and uncertain. The wait-and-see optimization model is used to obtain point estimates of desired parameters that can be used for waste production and LHV forecasts. In addition, for randomly simulated input data reflecting real-world uncertainties empirical confidence intervals of input and output values can be computed. The practical contribution of this tool is presented through a case study.

1. Introduction

All methods of the waste treatment, in line with the waste management hierarchy (Directive 2008/98/EC, 2008), such as WTE, are embodied in the effective waste management. WTE process residual waste with energy production and thus significantly contributes to minimize the landfilling, which is in the last place of this hierarchy due to no waste utilization, and therefore, it is the least appropriate option. Based on examples of European countries with high maturity level of the waste management, such as Germany or Austria, it can be shown that there is still about 50 % of waste that must be diverted from landfill by using another way of treatment, even when using the potential of the first three levels of the waste management hierarchy and high usage level of recycling and composting. This amount of waste is designated as residual solid waste (RSW) and WTE is a suitable technology for its processing (Eurostat, 2014). In many countries, both in Europe (Šomplák et al., 2013) and outside of Europe (Santibañez-Aguilar et al., 2014), the effective waste management becomes very current topic. Therefore there is an increasing motivation for construction of new WTE units. However, there is a necessity to know the amount of available RSW and its LHV, both in the present and with respect to future trend, in order to be able to plan operations and economy of WTE (Touš et al., 2013).
This article builds on a study Putna et al. (2014), where the concept for a new computational system designed to predict waste production and LHV based on a realistic assumption of differences in availability

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of spatially heterogeneous and hierarchical input data, was introduced. In this paper, the model and implementation of the above mentioned concept and the case study will be presented (see Section 4).

2. Principal modeling ideas

Generally, available data on the production of RSW and its LHV are variable both in time and within territorial location, which makes the process of planning of new WTE processing capacities more complicated. Furthermore, countries with less developed waste management generally suffer from poor data base regarding the RSW production. The LHV is known only sporadically because the systematic surveys on the waste composition are very rare. Usually, there are available only non-complex data sources, such as public databases, operating data or local waste studies. An important feature of data sources is and inaccuracy of provided values. The aim is then to design a comprehensive, predictive tool to estimate waste production LHV at several levels of territorial arrangement.

Theoretical concept of the tool is based on the assumption that searched RSW weight and LHV, required as inputs for further calculations (see motivation above), are not available in ideal quality. There are only measurement results or expert estimates, where they are expected to be burdened by the random error. Therefore, the aim will be to obtain relevant forecasts, as complete as possible, which are close to ideal values of the unknown parameters. Estimated representative amounts of the randomly fluctuating RSW (denoted *m*) and LHV are marked with an asterisk (*m**, *LHV**) and inaccuracy of this estimate to real value is denoted by ε. Superscripts then specify to which variable the error refers and subscripts denote territorial units.

The estimated values are then obtained by minimizing a suitable criterion – the objective function. The objective function is then formed by the sum of the absolute values of inaccuracies ε, and therefore, the emphasis is placed on the robustness of the estimation of unknown parameters (i.e. the weights of large deviations, which are frequently present in heterogeneous data, are not accentuated). Like in regression models, the theoretical (wait-and-see) model is considering the minimization of random errors, but for computational purposes their observed values are used. The above mentioned objective function related ideas are further utilized to obtain constraints taking into account both input data and hierarchical structure of territorial units. They also guarantee that the data for higher territorial unit is not contradictory with the aggregated data of sub-units involved in the higher unit. Specifically, the set of constraints is formed by energy balances for each type of territorial units and equipment. Total energy in a given area is determined as a product of the weight of the waste produced in this area and the corresponding LHV value. Due to these energy balances, the computational system becomes nonlinear and it is necessary to use the nonlinear programming techniques for minimization of the objective function subject to discussed constraints. Due to incomplete data, alternative optimal solutions can be expected. In addition, considering nonlinearities included in the equations, the problem is non-convex, and thus, the possible existence of the local extremes must be taken into account for the choice of a suitable solution algorithm. The model also envisages the possibility of the use of operational data and data inputs include both amounts of RSW generated or processed, as well as, information on LHV.

3. Mathematical model

The resultant calculation of *m* and LHV for the particular territorial area or facility is given by Eq(1)-(2). The equations together with related weighting of input data sets using parameters *v* are described in detail in Section 4. Due to the approach of minimizing the sum of the absolute values of the inaccuracies, the individual errors were divided into positive and negative component, denoted by signs (+) or (-) in the indices, see Eq(3)-(4). Both of those components are defined as non-negative, and so, the negative deviation can be described by their difference. Then, the sums of these components represent the absolute values of inaccuracies and are denoted by $\hat{\varepsilon}$ - see Eq(5)-(6). Eq(7) describe hierarchical relations for energy balances. For this purpose we denote territorial units by indices $i, j \in I$. If unit with index *j* immediately belongs to higher unit indexed by *i*, we say that *i* is an ancestor of *j* and write $i = a(j)$. We also identify for any index *i* a set of all successors *j* satisfying the same equality as above and denote it as $S(i)$. Then, set I^* collects indices *i*, which $S(i)$ is empty. Eq(8) represents the objective function involving standardized weight parameters φ_i for different groups of territorial units. Notation used in mathematical model (Eq(1)-(8)) is summarized in Table 1.

Input data related constraints

$$m_i = \sum_{p \in P} v_{i,p}^{m} \cdot \left(m_{i,p}^{*} + \delta_{i,p}^{m}\right) \cdot \varepsilon_{i,p}^{m}, \qquad i \in I, \tag{1}$$

$$LHV_i = \sum_{q \in Q} v_{i,q}^{LHV} \cdot \left(LHV_{i,q}^{*} + \delta_{i,q}^{LHV}\right) \cdot \varepsilon_{i,q}^{LHV}, \qquad i \in I, \tag{2}$$

where $m_{i,p}^{*}$, $\varepsilon_{i,p}^{m}$, $LHV_{i,q}^{*}$, $\varepsilon_{i,q}^{LHV}$ are variables and weight coefficients satisfy the conditions

$$v_{i,p}^{m}, v_{i,q}^{LHV} \in \langle 0;1 \rangle, \sum_{p \in P} v_{i,p}^{m} = 1, \sum_{q \in Q} v_{i,q}^{LHV} = 1, \; i \in I, \; p \in P, \; q \in Q,$$

$$\varepsilon_{i,p}^{m} = \varepsilon_{i,p}^{m+} - \varepsilon_{i,p}^{m-}, \qquad i \in I, p \in P, \tag{3}$$

$$\varepsilon_{i,q}^{LHV} = \varepsilon_{i,q}^{LHV+} - \varepsilon_{i,q}^{LHV-}, \qquad i \in I, q \in Q, \tag{4}$$

$$\hat{\varepsilon}_{i,p}^{m} = \varepsilon_{i,p}^{m+} + \varepsilon_{i,p}^{m-}, \qquad i \in I, p \in P, \tag{5}$$

$$\hat{\varepsilon}_{i,q}^{LHV} = \varepsilon_{i,q}^{LHV+} + \varepsilon_{i,q}^{LHV-}, \qquad i \in I, q \in Q, \tag{6}$$

where $\hat{\varepsilon}_{i,p}^{m}$, $\hat{\varepsilon}_{i,q}^{LHV}$ and $\varepsilon_{i,p}^{m+}, \varepsilon_{i,p}^{m-}$, $\varepsilon_{i,q}^{LHV+}$, $\varepsilon_{i,q}^{LHV-} \geq 0$, $i \in I, p \in P, q \in Q$ are variables.

Constraints reflecting the hierarchy of territorial units

$$\sum_{j \in S(j)} \{ \sum_{p \in P} v_{j,p}^{m} \cdot (m_{j,p}^{*} + \delta_{j,p}^{m}) \cdot \varepsilon_{j,p}^{m} \cdot \sum_{q \in Q} v_{j,q}^{LHV} \cdot (LHV_{j,q}^{*} + \delta_{j,q}^{LHV}) \cdot \varepsilon_{j,q}^{LHV} \} = \sum_{p \in P} v_{i,p}^{m} \cdot (m_{i,p}^{*} + \delta_{i,p}^{m}) \cdot \varepsilon_{i,p}^{m} \cdot \sum_{q \in Q} v_{i,q}^{LHV} \cdot (LHV_{i,q}^{*} + \delta_{i,q}^{LHV}) \cdot \varepsilon_{i,q}^{LHV}; \qquad i \in I^{*}. \tag{7}$$

The objective function

$$z = \sum_{i \in I} \varphi_i \cdot (\sum_{p \in P} \hat{\varepsilon}_{i,p}^{m} + \sum_{q \in Q} \hat{\varepsilon}_{i,q}^{LHV}), \tag{8}$$

where weight coefficients are standardized as follows $\varphi_i \in \langle 0;1 \rangle, \sum_{i \in I} \varphi_i = 1$.

Table 1: Mathematical model related notation

Symbol	Description	Unit
$i, j \in I$	indices of territorial units	[-]
$p \in P$	index determining data set for amount of waste generated	[-]
$q \in Q$	index determining data set for lower heating value	[-]
m_i	real amount of waste generated (result of calculation) for $i \in I$	[t/y]
$m_{i,p}^{*}$	estimated amount of waste generated (available data) for $i \in I, p \in P$	[t/ y]
LHV_i	real lower heating value (result of calculation) for $i \in I$	[GJ/t]
$LHV_{i,q}^{*}$	estimated lower heating value (available data) for $i \in I, q \in Q$	[GJ/t]
$\varepsilon_{i,p}^{m}$	inaccuracy of amount of waste generated for $i \in I, p \in P$	[%]
$\varepsilon_{i,p}^{m+}$	positive part of inaccuracy of amount of waste generated for $i \in I, p \in P$	[%]
$\varepsilon_{i,p}^{m-}$	negative part of inaccuracy of amount of waste generated for $i \in I, p \in P$	[%]
$\hat{\varepsilon}_{i,p}^{m}$	absolute value of inaccuracy of amount of waste generated for $i \in I, p \in P$	[%]
$\varepsilon_{i,q}^{LHV}$	inaccuracy of lower heating value for $i \in I, q \in Q$	[%]
$\varepsilon_{i,q}^{LHV+}$	positive part of inaccuracy of lower heating value for $i \in I, q \in Q$	[%]
$\varepsilon_{i,q}^{LHV-}$	negative part of inaccuracy of lower heating value for $i \in I, q \in Q$	[%]
$\hat{\varepsilon}_{i,q}^{LHV}$	absolute value of inaccuracy of lower heating value for $i \in I, q \in Q$	[%]
$\delta_{i,p}^{m}$	simulated error of the repeated measurements for RSW production $i \in I, p \in P$	[%]
$\delta_{i,q}^{LHV}$	simulated error of the repeated measurements for LHV, $i \in I, q \in Q$	[%]
$v_{i,p}^{m}$	standardized weight for the data set *p* for estimated RSW production for $i \in I$	[%]
$v_{i,q}^{LHV}$	standardized weight for the data set *q* for estimated LHV for $i \in I$	[-]
φ_i	standardized weight of territorial unit $i \in I$	[-]
$S(i)$	set of indices of territorial units immediately belonging to unit $i \in I$	[-]
$i = a(j)$	index *i* identifies territorial unit *j* that includes unit *j* i.e. $j \in S(i)$	[-]
I^{*}	set of indices $i \in I$ such that $S(i)$ is a nonempty set	[-]

4. Case study

Application of the model is focused on the calculations within the Czech Republic, and therefore assumes the inputs of four levels with respect to the territorial units Czech Republic, that is the state - CR (NUTS 0, Nomenclature of Units for Territorial Statistics), regions (NUTS 3), districts (LAU 1, Local Administrative Units) and municipalities with extended powers (MWEP, without NUTS/LAU classification). In total there are 206 territorial units on the MWEP level.

The data base available for the Czech Republic was used in the test calculation and results are presented in this paper. In this case study, there were considered two models for LHV and one data source for the production *m* (see Figure 1). Publicly accessible database ISOH (Waste Management Information System) contains data on production, waste management and information concerning facilities for waste treatment, recovery and disposal in the Czech Republic since 2002. For the purposes of this case study, the historical data only from 2008 to 2012 were used as models for *m*, because just for this period the consistency of data processing was kept. Unlike data on production, no database collecting the data on LHV is available for given territory. In professional practice there is often an assumption that LHV is of value about 10 GJ/t, i.e. simply and rounded LHV = 10 GJ/t, which reflects current LHV values reported by Reimann (2012) for Europe. It should be emphasized that this value is not good estimate for each the territorial area and also that it does not reflect the trends in the waste management, such as the waste separation increase affecting the LHV. Another LHV model (on the MWEP level) used in the study case is a model taking into account correlation between type of heating and waste composition reported in three particular MWEPs. Complex composition analyses were performed in these MWEPs in 2009 and 2010. Generally, the LHV determination is an important problem. Good example might be a study, Lin et al. (2013), which presented a description of solutions for calorific value of RSW calculation from several aspects, along with a comparison of different methods of determining the caloric content with respect to the composition and humidity of the waste.

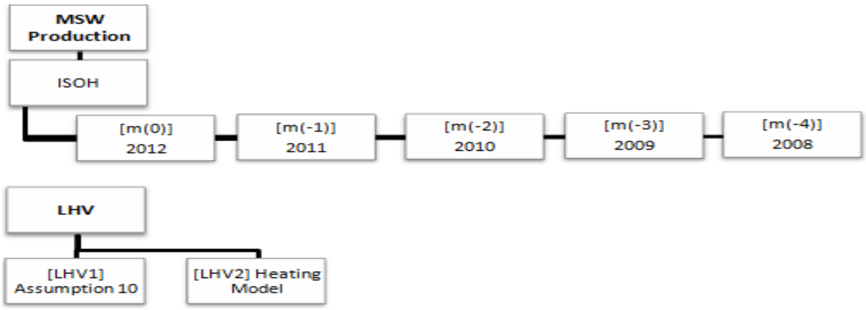

Figure 1: Data base available for the Czech Republic

As explained above, there is no sufficient data base on LHV currently available in the Czech Republic and additionally the input data is only an estimate of the real value. Also the real values are seasonable dependent. Therefore, the stochastic approach employing the Monte Carlo methodology was used in the model for testing and for pilot calculations. The artificial "blurring" of the input data (denoted by δ) was implemented, wherein the optimization model can be solved repeatedly for different sets of input data set. This blurring is realized by randomly generated value from a pre-selected probability distribution where the probability distribution parameters are determined based on the expert analysis of the credibility of the original data. Implemented options for the probability distributions are for now as follows: a) Fixed value: $\delta = 0$; b) normal distribution: $\delta \sim N(\mu,\sigma^2)$; c) uniform distribution: $\delta \sim U(a,b)$.

Practically, different scenarios are created when for the certain model value (e.g. LHV*=10) one scenario is generated with the value of LHV** = 10 + δ, where δ is a random number generated from the selected distribution, e.g. from normal with $\mu = 0$ and $\sigma = 0.08$LHV*. If the entry value is very reliable, the possibility of fixed data, i.e. no blurring, is selected. If the input data is quite reliable, the blurring value is generated from the normal distribution. If the entry value is more of general type of information (e.g. frequently used LHV = 10 GJ/t), it is preferable to use a value generated from a uniform distribution.

In the future, it can be assumed that the *m* and LHV data base will increase, most likely in the form of local studies, or from waste treatment facilities. Therefore, it will be necessary to suitably combine these data sets into a single optimization calculation. Then, it is convenient to consider the different weights for each input data (see Eq(1)-(2)), due to a variety of meaningful values for different data sources. Alongside it is possible to detect errors of the individual models employing the detailed analysis and to further develop proposed model.

By using ca. hundreds of Monte Carlo simulations, the variability of *m* and LHV in the respective areas can be observed, and thus, the sensitivity of inaccuracies on the resulting estimates can be detected. The average value, or the interval, for both of the parameters in the area can be determined. Figure 2 shows the results for the case of MWEP#2. Graph on the left side of the figure presents the variability of the results together with the estimate of the mean value and 95 % interval for point results for 500 simulations. The graph on the right side of the figure then provides another perspective of the results using the histogram of generated data. The input models values for this particular case of MWEP#2 were LHV1=10

GJ/t and LHV2=9,176 GJ/t. From the graph it can be concluded that in the range of the LHV value in MWEP#2 is 9,339±1.0875 GJ/t. Analogous information for the *m* in MWEP#2 is presented on Figure 3. Presentation of the results using a histogram, instead of a single value, is an important benefit of this tool, since in the reality it is not possible to achieve the constant value of *m* and homogeneous LHV, as already mentioned by Putna et al. (2014). Production and LHV also change during the year, and therefore, it is necessary to calculate the predictions with the variability of both parameters. Therefore, another possible extension of this tool is calculation performed on a monthly basis.

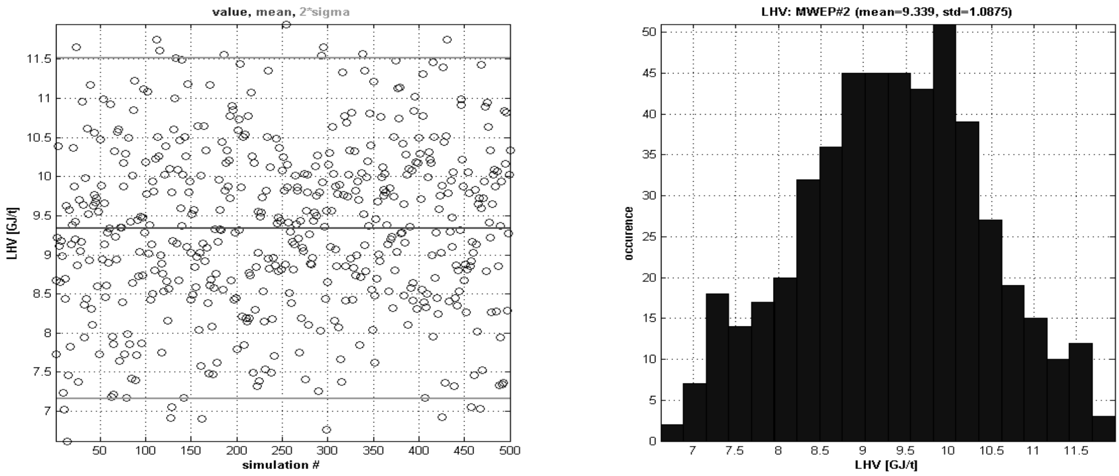

Figure 2: Simulations output – LHV estimation for MWEP#2

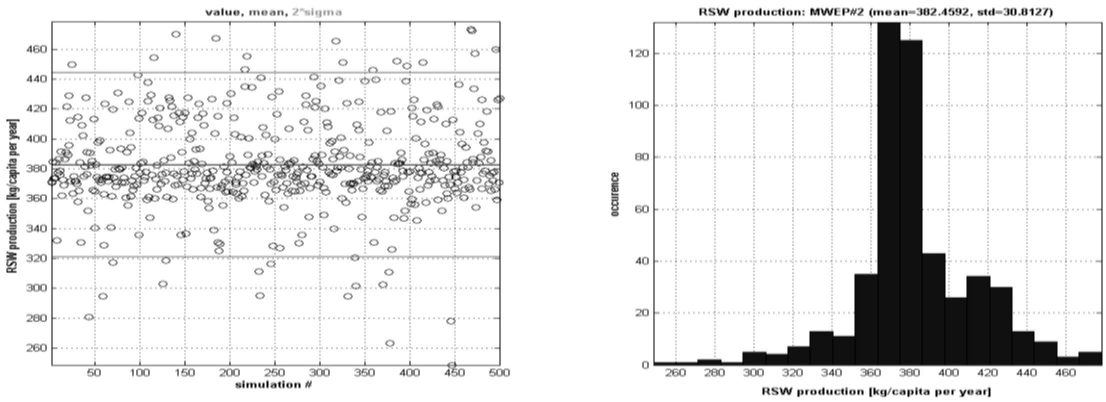

Figure 3: Simulations output – RSW mass production estimation for MWEP#2

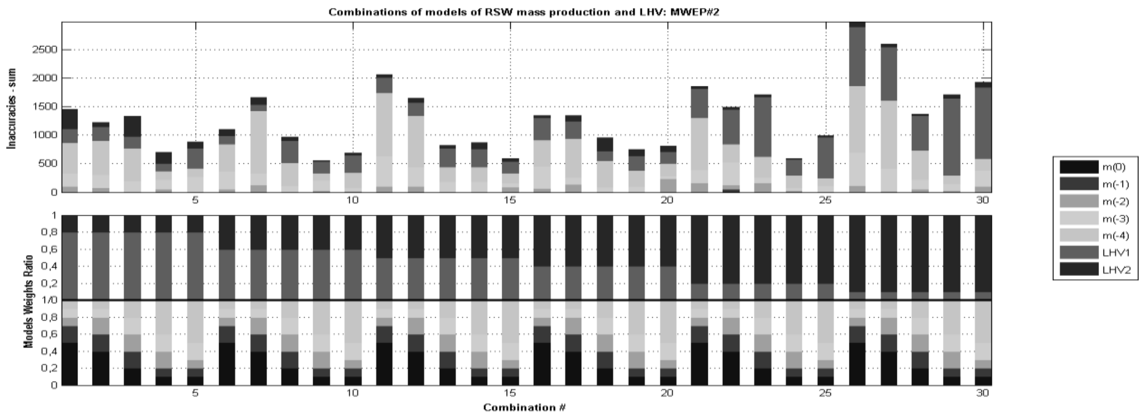

Figure 4: Comparison of credibility of the models for input data for RSW production and LHV in MWEP#2

Finally, the implementation offers also the possibility to compare the credibility of the models that provide the input data for *m* and LHV in terms of the sum of inaccuracies (see Eq(5)-(6)). The top graph in Figure 4 presents the evolution of the sum of inaccuracies ($\hat{\varepsilon}$) in dependence on the weights reflecting the credibility of individual models (*v*), for combinations including production models and LHV models within MWEP#2. The bottom graph in Figure 4 presents the models (*v*) weights ratio (the weights are standardized - see assumptions for Eq(1)-(2)). For the sake of clarity the weights for RSW production models and LHV models were put into the same graph separated by the line.
Apart from the total error we can also observe the proportion of individual models to a total error (Figure 4 – top). By detailed analysis, it is possible to detect errors among different models from the perspective of a specific locality. These outputs can serve to improve the estimation of weights for each model.

5. Conclusions

This article, building on a study Putna et al. (2014), introduced current computational model and its results of the practical implementation of tool for predicting RSW production and LHV in the Czech Republic. Despite of a limited number of input data, the results provide information about the likely state of the RSW production and LHV in relevant territorial units. This information represents the valuable inputs for the design process of new waste management facilities. The knowledge of the RSW quantity and LHV are required already in the design and concept phase of WTE design, which is the leading technology in effective waste management. The concept described in the study Putna et al. (2014) was further extended with practical solutions to the implementation and with respect to the quantity of currently available data.
Further development of the tool is connected to the growing data base that will contribute to more accurate results. Other possible extensions of the tool are the calculations on a monthly basis. Input models can be extended to the socio-economic factors and their influence on the parameters of RSW in relevant area.

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References

Directive 2008/98/EC of the European Parliament and of the Council on waste and repealing certain Directives (Directive 2008/98/EC), 2008, Official Journal of the European Communities 22.11.2008, L 312, 3-30.

Eurostat, 2014, Statistical Office of the European Communities, Municipal waste statistics <ec.europa.eu/eurostat/statistics-explained/index.php/Municipal_waste_statistics> accessed 13.12.2014.

Lin C.-J., Chyan J.-M., Chen I.-M., Wang Y.-T., 2013, Swift model for a lower heating value prediction based on wet-based physical components of municipal solid waste, Waste Management, 33(2), 268-276.

Ministry of the Environment of the Czech Republic, 2002-2014, Public information system of waste management, Ministerstva životního prostředí (VISOH, ISOH) <isoh.cenia.cz/groupisoh/> accessed 14.08.2014 (in Czech)

Putna O., Kropáč J., Frýba L., Pavlas M., 2014, Prediction of heating value of waste and its importance for conceptual development of new waste-to-energy plants, Chemical Engineering Transactions, 39, 1273-1278.

Reimann D.O., 2012, CEWEP Energy Report III (Status 2007-2010) Results of Specific Data for Energy, R1 Plant Efficiency Factor and NCV of 314 European Waste-to-Energy (WtE) Plants, Bamberg, Germany, <cewep.eu/m_1069> accessed 28.2.2015.

Santibañez-Aguilar J.E., Ponce-Ortega J.M., González-Campos J.B., Serna-Gonzaléz M., El-Halwagi M.M., 2014, Optimal planning of supply chains for multi-product generation from municipal solid waste, Chemical Engineering Transactions, 42, 55-60.

Šomplák R., Procházka V., Pavlas M., Popela P., 2013, The logistic model for decision making in waste management, Chemical Engineering Transactions, 35, 817-822.

Touš M., Frýba L., Pavlas M., 2013, Improving Calculation of Lower Heating Value of Waste by Data Reconciliation – Analysis and Evaluation, Chemical Engineering Transactions, 35, 877-882.