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Forecasting of Waste Production Data with Changes in Credibility and Trend

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Waste management is currently a very actual area which is subjected to many changes and ongoing development. The aim is to maximize the use of waste as secondary material. Especially, processing facilities must respond to new rules in time because the construction of a new facility or modification of existing one usually takes several years. The efficient waste management planning requires both quantitative and qualitative estimates of future waste production reflecting analyzed timeframe. The forecasting of waste production is the challenging task due to the various barriers in terms of short time series, faulty reporting data or production sudden shift caused by multiple factors such as legislation, technology or system changes. These external influences can reverse the waste production substantially and then the historical data loses its explanatory value due to trend change and waste production in the new direction. However, the trend in historical data can be successfully modeled by S-curve function. The proposed method analyses the waste production historical data by combining credibility theory (usually used in the insurance industry) and the evaluation of trends in the time series. The so-called credibility approach uses the principles based on the combination of the collective and individual information to improve estimation accuracy. In this way, the classic S-curve trend model is corrected by overall information and utilizes the already known development of separation in other areas. The presented procedure determines the credibility of the individual data according to fulfilling separation potential. The testing dataset comes from the bio-waste production in the Czech Republic on the micro-regional level. In addition, the difference between rural and urban area is taken into account. The new methodology is generally applicable when the waste production was influenced in history and thereby the trend was changed.

1. Introduction

The development of society in terms of demographic conditions coupled with technological advances leads to increasing production of waste (Hoornweg and Bhada-Tata, 2012). These circumstances require a new attitude toward waste management and efficient waste processing. The current trends use waste as secondary raw material and thus moving from traditional waste management to the circular economy appears (Prieto-Sandoval et al., 2018). A preferred way of waste processing is anchored in the so-called Waste hierarchy (Directive (EU) 2008/98/EC). For a sustainable change to the circular economy, the processing infrastructure has to be adapted. Attention is increasingly paid on the processing of materially recoverable waste, where processing capacities are missing. The construction of new facilities is a complex task, for example, the sorting line technology modeling was described by (Gregor et al., 2018). The fixed milestones anchored in national legislation require a timely response because the construction of new facilities or modification of existing ones can take several years. The waste management plans must be based on high-quality forecasts, especially waste production reflecting analysed timeframe.
Based on the review from 2016 (Kolekar et al., 2016), the conventional waste generation models used the correlation and regression analysis with respect to demographic and socio-economic factors (Ojeda-Benitez et al., 2008). The multivariate analysis considers more independent variable (Keser et al., 2011), but the problem with the interaction between variables can appear. The data of this type are not always available, and the only

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explanatory variable is time, which leads to time series analysis (Mwenda et al., 2014). This approach is applicable only to long enough time series, annual waste production data, unfortunately, do not provide sufficient dataset. The common problem of the plenty of waste prognostic models is short time series which was the only one data source in the paper (Pavlas et al., 2017). The forecast was made there by plain trend analysis at multiple levels of the hierarchical structure of aggregated data and then the estimates were balanced for validity links between territorial units and waste commodities. The approach presented in (Pavlas et al., 2017) is profitable for forecasting of many waste production data, although some of the waste types are characterized by specific properties and it requires individual access.
The sudden change in waste production can be observed after external interference, for that reason the historical data do not have implying ability for future production estimation. The valuable information can be gained if the reaction on this change of another subject is monitored. It is possible to find the significant similarity of the reaction but with the different time of onset. The tool used for the combination of individual and overall information for predicting future development is called credibility theory (Mahler and Dean, 2001), originally used in the insurance industry. The credibility is built on the principle of weighting together two estimates, the basic formula for credibility estimation of parameter e is:

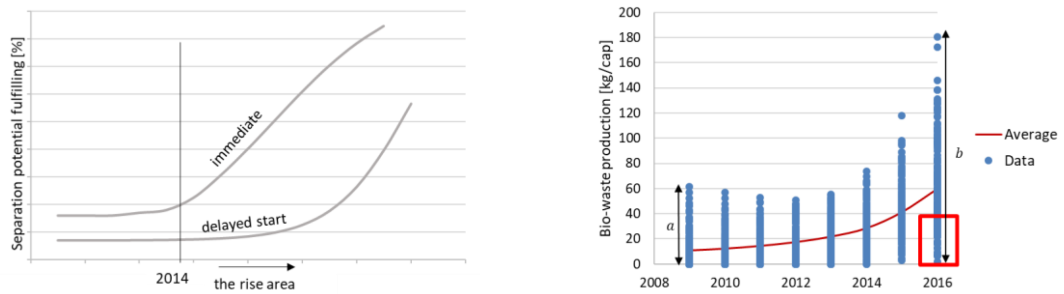
$$e = \lambda x + (1 - \lambda)y, \quad (1)$$

$$0 \leq \lambda \leq 1, \quad (2)$$

where λ is the credibility factor, x denotes the individual data and y average of overall dataset. The credibility λ is closer to 1 if the dataset is large and not likely to vary much from one period to another. The credibility theory formulates several special types e.g. Bühlmann credibility model (Bühlman, 1967) which works with variance across the dataset.
In this paper, the novelty approach to forecasting of waste with the significant change due to legislation, technology, system or other interference is presented. The method is described using bio-waste production data in the Czech Republic. Bio-waste production was influenced by legislation, i.e. the municipalities are obligated to provide the possibility of bio-waste separation from 2014 and from this year faster production increase is observable. The available dataset consists of annual waste production data in the years 2009–2016 on the micro-regional level (206 units). Bio-waste takes a significant part in municipal solid waste production, in 2016, it occupied 16.6 % of municipality solid waste in the Czech Republic. The favorable option of bio-waste handling is composting, the paper (Sabki et al., 2018) provides a review of the economic feasibility of this process. The bio-waste facility location was discussed in (Hrabec et al., 2017), the key information about future production was given by aggregated forecast and subsequent averaging for lower territorial units with regard to population size. The authors have worked across more possible scenarios of future bio-waste production. The similar application motivates to develop the procedure for waste forecasting as key information for waste management planning and building the sustainable system of infrastructure.

2. Bio-waste production in the Czech Republic

The major intervention in bio-waste production in the Czech Republic has taken place in the year 2014. From this time, municipalities are obliged to provide an option for inhabitants to separate bio-waste (Amendment to the Waste Management Law 229/2014). Due to the legislation, there was a change in the established trend and this situation is very hard to predict. Figure 1a illustrates schematically bio-waste production with the two possible reactions to the legislative changes in the year 2014.

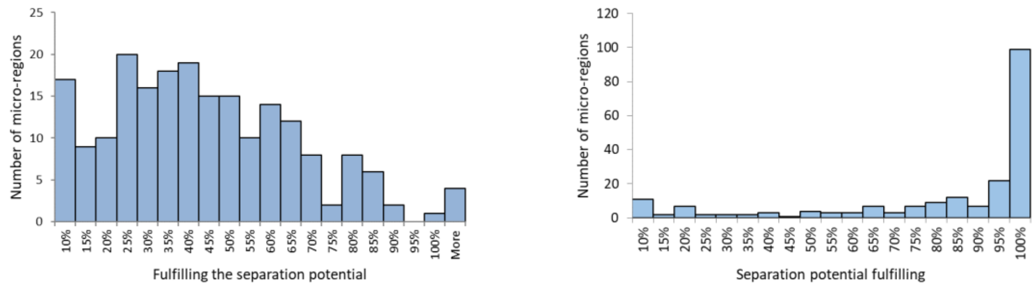


a) The schematic representation of possible bio-waste production development

b) Bio-waste production trend in the real data set 2009 - 2016

Figure 1: Bio-waste production trend on the micro-regional level in the Czech Republic

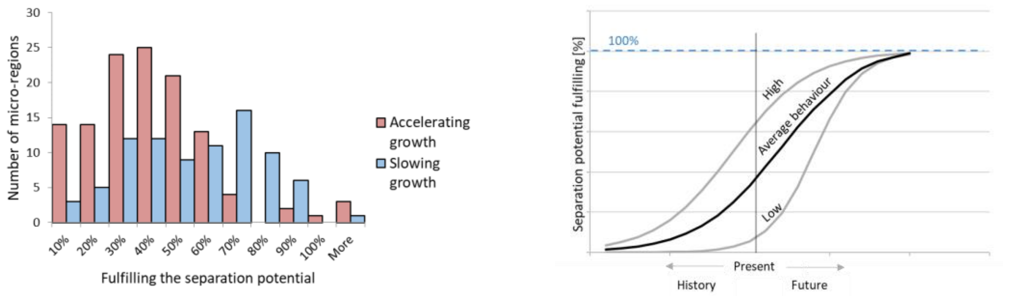
Figure 1b shows the trend in the bio-waste production per capita in the Czech Republic for the available time period (2009 – 2016) for 206 micro-regions, except the outliers - upper and lower deciles were removed for clearer representation. The growing production is simultaneously illustrated by average production (red curve). During the reference period, a significant increase in bio-waste production can be observed, the break is evident in the year 2014. Based on the difference in range a and b it is obvious that individual micro-regions did not start to separate bio-waste immediately or they have started to separate bio-waste with the unlike efficiency. Especially the points (micro-regions) in the red frame in the Figure 1b shows that several micro-regions have not started bio-waste separation yet. This effect makes it unreliable to predict bio-waste production based on historical data which changed the trend in some part or not at all yet.
The indicated trend in historical data can be successfully modeled by so-called S-curve (Smejkalová et al., 2017). The maximal amount of bio-waste which is possible to produce annually is estimated at 60 kg/cap for the urban area (given by kitchen waste) and 200 kg/cap for the rural area (combining kitchen and garden waste). Potential of kitchen waste production comes from information about the bio-waste part in mixed municipal waste. In further work potential of garden waste production should be clarified. Current estimation 140 kg/cap of garden waste in rural areas corresponds with the lower bound of garden waste production in China (Shi et al., 2013). Climate conditions can cause significant differences, but it may be said that the estimation of 140 kg/cap does not contradict the study from Denmark (Boldrin et al., 2011). The separation potential of bio-waste in Czech micro-regions is given by weighted average according to the type of buildings. These estimations are in line with the paper (Hrabec et al., 2017), but the individual micro-regions fulfill the stated potential with varying successes. The histograms in Figure 2 show fulfilling of the separation potential, Figure 2a in the last year of available data – 2016. Several micro-regions exceed the separation potential even already in the year 2016. It is obvious that the potential is actually different in these areas and its setting will be part of the follow-up activity. For the time being, these micro-regions will be considered as with 100% current separation. The forecasting in the year 2024 (Figure 2b) is shown based on trend analysis as was introduced by (Pavlas et al., 2017). Although the S-curve is able to fit data well, the results show the unreal scenario. Two situations prevail, if the micro-region data showed the increasing trend during 2009–2016 until 2024 they will achieve the maximal separation potential. Otherwise, if they did not report the growing trend in the dataset, the model, of course, does not assume the trend change. Based on an objective assessment of the results this is not likely to happen.



a) Last year with available data – 2016, the histogram for real data

b) Forecasting of the year 2024 using the S-curve model of the historical data

Figure 2: The fulfilling of separation potential in the year 2016 and according to the S-curve model in 2024



a) Fulfilling the separation potential in micro-regions in the year 2016 based on the real data

b) Schematic illustration of producers behavior

Figure 3: The behaviour of producers with different separation potential fulfilling

In the case that the particular micro-region is at the beginning of the bio-waste separation, the sharp increase in the following term is expected. Otherwise, the successful fulfillment of the separation potential indicates deceleration because the separation is close to the maximum (possible boundary). This assumption is observable in Figure 3. The micro-regions were divided into two groups in Figure 3a. If the shift from 2015 to 2016 in the real data is greater than 2014 to 2015 currently data shows the accelerating growth, otherwise slowing growth. The accelerating growth in the last year (2016) is typical especially for micro-regions with low current separation (red colour in Figure 3a), conversely, the slowing growth is reported by the areas with high separation (blue colour). Figure 3b schematically illustrates the separation change over time for three special cases. The idea is, that in future the micro-regions with high contemporary separation will slow down the growth. On the contrary, the low separated micro-regions will accelerate the growth and copy the behaviour of others. Anyway, both of them will be getting closer to average micro-region. Some micro-regions already exceed the limit potential separation in the year 2016, as Figure 3a shows. The setting of separation limit is a challenging task and it will be the aim of future development.

The using of historical time series to forecast the development of bio-waste production is very limited because the trend established in the year 2014 will not continue in the long term. The model is modified with the utilization of credibility theory and the information about bio-waste production is taken over from micro-regions with more experiences.

3. Credibility model for bio-waste production forecasting

The novelty approach presented in this paper utilizes the principle of credibility theory, which was concisely introduced in Section 1, in the context of combination micro-region's own and collective information. The forecasted value is given by the difference between production from the S-curve model in present and the following year. The method follows the idea from Figure 3b assuming micro-regions will move toward average behavior in the following year. Briefly, the production difference for next year will be given by a linear combination of the difference of micro-region and collective difference. They are both calculated prior to the computation of credibility model from the S-curve regression. As a result, the micro-regions with currently low fulfilling of separation potential will accelerate the growth in the next year and at the same time the high growth ones will slow down. Simultaneously, the changes are based on other experiences, so the unreal separation growth is not expected within the long-term prognosis.

The set of territories (micro-regions) is denoted as J and the set of years in the interest as I. The bio-waste production difference $d_{j,i}$ is estimated and the change in production from the year $i-1$ to i is set as follows:

$$d_{j,i} = \begin{cases} w_j(1-\lambda_{j,i})\bar{m}_i + \lambda_{j,i} m_{j,i}, & s_{j,i-1} < 0.5, \\ \left(w_j(1-\lambda_{j,i})\bar{m}_i + \lambda_{j,i} m_{j,i}\right)\left(1-(2s_{j,i-1}-1)\right), & s_{j,i-1} \geq 0.5 \end{cases} \qquad \forall j \in J, \forall i \in I \qquad (3)$$

$$\bar{m}_i = \frac{\sum_j m_{j,i}}{|J|} \qquad \forall i \in I \qquad (4)$$

$$\lambda_{j,i} = s_{j,i-1}, \qquad \forall j \in J, \forall i \in I \qquad (5)$$

$$w_j = 1 + \frac{o_j - \bar{o}}{\bar{o}}, \qquad \forall j \in J \qquad (6)$$

where $m_{j,i}$ is the difference within the S-curve production model in the particular territory j and year i. Using the weight $\lambda_{j,i}$ the linear combination of $m_{j,i}$ and average $\bar{m}_i$ is given with adjustment that average $\bar{m}_i$ is multiplied by w_j (normalisation parameter) in Eq(3). For the fulfilling of separation potential $s_{j,i-1} \geq 0.5$ the formula is multiplied by $\left(1-(2s_{j,i-1}-1)\right)$ in order to stop growth when the production draws near to limit of production. Eq(4) gives the average difference $\bar{m}_i$. The $\lambda_{j,i}$ sets up the credibility of micro-region's own data and it increases with higher fulfilling of separation potential $s_{j,i-1}$, Eq(5). The reason is that the low separated micro-regions will copy the behaviour of micro-regions which are more advanced in bio-waste separation process and they can provide the inspiration in production behaviour. The parameter w_j normalizes the territories and moves the average $\bar{m}_i$ based on rural/urban region, so for rural regions it increases and against for urban regions because the potential of separation is significantly higher in rural regions. w_j is given by Eq(6), where o_j means the percentage representation of rural buildings in territory j and $\bar{o}$ is the average rural building in territories j. The production estimation $p_{j,i}$ in the territory j and year i is then given by Eq(7).

$$p_{j,i} = p_{j,i-1} + d_{j,i}. \qquad \forall j \in J, \forall i \in I \qquad (7)$$

The procedure continues iteratively and so the production based on the S-curve model is modified by credibility approach for each micro-region $j \in J$ in each year $i \in I$.

4. Results

The introduced method is tested using bio-waste production data restricted on 2009 – 2015 and the last year 2016 is kept for model verification. The credibility model reliability is compared with the traditional S-curve trend model and the output is illustrated through a model error in the year 2016, see Figure 4. The micro-regions with separation potential fulfilling less than 10 % were removed because in those cases each small absolute error gives a high percentage error and distort the results. Out of 206, 189 micro-regions remained. The newly developed model forecasting is more accurate in this testing computation than simple trend analysis – more micro-regions achieve the error within -20 % and 20 %. The average absolute error after removing mentioned micro-regions is 23.5 % for the credibility model and 36.0 % for the trend model. The large scale of errors is caused by limited dataset, the only two historical data points from the change year 2014 are available, and therefore the 50 % of terms is forecasted. In spite of the credibility, approach achieves more accuracy prognosis then trend analysis. The next results utilize the complete dataset from 2009 to 2016. Figure 5 illustrates the bio-waste production forecasting for the particular micro-regions marked by L2.5 and L2.40 as an example. The colors correspond to Figure 3a, the red for accelerating and blue for slowing growth.

The presented credibility model achieves more accurate estimations for short-term forecasting than the existing approach. Unfortunately, the available data give very short time series, so it is not possible to validate longer prognosis in way of comparison with real data. On the other hand, the usability of the novel presented model is supported by more real outputs. Figure 6 summarized the expected fulfilling of separation in the years 2024 and 2030 using the whole available dataset 2009 – 2016. The forecasted separation fulfilling is approximately 71.8 % on average in the year 2024 and 75.4 % in the year 2030. So, it seems to be a more reliable prediction than results from the S-curve trend model shown in Figure 2b. The expected growth of the bio-waste separation for the micro-regions L2.5 and L2.40 between the years 2024 and 2030 are marked by red and blue lines in Figure 6. In the case of lower separated micro-region (red) bigger shift in the separation is estimated than in the other micro-regions.

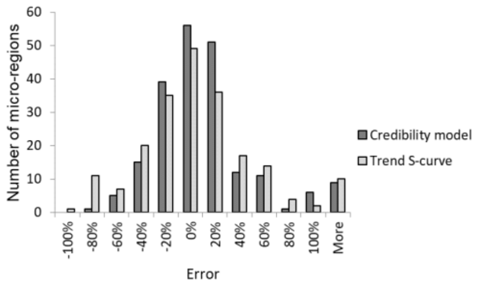


Figure 4: The comparison of two forecasting approaches: credibility model and trend analysis the errors of the forecasted bio-waste production

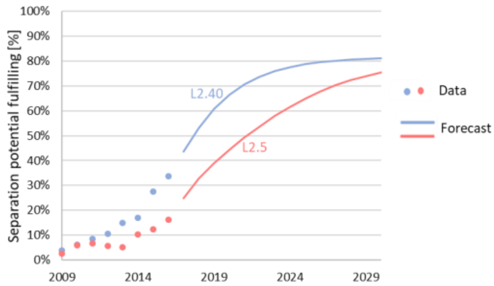
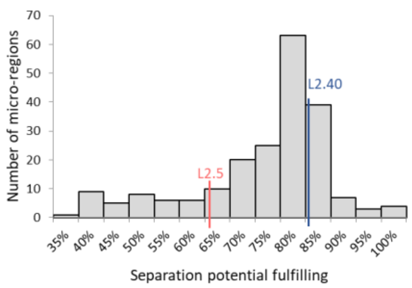
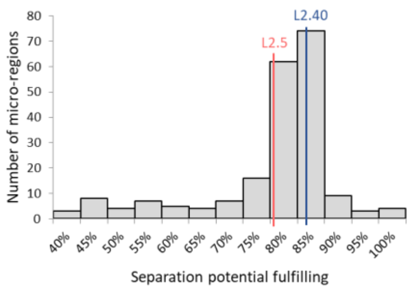


Figure 5: The bio-waste production forecasting for the particular micro-regions L2.5 and L2.40



a) Forecast in the year 2024



b) Forecast in the year 2030

Figure 6: Forecasted fulfilling of the separation potential based on the historical data 2009 - 2016

5. Conclusion

The novel approach for waste forecasting using the idea of credibility theory is introduced in this paper focused on the waste types with trend change due to the intervention in the existing system. The benefit of this approach is hidden in the principle, that micro-regions often copy the behavior of others for the reason of varying responses speed to change. Particularly this behavior was confirmed for the bio-waste production data which were affected by legislation changes, each micro-region starts to apply it with different efficiency. The established process of separation is often repeated and this method uses already acquired experiences to predict other micro-regions. The results show that this credibility approach reaches more quality estimations for short-term prognosis and in addition, the long-term prognosis gives more realistic outputs in the comparison of classical trend analysis, which is a useful method for forecasting several waste types. The expected fulfilling of the separation potential is 75.4 % on average in the year 2030. This approach opens the door for the setting of separation potential. This paper is the primary application of the credibility model for waste forecasting and the subsequent development is required, especially with regards to weights setting. In spite of this, the forecasts are already performing better than previous approaches. Future work should be a focus on the extensive case study of bio-waste production forecasting. Current data shows that some micro-regions produce more bio-waste than the separation potential is set (Figure 2a). Moreover, they have still increasing trend and that effect brings the question of whether the separation potential should be different. The estimation of bio-waste separation potential with respect to each individual area is the possible way how to improve the bio-waste production forecasting.

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