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Sewage Volume Forecasting on a Day-Ahead Basis – Analysis of Input Variables Uncertainty

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ABSTRACT
Water consumption and the resulting sewage volume (both strongly impacted by meteorological parameters) are of key importance for an efficient and sustainable operation of waterworks and wastewater treatment plants. Therefore, the objective of this research is to analyze the potential impact of input variables uncertainty on the performance of sewage volume forecasting model. The research is based on a real, three-year long, daily time series collected from Toruń (Poland). The used time series encompassed: sewage volume, water consumption, rainfall, temperature, precipitation, evaporation, sunshine duration and precipitation at a six hours interval. Neural network has been selected as a forecasting tool a multi-layer perceptron artificial. , a simulation model for the sewage volume was created which considered the above-mentioned time series as exogenous variables. Further, its performance was tested assuming that all non-historical input variables are prone to their individual forecasting errors. The analysis was dedicated firstly to each variable individually and later the potential of all of them being uncertain was tested. A lack of correlation between the input variables error was assumed. The research provides an interesting solution for visualizing the quality and actual performance of forecasting models where some or all of input variables has to be forecast.

Keywords: artificial neural network, error forecasting, exogenous variable uncertainty

INTRODUCTION

Water and sewage management is essential for the functioning of society and the economy, and its individual elements are classified as the critical infrastructure. That is why a correct and undisturbed functioning is so important. Due to the climate change extreme weather conditions some related to the water follow more often which results in damages and material loss (Jia et al., 2019; Kaźmierczak and Kotowski, 2014; Wallace et al., 2014). In a special way, this applies to the urban areas subjected to the greatest transformations – especially in the area of surface sealing. As a result, short-term and intense rainfalls in cities often result in so-called instant floods (Elkhrachy, 2015; Ma et al., 2018; Yin et al., 2016). An extensive sewerage network is not able to discharge such a large amount of water in a short time. Another problem is the increase in the amount of sewage flowing to the wastewater treatment plant. In extreme cases, the amount of sewage may increase up to several times in a short time (Bugajski et al., 2017). This situation poses high hazard in case of mixed type sewage system, where some fragments fulfill the function of combined storm and foul drainage system. Such cases are very common in many cities across Poland (Pawęska and Duda, 2018), where many projects have been implemented in the field of water and sewage management since the 1990s. Therefore, a large improvement is evident in this area (Chmielewski et al., 2016; Obarska-Pempkowiak et al., 2015). Some projects related to the separation of storm sever system from the sanitary drainage. However, a lot of storm water flows to the wastewater treatment plants with sewer piping in many cities (Kaczor et al., 2017; Młyński et al., 2018). In extreme cases, storm overflow weirs protect the sewer piping and wastewater treatment plants against excessive quantity of sewage (Kaźmierczak, 2013). From an ecological point of view, the operation thereof brings many disadvantages as the mixture of storm and wastewater is discharged directly to the natural tank (a river or lake mainly).

An important aspect is continual operation of wastewater treatment plant. Any rapid changes in the amount of sewage supplied to the wastewater treatment plant are disadvantageous as they results in disturbances of its operation. The most dangerous in this respect is the possibility of leaching the activated sludge, responsible for the reduction of organic and biological pollution in the sewage (Beheshti et al., 2015; Yap and Ngien, 2017). Large and rapid changes in the amount of sewage also affect the increase in the failure rate of the sewerage network (Kutyłowska and Hotloś, 2012). Therefore, from the point of view of enterprises responsible for the operation of wastewater treatment plants, it is important to know about the possibility of these negative situations. The factors influencing the stream of sewage flowing into the wastewater treatment plant include: variability of meteorological conditions, random character of water intake, technical condition of the network and groundwater level (infiltration).

The work focuses on the analysis of the uncertainty of input variables used to predict the amount of sewage flowing into the wastewater treatment plant. An extreme situation related to intense rainfall was not considered. The reason was their small number and the mentioned storm overflow weirs, reducing the direct threat to the wastewater treatment plant.

The object of the study was a municipal wastewater treatment plant located in the city of Toruń (Figure 1). The wastewater treatment plant was put into operation in 1998. In the following years, the wastewater treatment plant underwent numerous modernizations and improvements. It is a mechanical and biological treatment plant with automatic control of the aeration process as well as stabilization and utilization of sewage sludge. Its maximum daily flow capacity is 90,000 m^3, and the degree of pollution reduction amounts to: total phosphorus 96.3%, COD 95.2%, BOD$_5$ 98.6%, total nitrogen, 90.0%, total suspension 98.1%. The wastewater treatment plant serves mainly the city of Toruń (about 200,000 inhabitants), and in recent years, also the surrounding suburban municipalities. In the

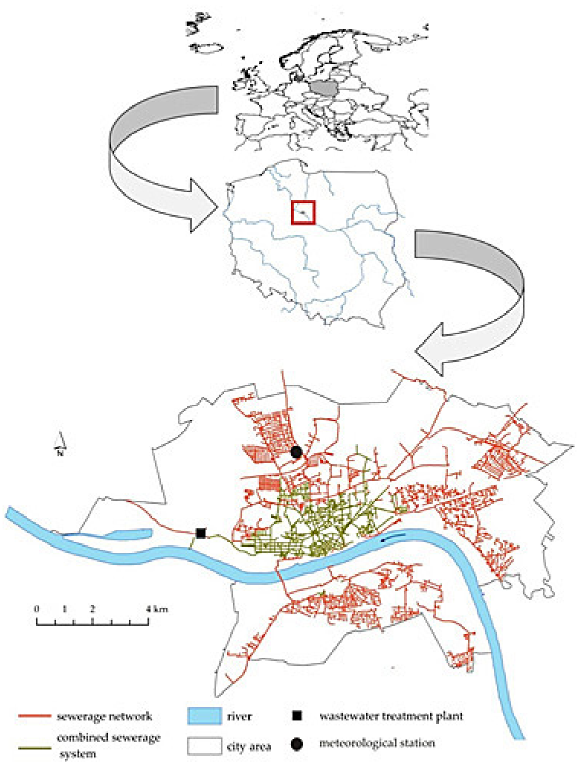

Figure 1. Location of the study area

last dozen, numerous investments in the field of sewage management were carried out in the city (Marszelewski and Piasecki, 2017). As a result, almost all residents of the city were connected to the sewerage network. The length of the sanitary sewer network is currently 486.2 km, and the total sanitary sewer network is 123.7 km. The length of the storm drain system discharging storm water directly to the receiver (mainly the Vistula River) is 302 km.

MATERIALS AND METHODS

Materials and data

The work uses the meteorological data from the Toruń-Wrzosy station belonging to the Institute of Meteorology and Water Management – National Research Institute (IMWM-NRI). The station is located in the north-central part of the city and has carried out measurements since 1945 (Figure 1). The analysis includes the data from the years 2015–2017 regarding the following meteorological parameters: average temperature, minimum temperature, maximum temperature, atmospheric precipitation, wind speed, humidity, sunshine duration. On their basis, evaporation was also calculated using the Penman-Monteith method (Allen, 2000). The annual values of these parameters are summarized in Table 1. The year 2015 was the warmest and driest year in the analyzed period. In 2017, the amount of precipitation was almost twice as large as in 2015. In addition, the lower values of air temperature and sunshine increased the evaporation (by approx. 120 mm).

Artificial neural networks

The artificial neural network (ANN) consistutes a group of computing systems vaguely inspired by the operation of biological neurons found in brain. Their popularity results from a relative ease of implementation. They tend to be superior over conventional statistical approaches and are well-suited for solving non-linear problems, which are hard to describe by precise mathematical equations (Kutyłowska, 2017; Czapczuk et al., 2015). However, as the process or creating an ANN model is based on tuning/teaching it based on some sample data, the performance of the model might be constrained by the data availability. What is more, the model may perform poorly if faced with the data, which is out of the range of the initial sample case.

The process of creating an ANN model can be divided into four main stages: data acquisition, curing and processing; ANN architecture selection and input data division into teaching, validation and testing subsets; teaching method selection; teaching process and results validation. The first stage focusses on a) acquiring the data that is describing the investigated phenomena (like sewage discharge) and potential variables which may explain the volume of sewage discharge (for example rainfall) b) curing the data for missing values, outliers and errors c) selection of variables which are most suitable as explanatory variables.

In general, the ANN model has three connected layers: input, hidden and output layer. Inside the ANN structure, the input signal is processed by so-called activation functions which transfer it into the output signal. Usually, during the creation of ANN network, five activation functions are considered: linear, exponential, logistic, sine and hiperbolic tangent.

The selection of input variables for the ANN model is the crucial stage which if performed incorrectly may significantly influence the performance. Considering the importance of this step, various approaches have been proposed. Bowden et al. (Bowden, 2005) presented a critical review of input data selection techniques, which include:

- expert knowledge on the considered system;
- interchangebility between input and output variables calculated based on the coefficient of correlation;

Table 1. The annual values of selected meteorological parameters from the Toruń-Wrzosy station

Year	Temp avg, °C	Temp min, °C	Temp max, °C	Rainfall, mm	Wind speed, m/s	Humidity, %	Insolation, hour	Evaporation, mm
2015	9.9	5.4	14.8	379.4	2.4	74.2	1958.7	788.3
2016	9.5	5.3	13.9	680.2	2.2	77.2	1776.1	723.1
2017	9.3	5.6	13.4	751.1	2.3	79.0	1588.0	665.0

- heuristic approach, based on subsequently adding or removing some variables from the input set;
- hybrid method based on the combination of the methods described above.
- In this study, a hybrid method which considered the expert knowledge om the modeled system and the correlation coefficient between considered variables, was selected.

The teaching process of the ANN model was realized in the Statistica v.10 software. Statistica offers an option to use the most commonly used applied ANN architecture in the form of a multilayer perceptron (MLP). The input set has been divided into the teaching, validation and testing subsets (in proportion of 70%, 15% and 15%) based on an automatic tool available in Statistica.

Another crucial decision in the case of the ANN models refers to the number of neurons in the hidden layer (Kavzoglu, 1999). According to Shibata and Ikeda (Shibata and Ikeda, 2009) the number of neurons in hidden layer should not be smaller than the square root of the sum of neurons in input and output layers and no greater than three times the minimal number of neurons in hidden layer plus one. The results of this ANN model creation approach are presented in section 3.

Performance assessment criteria

The forecasting accuracy of the ANN model was assed based on two commonly applied indices. Namely, the absolute percentage error (APE) and mean absolute percentage error (MAPE). They are calculated based on the following formulas:

$$APE = \left| \frac{S_i^O - S_i^F}{S_i^O} \right| \tag{1}$$

$$MAPE = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{S_i^O - S_i^F}{S_i^O} \right| \tag{2}$$

where: S_i^O – observed sewage discharge in hour i [m³], S_i^F – forecasted sewage discharge in hour i [m³].

METHODS

1. First step: creation of a sewage volume simulation model, which assumes certainty when it comes to the values of the input variables.
2. Second step: testing the model performance by manually introducing an error to the values of individual input variables. This gave a general overview on the variable impact on the model performance.
3. Third step: testing the model performance assuming that all variables are subject to certain error the value of which is given by a normal distribution (errors are not correlated).
4. Final step: presenting forecasting model performance in a visual form where each value of forecast has been attributed certain range and probability.

We make an assumption that when the input to the model is assumed to be known in advance, the ANN model is understood as a simulation model (we aim at simulating the sewage discharge assuming that we are certain about the input variables). In reality, the input variables for forecasting sewage discharge (like for example rainfall or temperature) will come from another forecasting model and are subject to some errors.

SEWAGE VOLUME FORECASTING

Input variables and their selection for forecasting model

In this paper, the following time series were considered as potential explanatory variables which can be used in the forecasting model: water consumption; minimal temperature; maximal temperature; average temperature; precipitation (daily sum as well as values recorded on a 6 hours interval); evaporation; duration of sunshine; humidity; categorical variable (0 – working day, 1 – holidays). All of them were available as daily sums/averages and only in the case of precipitation, the data with a 6-hours' time step was used.

The validity of this data had to be checked by Institute of Meteorology and Water Management National Research Institute in Poland (meteorological data) and by the Toruńskie Waterworks (sewage volume and water consumption). No missing data was observed. Figure 2 visualizes the annual variability of water consumption and sewage volume whereas the charts in Figure 3 present the relationship (on scatter plots) between the endogenous (sewage volume) and potential exogenous variables (noticeable is a lack of significant linear relationship between investigated variables).

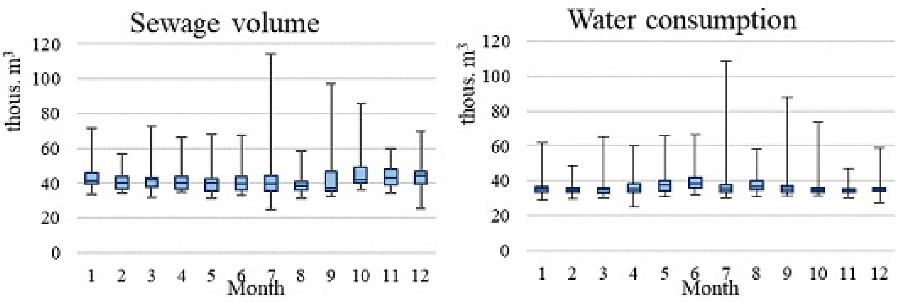

Figure 2. Box plots presenting daily values of sewage and water consumption over the years 2015–2017 in Toruń. The presence of extreme values of both variables in July is especially noticeable

The input variables selection for simulation and forecasting models is a well-known and well-described in the literature problem, which always raises many questions. This process is especially complex, when none of the potential explanatory variables exhibits a significantly strong either negative or positive correlation with the simulated/forecasted variable.

On the basis of the created correlation matrix, we found that the following variables have a coefficient of correlation greater than 0.3 (in absolute terms, value selected arbitrarily, all exhibited a statistical significance with a p-value < 0.05): sewage volume in the proceeding day (0.455); sewage volume two days before (0.359); sewage volume three days before (0.324); water consumption in given day (–0.352); precipitation in given day (0.447) and in the previous day (0.507); humidity in given day (0.395); sunshine duration in given day (–0.348); rainfall at six hours intervals measured at 00:00 (0.453); 06:00 (0.425); 12:00 (0.547) and 18:00 (0.507).

Our selection of input variables finds confirmation in the available literature, where researchers used the following explanatory variables in sewage volume forecasting: rainfall, sewage volume, day of the week (El-Din and Smith, 2002; Fernandez et al., 2009; Bartkiewicz et al., 2016). Szeląg et al. (2018) also considered a reiver water level (Wisłoka river) which flows through the considered city (Rzeszów). The authors motivated this choice by a strong correlation between ground water level and river water level. The high level of the second one leads to fast filling of sewage collectors.

To sum up, the selection of above presented variables seems to be a reasonable choice. It is worth to mention that during the teaching (tuning) process of the artificial neural network, the input variables which have a naturally weak impact on the exogenous variable, will be most likely assigned a low values and significance in formulating the model output.

Structure and performance of deterministic model

The deterministic (assuming input variables certainty) simulation model has been created and 13 variables in total were selected as explanatory ones. It means that there are 13 neurons in the input layer. Considering this, the number of neurons in the hidden layer should range from 4 to 13. Bearing in mind that there are five possible activation function in the hidden layer and also five in the output layer, a total of 250 variants of ANN architectures should be considered: the number of variants of the neurons in the hidden layer (10) · the number of different activation functions in the hidden layer (5) · the number of different activation functions in output layer (5).

The teaching process was realized based on the Broyden–Fletcher–Goldfarb–Shanno (BFGS) algorithm. After completing the teaching phase of the model, the best performing one has been selected based on the simulation performance of the testing subset. In order to limit the scope of further analysis, only one model was considered in the further analysis as the objective of this study was not to compare the performance of various ANN architectures but rather to investigate the impact of input variables uncertainty.

The ANN model obtained in the Statistica software is characterized by the following parameters: there are 13 neurons in the input layer, 13 neurons in the hidden layer and 1 neuron in the output layer. The activation function from the input layer is logistic and the output activation function is a hyperbolic tangent.

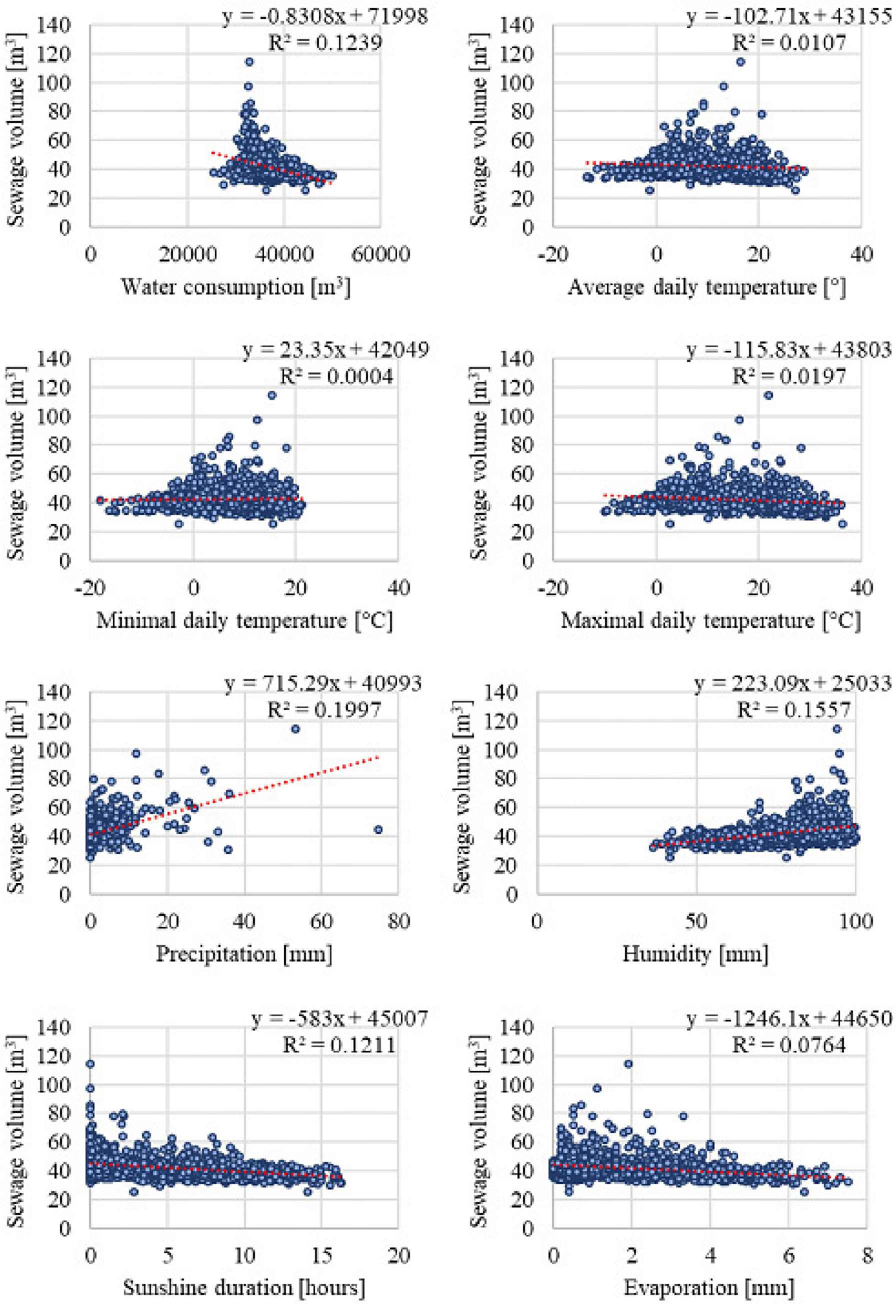

Figure 3. Scatter plots presenting relatively week relationship between potential explanatory variables and sewage volume

The deterministic model was performed as presented in Figure 4. For the testing subset, the value of MAPE criterion was 6.63% and will be in further analysis used as a benchmark. The value of absolute percentage error ranged from 0.02% to over 43%. In terms of the volume of the simulated sewage discharge, the largest under- and overestimation amounted to slightly over 15 thousand cubic meters. In general, the model showed a small tendency to overestimate the volume of sewage discharge as the average error was 92.9 cubic meters (with a mean daily discharge of 42.1 thousand cubic meters).

Impact of individual variables uncertainity on the forecasting performance

The first part of the input uncertainty analysis focuses on individual variables and tests how each one of them impacts the forecasting performance of the ANN model created in section 3.2. In the analysis, it has been assumed that the value of the input variable will be artificially changed by -20% to +20% with a step of 5%. For example, if the actual observed rainfall was equal to 10 mm we have tested the impact of its values equal to 8.0 mm, 8.5 mm, 9.0 mm, 9.5 mm, 10.5 mm, 11.0

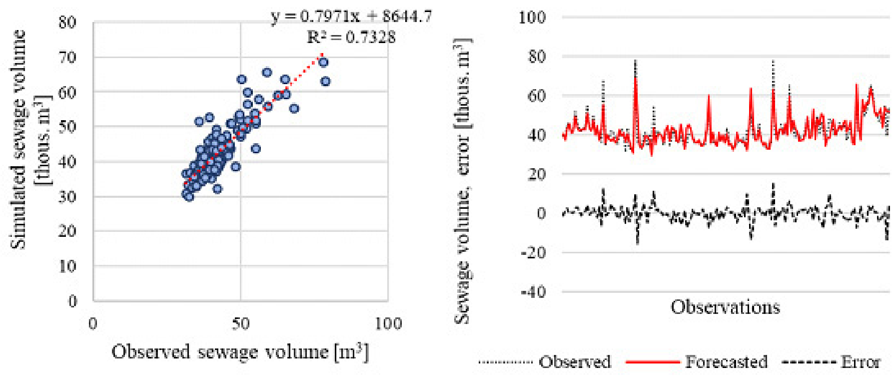

Figure 4. Performance of the simulation model which used as inputs variables without potential forecasting errors

mm, 11.5 mm and 12.0 mm, respectively. The tests were performed only on the testing sample of input variables used also in the deterministic model. The results of the analysis are presented in Figure 5. The following conclusions can be drawn:

- Rainfall, duration of sunshine, rainfall measured six hours before 18:00 and six hours before 6:00 in the morning have relatively small impact on the overall performance of the forecasting model, in general. Even if their input values are off by 20%, the performance of the model deteriorates by less than 0.05 percentage points. Interestingly, if the value of input variable denoted as rainfall before 6:00 in the morning is used in the model and is smaller than the observed in reality, the performance of the forecasting model, slightly increases.
- For variables: water consumption, humidity, rainfall six hours before 00:00 and rainfall six hours before 12:00, the direction of input variable uncertainty (underestimation or overestimation) have different impact of the forecasting model performance deterioration. For example, in the case of water consumption overestimating the water consumption by 1%, the model performance is reduced by 0.18 percentage points, on average, whereas if water consumption is underestimated, the model performance is reduced by 0.12 percentage points. For the remaining parameters, this impact was as follows, humidity 0.34 and 0.19; rainfall six hours before 12:00 0.35 and 0.18. The impact in the case rainfall six hours before 00:00 was the same as in the case of water consumption. It must be mentioned that this impact is clearly not-linear, meaning that the larger the input variables error, the more likely is a greater forecasting error of the main model.

Impact of individual variables uncertainity on forecasting performance

Figure 6 presents the results of using the forecasting model on a sample of 50 thousand potential combinations of input variables (source for the number of samples needed). The forecasting error of input variables (or in other words their uncertainty) was assumed to be given by a normal distribution with a mean of 0% and standard deviation of 5%. The lack of correlation between input variables errors was assumed as this introduces another dimension of the analysis; however, this should be considered in the future research.

A procedure how to read the results presented in Figure 6 is given in number 1–3 (yellow circles). Let us assume that the forecasting model results in a predicted volume of sewage equal to 49 thousand cubic meters (value on the horizontal axis, denoted by “1” in yellow circle). From the vertical axis, one can read that for such forecasts the usually observed/real sewage volume 47.7 thousand cubic meters (denoted by “2”). This means that the forecasts provided by the model are exaggerated, on average. Further analysis (step “3”) provides additional information with regard to the probability of the actual range of the observed value of sewage volume. This indicates that there is 34% chance that if the forecasting model is indicating a discharge volume of 49 thousand cubic meters then the observed volume will be in range of 42.9 to 47.7 thousand cubic meters, or the probability is equal to 99.7% that it will be from 33.5 to 61.9 thousand cubic meters.

Furthermore, Figure 6 reveals a common problem in the case of forecasting models which refers to the availability of data and especially

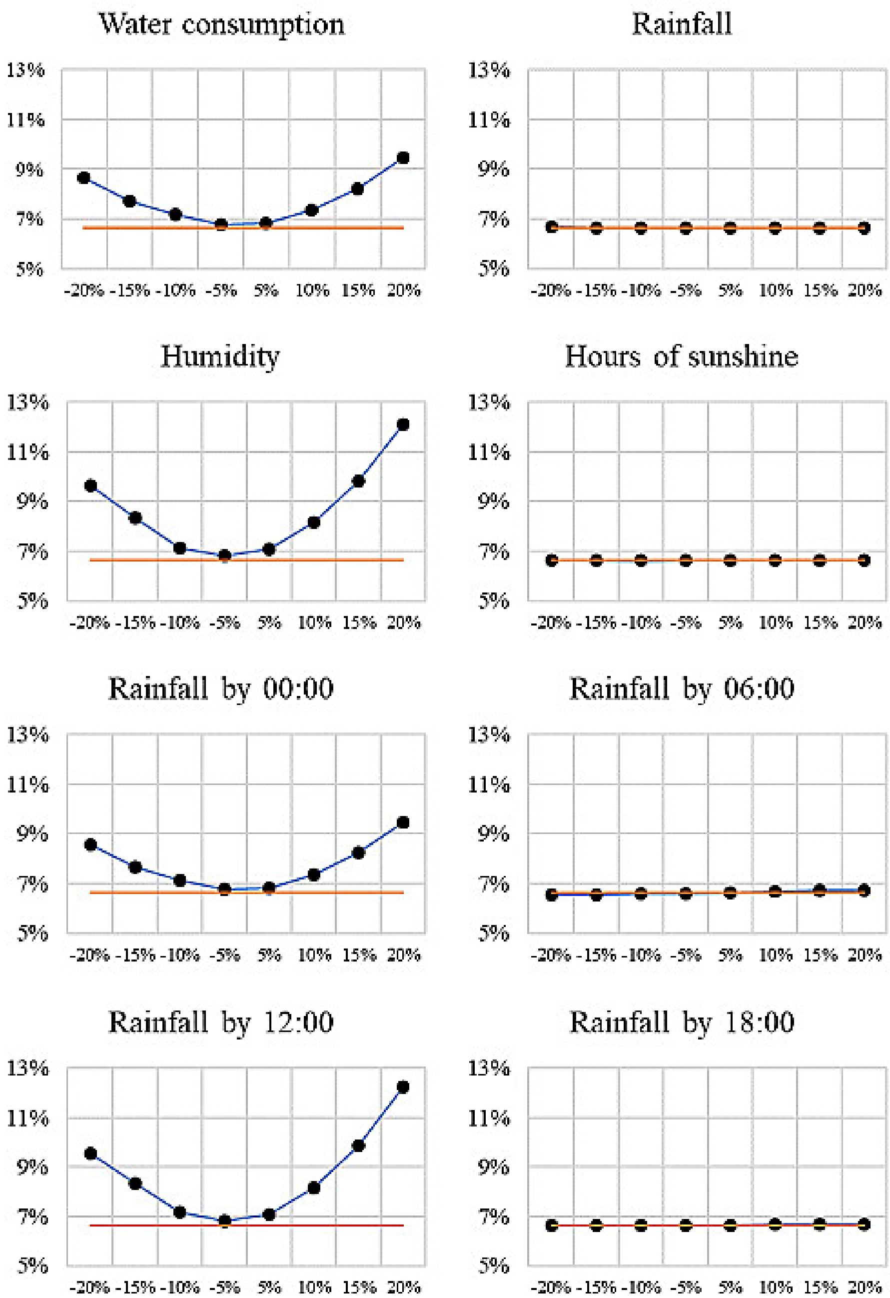

Figure 5. Impact of individual input variables error (horizontal axis) on the overall performance of the forecasting model (vertical axis). Red, horizontal line indicates the performance of the model assuming lack of error in input variables

the sample size in case of extreme values. As can be seen on the right vertical axis, some ranges of sewage volumes are represented by a very small sample (or even a lack of representation) of model outcomes. This indicates that the forecasting model is relatively weak at predicting the extreme events. For example, the maximal sewage volumes of 78 and 78.5 thousand cubic meters (right top corner of the chart) were observed for model outputs ranging from 75 to 83 thousand cubic meters.

DISCUSSION

The increase in the amount of sewage flowing into the wastewater treatment plant is a great problem, because it disturbs its proper operation due to hydraulic overloading and leaching of activated sludge, responsible for the reduction of organic and biological pollution in the sewage. As noted by A. Borowa et al. (2007) wastewater treatment belongs to the group of non-linear, non-stationary and dynamic processes. It should

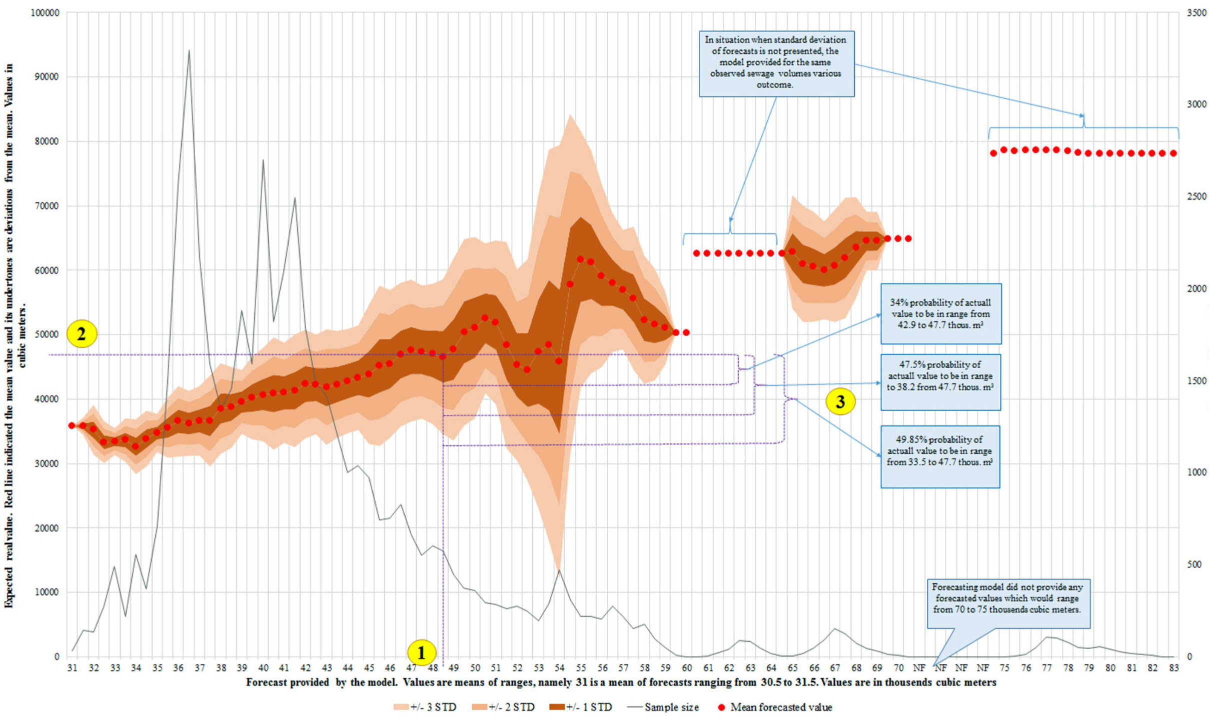

Figure 6. Potential output of the forecasting model assuming uncertainty of input variables

be treated together with the stage of sewage inflow to the wastewater treatment plant, because it significantly determines its specificity. The wastewater treatment mechanism is very similar in all modern wastewater treatment plants. However, due to the specificity of local conditions associated with high time variability of inflow and concentration and the composition of pollutants in sewage, it is often individual. Therefore, in the study of the wastewater treatment process there is a trend towards case studies (Dellana and West, 2009). As O. Cinar (2005) notes, it is not possible that the knowledge and experience related to operational difficulties in one treatment plant could be easily applied in another.

The aim of the study was to analyze the potential impact of the uncertainty of input variables on the performance of the wastewater volume forecasting model. A significant influence of the uncertainty of the input variables was demonstrated as: water consumption, humidity, rainfall six hours before 12:00 am and rainfall six hours before 12:00, and a relatively weak impact uncertainty of input variables as: rainfall, duration of sunshine, rainfall measured six hours before 18:00 and six hours before 6:00 in the morning.

The research performed does not fully cover the subject matter. They should be treated as a kind of introduction to the further work aimed at forecasting the content of biogenic compounds in effluents flowing on the basis of the flow rate. This approach is very important from a practical point of view. If positive results are obtained, it will be possible to limit the costly tests regarding the sewage quality. In addition, the time to obtain the information on the value of wastewater quality indicators will be significantly shorter (e.g. BOD_5) (Szeląg et al., 2016).

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