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Forecasting the municipal sewage sludge amount generated at wastewater treatment plants using some machine learning methods

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ABSTRACT

Sludge management account for high economic costs and energy consumption in wastewater treatment. Accurate forecasting of sewage sludge generation thus can be important for the planning, operation and optimization of processes at wastewater treatment plant (WWTP). In this study data from a municipal treatment plant with a capacity of 88 thousand cubic meters of sewage per day located in south part of Poland were used to find a good forecasting model for sludge amount prediction. Among models an autoregressive integrated moving average (ARIMA) is one of the popular linear models in time series forecasting. Since the ARIMA model cannot capture the non-linear structure of the data research activities in forecasting suggest using neural networks. Long-short term memory (LSTM) recurrent neural network proved its usability in time series forecasting. Looking at the curve representing data of sludge amount generated in the previous years at WWTP the linear and non-linear patterns could be distinguished. To address these issue a hybrid methodology that combines advantage of ARIMA and LSTM was proposed and used for forecasting purpose. Experimental results showed that the combined model can be an effective way to improve the forecasting accuracy of sludge amount generated at this WWTP.

Keywords: Sewage sludge; Time series forecasting; Hybrid methodology; Autoregressive integrated moving average; Long-short term memory; Wastewater treatment plants

1. Introduction

Sewage sludge, a byproduct of wastewater treatment plants (WWTPs), is still an ever-growing problem which needs to be manage in an environmentally safe way. Its quantity, physical and chemical properties vary depending on the quality of sewage and the applied treatment scheme [1]. EU countries rely on different sewage sludge disposal practices: use in agriculture, composting, land reclamation, incineration, gasification or disposal in landfills and long-term storage, however the last one is the least preferably [2–4]. Across the EU-28 member states the most widespread disposal practices for municipal sewage sludge are application as fertilizer on agricultural lands (47.5%), composting (11.4%), incineration (27.2%), landfilling (5.6%), and others (8.3%) [5]. Poland, in terms of the amount of municipal sewage sludge ranks the second place behind Germany [5]. In 2020 the amount of municipal sewage sludge generated in Poland was 568.8 thousand tons of dry mass. Different routes were applied for its disposal and utilization. Almost 24.2% of sludge was applied in agriculture, 3.1% in land reclamation and 5.2% in cultivation of plants intended for compost production. Nearly 17.3% of sludge was thermally transformed whereas only 1.2% was landfilled [6].

The quality of sludge as well as its volume is an essential element in the efficient operation of wastewater treatment plants. It is estimated that the treatment and management of sewage sludge accounts for 50% of the WWTP's operational costs [7]. Hence, there is a real need to get the information about the sludge at WWTP. The accurate projection of its

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quantity is important and plays a vital role in efficient sludge management. Then appropriate actions can be planned and taken at WWTP. However, predicting the sludge amount is not easy, moreover it is challenging. Many factors, sometimes unexpected, may influence on sludge amount, for example, anticipated urban growth, quality of wastewater, new more efficient wastewater and sludge treatment processes, allowed regulations and policies etc. Abbasi et al. [8] distinguish five main categories among techniques used for predicting the future trends or events. So far, mostly statistical tools with descriptive methods acted as a planning tool that helped to get ready for making the best decisions. Nowadays this method is rarely used. It has serious limitations in many situations including the poor structural and practical identifiability, mostly lack of data or information. It also requires much time to prepare such model. Therefore, recent development in soft computing techniques encourages the implementation of linear/non-linear-based models for modeling the parameters of the wastewater treatment facilities.

Machine learning methods and models become more and more popular and effective in forecasting future trends and are willingly used for planning purposes [9]. In the WWTP operation machine learning methods are used to train models capable of identifying abnormal operational conditions and for predicting of wastewater treatment processes parameters. Such methods use mathematical regression methods, parallel tree boosting, time series analyses or artificial intelligent systems (adaptive neurofuzzy logic, artificial neural network, genetic algorithms). It is obvious that each method has advantages in addition to its limitations, which can lead to a lack of accurate and efficient modeling.

One of the most important and widely used time series model for forecasting water and wastewater quality indices is autoregressive integrated moving average (ARIMA) model. Ahmad et al. [10] used this model with success to predict the conductivity, chlorine and biological oxygen demand (BOD) parameters in river water. Suitability of ARIMA models to generate and forecast the quality of water were also reported by many researchers [11–14]. In general, the results of this studies showed the good performance of ARIMA proposed models for water quality estimation. However, the wastewater treatment process has a complex and mixed linear and non-linear nature. Therefore, modeling this process using linear methods such ARIMA cannot be recognized as a comprehensive approach. For non-linear problems neural networks have shown tremendous growth in recent years and various types of neural networks have been introduced to deal with different types of problems reflecting a complex nature of wastewater treatment processes. Oliveira-Esquerre et al. [15] applied a multi-layer perceptron (MLP) artificial neural networks (ANN) model to predict the input and output BOD_5 concentrations in aerated lagoons in Brazil. Dogan et al. [16] used an ANN, for predicting BOD_5 inputs to a wastewater treatment plant in Turkey. Further, Pai et al. [17] predicted the quality parameters of a hospital wastewater treatment plant effluent using two methods of artificial networks and fuzzy systems.

ANN have also been developed to predict the performance of a wastewater treatment plant [18] and applied in forecasting biogas production from various raw materials [19–21]. Using such models in process parameters' optimization enabled a 20.8% increase in biogas production from sewage sludge [22]. Sakiewicz et al. [23] used an innovative ANN approach to prove that plant control process parameters in anaerobic digestion of sewage sludge have the dominant effect on biogas yield compared to wastewater quality parameters such as chemical oxygen demand (COD), BOD_5, total suspended solids, phosphorus (P_g), nitrogen (N_g). Neural models were trained, validated, and tested based on real-scale industrial data (covering 3 y of continuous plant operation), considering both technological aspects of the process and treated wastewater quality [23]. Some others research showed that through ANN application it was possible to reduce experimental workload reaching the optimum conditions in co-digestion [24,25]. Other types of neural networks have found use in solving problems at wastewater treatment plants. For example, Baruch et al. [26] applied recurrent neural networks (RNNs) in modeling an adaptive control of WWTP processes. Han et al. [27] used fuzzy neural networks to predict ammonia and nitrate concentrations. Qiao et al. [28] designed a recurrent fuzzy neural network (RFNN) to control the dissolved oxygen (SNO) and suspended solids concentration (TTS). Wang et al. [29] showed that convolution neural network in connection with long-short term memory network (CNN-LSTM) enables the prediction of COD at real-time at a WWTP. Other prediction models related to the WWTP was made by Groenen [30] where the amount of inflow to the plant was predicted using gated recurrent neural networks (GRNN).

The literature survey indicated that there are no reports focused on sewage sludge quantity forecasting. The accurate projection of sludge quantity is important and plays a vital role in efficient sludge management at each WWTP. In this study the main purpose was to make a prediction of sewage sludge amount generated at local WWTP using time series forecasting different approaches. Knowing the implications of linearity and non-linearity of data in such cases and based on work reported by Zhang [31] a hybrid model ARIMA-LSTM-RNN was developed, tested and the result was compared with this given by a linear ARIMA model and non-linear neural network model, respectively. The results showed that the hybrid model gave better performance in comparison to any other single model.

2. Methodology

2.1. Source of data

Data for further forecasting of the amount of municipal sewage sludge comes from a municipal treatment plant with a capacity of 88 thousand m^3/d of sewage. The technological system of the sludge section includes:

- thickening of the preliminary sludge in the preliminary setting tanks,
- thickening of the excess sludge in mechanical thickeners,
- anaerobic digestion of sludge in digesters at a temperature of in the range of 35°C–37°C,
- stabilization and thickening of digested sludge in open digesters,
- mechanical dewatering of sludge done on belt presses,
- thermal drying of dewatered sludge.

The preliminary sludge, thickened to a dry matter content of about 2% in the hoppers of the preliminary setting tanks is directed to gravity thickener where it is further thickened to about 4%–6% dry matter. Excess sludge, generated in the biological stage, after being thickened to about 5%–6% of dry matter in the mechanical thickener is then directed to the mixed sludge tank, where it is averaged with the thickened primary sludge also delivered there. The mixed sludge is then pumped to separate digesters, where it undergoes anaerobic digestion at a temperature of 35°C–37°C. The biogas produced after treatment is used to produce electricity and heat in a generator developed on the Czestochowa University of Technology concept. The digested sludge is next pumped to open digesters, where the sludge is degassed and further thickened before mechanical dewatering. The dewatering station is equipped with three belt presses with a capacity of about 15 m^3/h each. The dewatered sludge with about 22% dry matter is next dried and granulated. The sludge dry matter after drying is about 90%–95%. The annual amount of sludge dry mass generated at wastewater treatment plant over the past 20 y is shown in Fig. 1.

The technology for sewage sludge processing has not changed over the years. The decrease in the amount of sludge is mainly due to decrease of wastewater flowing into WWTP, which is related to the depopulation of the city in the recent period. Before modelling and forecasting the sludge data was transformed into time series. This modelling approach was necessary due to data restriction given by WWTP. Time series analysis comprises methods that attempt to understand the nature of the series. Past observations are collected and analyzed to develop a suitable mathematical model which captures the underlying data generating process for the series. In a standard approach the forecast variable is influenced by the exogenous predictor variable.

To assess the forecasting performance of machine learning models data representing annual amount of sludge dry mass is divided into two samples: training and testing set. The training data set is used for model development and then the testing data set is used to evaluate the established model. The data composition is given in Table 1.

2.2. Forecasting models

A hybrid model based on an ARIMA model and long-short term memory recurrent neural network (LSTM-RNN) was constructed in order to make a prediction of sewage sludge amount generated at wastewater treatment plant.

2.2.1. ARIMA model

ARIMA states for autoregressive integrated moving average model. The general equation of ARIMA is constructed as follows:

$$y_t = c + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \ldots + \phi_p y_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \ldots - \theta_q \varepsilon_{t-q} \quad (1)$$

where y_t and ε_t are the actual value and random error at time period t, respectively. The parameter y represents information on the amount of sewage sludge produced at the wastewater treatment plant on an annual basis. Random errors, ε_t are assumed to be distributed with a mean of zero and constant variance of σ^2. Coefficients ϕ_i (i = 1, 2, …, p) and q_j (j = 1, 2, …, q) are model parameters, where p is the number of autoregressive terms and q is the number of lagged forecast errors. One central task of the ARIMA model is to determine the appropriate model order (p,d,q), where additional d parameter is the number of nonseasonal differences needed for time series stationarity [32]. Stationarity is a necessary condition in building an ARIMA model useful for forecasting. In general, a stationary time series

Table 1
Sample composition

Series	Sample size	Training set (size)	Testing set (size)
Annual amount of sludge dry mass generated at the wastewater treatment plant	19	2003–2018 (16)	2019–2021 (3)

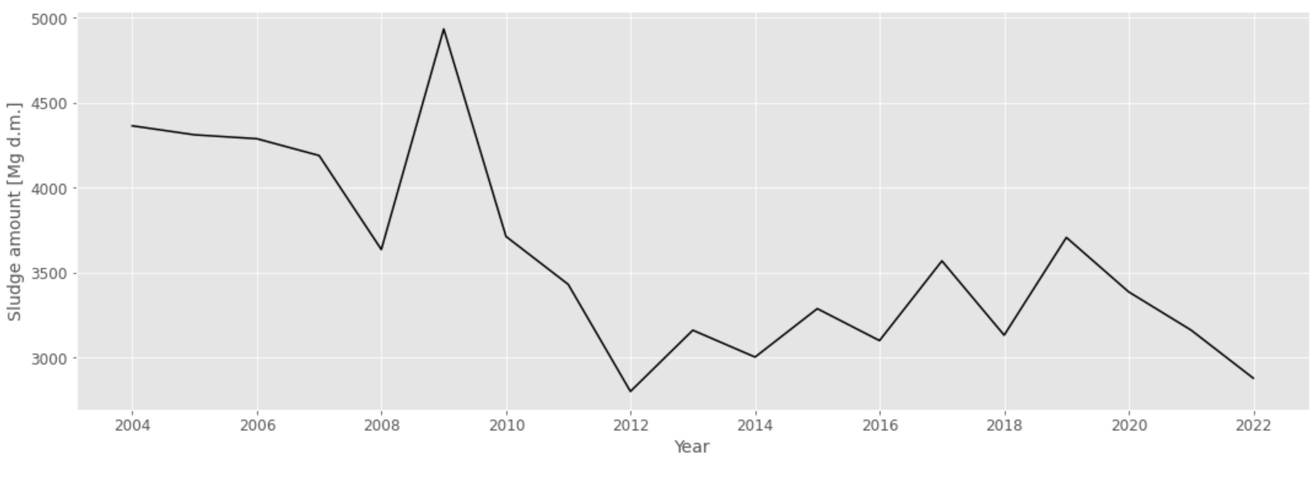


Fig. 1. Amount of sludge generated at wastewater treatment plants over the past 20 y.

represents such a series for which the mean and the autocorrelation structure are constant over time. Augmented Dickey–Fuller (ADF) test is often used to check the stationarity of time series. For p and q identification Box and Jenkins [33] developed a practical approach where the autocorrelation function and the partial autocorrelation function are used. Having these tentative parameters for an ARIMA model an estimation is done such that an overall measure of errors is minimized. In the last step of model building the assumptions about the errors, ε_t are satisfied. Mostly plots of residuals are used for that reason. If the model is adequate it can be used for prediction purposes.

2.2.2. Long-short term memory recurrent neural network

LSTM-RNNs have a highly advanced structure of cells which in a structure of neural network are capable of learning long-term dependencies. The architecture of an LSTM cell is given in Fig. 2.

An LSTM cell contains three gates: F_t – a forget gate, which is capable of deciding what information is passed from the previous state C_{t-1}, I_t – an input gate, which gets new information and decides how much of this information should be stored inside the cell state and be passed to the next state C_t, O_t – an output gate, which gives an output H_t based on the state of the cell and the last value [34]. The different gates inside LSTM boost its capability for capturing non-linear relationships for forecasting.

2.2.3. Hybrid model

As it was mentioned ARIMA works well with linear problems. When non-linear structures exist in data, another approach is necessary to describe and forecasting a time series because of approximation of ARIMA model may not be adequate. Zhang [31], Araújo Morais and Silva Gomes [35] proved that a combination of ARIMA model with ANN model is an interesting option and it can combine the best features of both models to create a more powerful forecasting tool. This is due to that ARIMA and neural network models have achieved good results in solving linear and non-linear problems, respectively, but none of them is a universal model that is suitable for all cases. Even it was noticed that neural networks can significantly outperform linear regression models and its performance depends on

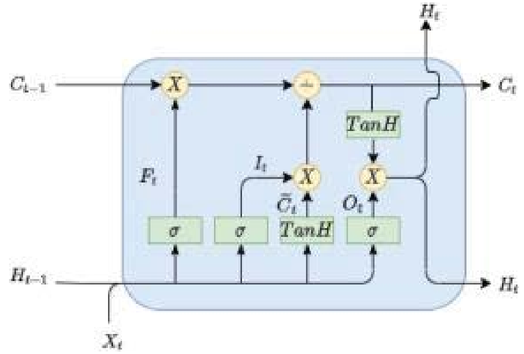


Fig. 2. Long-short term memory cell.

the sample size and noise level [36]. The idea proposed by Zhang [31] considers a time series to be composed of a linear autocorrelation structure and a non-linear component. The concept can be summarized with the following equation, where L_t is the linear part and N_t is non-linear part.

$$y_t = L_t + N_t \tag{2}$$

These two components have to be estimated from the data. First, we use ARIMA to model the linear component. Since ARIMA cannot capture the non-linear structure of data, then the residuals from the linear model have information about non-linearity. Simplifying, in such approach ARIMA model is responsible for a linear component, whereas neural network model uses the residual (e_t) given by the following equation:

$$e_t = y_t - L_t \tag{3}$$

from the ARIMA model to discover non-linear relationships in data. In that way the hybrid model can be a good strategy for practical use, when combining different models with unique feature and strength, in determining different patters. The results shown by Farhi et al. [34] proved such approach could help to find a model with better fitting in some cases and in general the problem of model selection can be eased with little extra effort.

2.2.4. Statistical metrics for fitting model

There are many statistical metrics that can be used for choosing the best linear regression model: root mean squared error (RMSE), mean squared error (MSE), mean absolute percentage error (MAPE), mean absolute error (MAE), coefficient of determination (R^2), Akaike information criterion (AIC) [37]. To analyze the best model for the data we used three of them: MAPE, MAE, RMSE. As the values of these indices become close to zero it represents a better result. RMSE, the square root of the MSE, is a very popular statistical metric used for regression problems because it gives a metric with scale as the target values. However, if we choose model based on the minimum RMSE the model may be overfitted. In general, the combination of different metrics together should provide a better view on model adequacy.

3. Results

Initially, ARIMA and LSTM-RNN models were adjusted, then the models with the best statistical metrics were used to build the final hybrid model for forecasting of annual sludge amount.

3.1. Forecasting with ARIMA

The ARIMA model requires a time series to be stationary. ADF test has been used to check the stationarity of a time series representing the annual amount of sewage sludge. The ADF test's result gave a weak evidence against the null hypothesis, a time series was non-stationary. The usual method for changing non-stationary time series into a stationary series is differencing and this operation was carried out. As a result, stationary time series was achieved and *p*, *q* parameters were found by applying Box–Jenkins classical approach with autocorrelation (Fig. 3a) and the partial autocorrelation (Fig. 3b) functions.

As result, the ARIMA model was defined with the following parameters (p = 1, d = 1, q = 0) forming the ARIMA(1,1,0) model. Using *auto_arima* function from *pmdarima* packet confirmed the choice of model parameters. For ARIMA(1,1,0) AIC has shown the lowest value confirming the model with the best fit of data and avoiding over-fitting. In this study, all ARIMA modelling was implemented via *arima_model* class from *statsmodels.tsa* packet. Table 2 shows the ARIMA model structure with statistical tests. The comparison between the real value and the forecast value is given in Fig. 4.

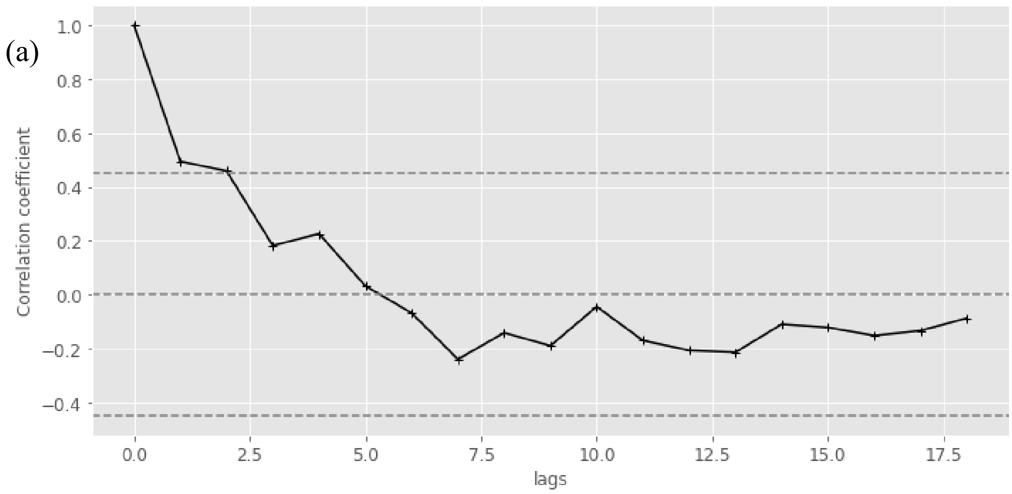
Table 3 gives the metrics for sludge time series forecast with ARIMA model.

3.2. Forecasting with LSTM-RNN

The LSTM architecture accepts its data as a series of timestamps, so the sludge time series is used as a input data. However, the dataset needs to be transformed into a proper shape. In our case a 3 y window was adopted for training set, and the input LSTM data was generated by sliding the window by period of 1 y in a time series. As the structure of input data were ready we experimented with several models that cover different numbers of hidden layers and cells in layer. Based on validation data the best of LSTM model was selected. It was composed of four layers with 40 cells in each layer, not including the output layer. The output layer was a dense layer with linear activation function specific for regression problem, due to fact that predicting a future state of sludge amount addressed the problem of regression. The proposed model was implemental using Keras [38] library with Tensorflow packet using Python. The training loss metric assessing how LSTM model fits the training data is shown in Fig. 5, and statistical metrics of final LSTM model are given in Table 4.

3.3. Forecasting with hybrid model

To address both linear and non-linear structure of the data we used the combination of ARIMA and LSTM



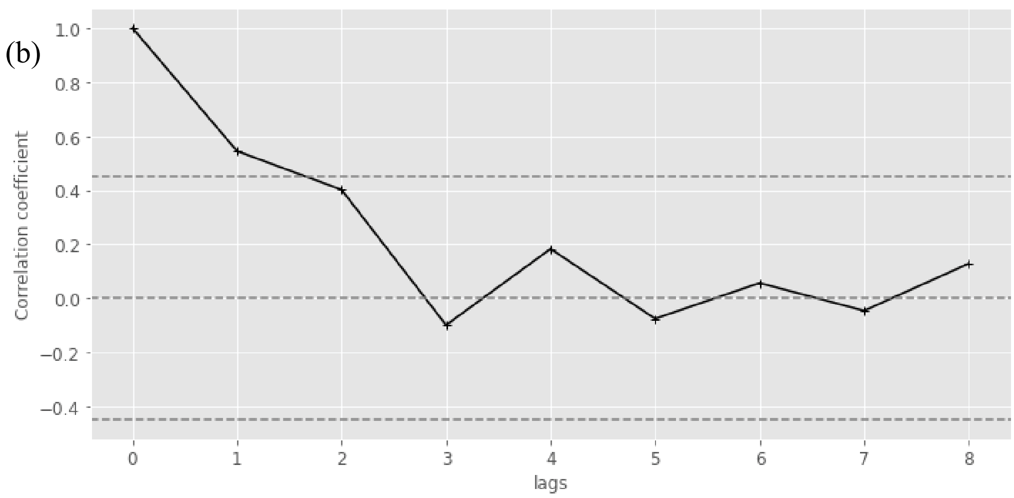


Fig. 3. Correlograms of annual sludge amount time series.

Table 2
Result of ARIMA(1,1,0) model parameters

ARIMA model results						
Model	ARIMA(1,1,0)		No. observations		16	
Method	css-mle		Log likelihood		–120.932	
Date	Fri, 07 Oct 2022		Akaike information criterion		247.864	
Time	06:35:21		BIC		250.182	
Sample	12-31-2004-12-31-2019		HQIC		247.983	
	Coeff.	Std. Err.	z	$P > \|z\|$	[0.025	0.975]
const	–55.2578	75.829	–0.729	0.466	–203.880	93.366
ar.L1.D	–0.5468	0.196	–2.795	0.005	–0.930	–0.163
Roots						
	Real	Imaginary		Modulus	Frequency	
AR.1	–1.8287	+0.0000j		1.8287	0.5000	

Table 3
Metrics for autoregressive integrated moving average model

Series	MAPE	MAE	RSME
Annual amount of sludge dry mass generated at the wastewater treatment plant	13%	388.8	395.8

Table 4
Metrics for long-short term memory recurrent neural network model

Series	MAPE	MAE	RSME
Annual amount of sludge dry mass generated at the wastewater treatment plant	10.2%	332.5	397.78

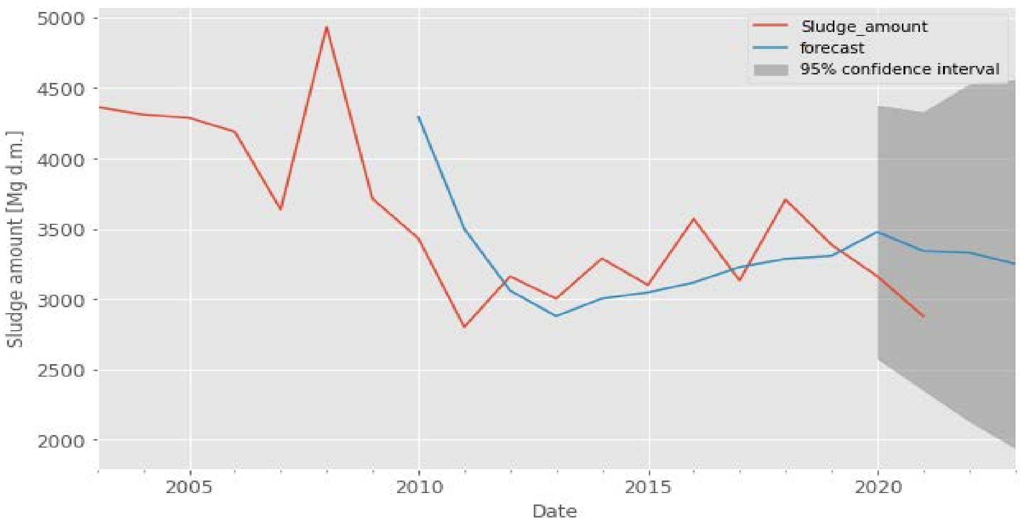


Fig. 4. Autoregressive integrated moving average prediction of sludge amount.

models. At first, the non-stationary time series representing annual sludge amount generated at WWTP was pre-processed to be stationary. Then these data were modeled using ARIMA linear model. The residuals from the linear model were used as input series for LSTM model. Finally, the statistical metrics for hybrid model were calculated and are given in Table 5.

Table 5
Metrics for hybrid model

Series	MAPE	MAE	RSME
Annual amount of sludge dry mass generated at the wastewater treatment plant	9.4%	280.68	358.58

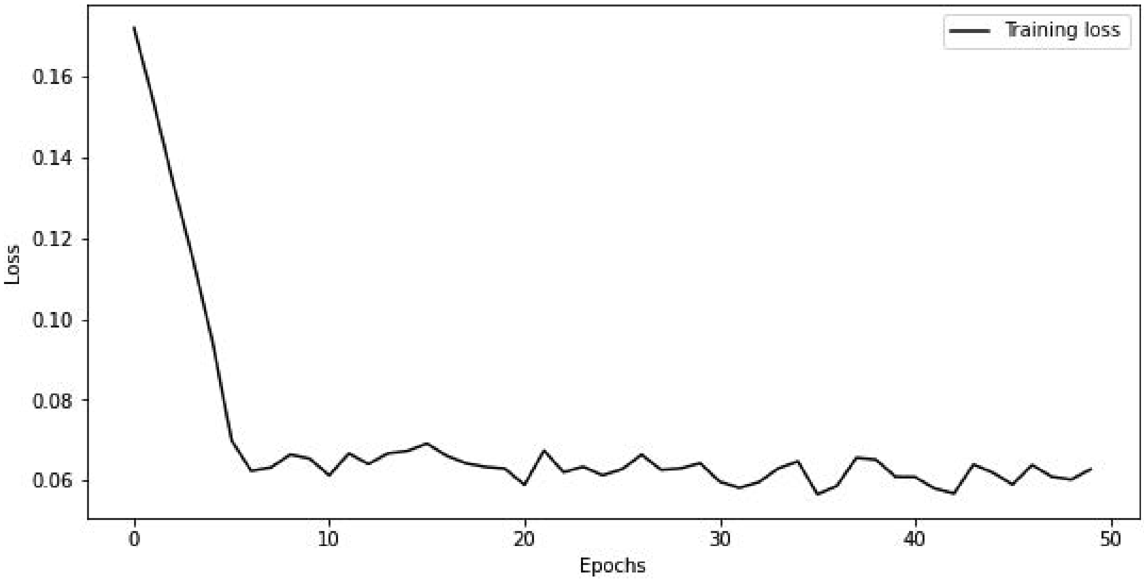


Fig. 5. Training loss curve for long-short term memory model.

4. Discussion

In this study, different models, ARIMA, LSTM-RNN and its joining use as a hybrid model, were implemented for forecasting the annual amount of sludge produced at a wastewater treatment plant. The ARIMA(1,1,0) model was found to be the best fit for the data based on AIC, with a MAPE of 13% and MAE and RMSE values of 388.8 and 395.8, respectively. The LSTM-RNN model, which was composed of four layers with 40 cells in each layer, had a MAPE of 12% and MAE and RMSE values of 320.5 and 366.9, respectively. The results of the study showed that the hybrid model combining ARIMA and LSTM-RNN models was the best performing model for forecasting the annual sludge amount generated at the wastewater treatment plant. The hybrid model outperformed the single models in terms of accuracy, with a MAPE of 9.4%, MAE of 280.68 and RMSE of 358.58. This indicates that the hybrid model was able to capture the linear and non-linear patterns in the data more accurately than either of the single models. However, it is important to note that both models had limitations, as the ARIMA model required the time series to be stationary and the LSTM-RNN model had a relatively small sample size for training. Additionally, both models were only tested on a 3-y window and may not generalize well to longer time frames. Despite these limitations, the results of this study suggest that both ARIMA and LSTM-RNN models can be effective for forecasting the annual amount of sludge produced at a wastewater treatment plant.

5. Conclusions

Since the ARIMA model cannot capture the non-linear structure of data a hybrid model combining the ARIMA and LSTM neural network models, which were first adjusted, was developed for forecasting of sewage sludge amount generated at WWTP. The linear ARIMA model and the non-linear LSTM model were used jointly, aiming to capture different relationship in the time series data. The idea behind this is to take advantages of unique strength ARIMA and LSTM in linear and non-linear modeling. The ARIMA and LSTM models used for final hybrid model were those with the lowest statistical indices. The sewage sludge amount forecasting were performed for all of models developed. The results showed that the combination of methods can be an effective way to improve the forecasting performance. The lowest values of statistical indices, good error metrics, were achieved when a hybrid model was applied for sludge amount prediction. It confirmed that jointly use of these two models which addressed the different patterns in data could improve forecasting accuracy.

The use of proposed models should therefore be considered as a tool to assist in better decision-making in short, medium or long-term planning of the sludge management in the WWTP. Machine learning models gives a greater use for the improved actions than an objective forecast mainly due to the dynamic update and making adjustments as a result of acquiring new data. Of course, it is also important to point out that there are a few limitations in such approach and developed model may not be ideal, but the preparation and verification of such a model may bring up good results for longer forecast horizons.

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