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Forecasting municipal waste accumulation rate and personal consumption expenditures using vector autoregressive (VAR) model

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Abstract
Accurate forecasting of municipal solid waste (MSW) generation is important for the planning, operation and optimization of municipal waste management system. However, it’s not easy task due to dynamic changes in waste volume, its composition or unpredictable factors. Initially, mainly conventional and descriptive statistical models of waste generation forecasting with demographic and socio-economic factors were used. Methods based on machine learning or artificial intelligence have been widely used in municipal waste projection for several years. This study investigates the trend of municipal waste accumulation rate and its relation to personal consumption expenditures based on the yearly data achieved from Local Data Bank (LDB) driven by Polish Statistical Office. The effect of personal consumption expenditures on the municipal waste accumulation rate was analysed by using the vector autoregressive model (VAR). The results showed that such method can be successfully used for this purpose with an approximate level of 2.3% Root Mean Square Error (RMSE).

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1. Introduction

Recently, an urban structure, a development of the economy and improved living standards and lifestyles in households have caused a sharp growth in municipal solid waste (MSW) (Liu et al., 2019). In particular, municipal waste, generated in households includes: packaging of purchased goods, food leftovers, expired food and used items. More often these are also unused products, bought without a real need or received as an addition to other purchased goods. Consumerism, as a lifestyle focused mainly on consuming and possessing, is now widely described in the literature (Aldridge, 2003; Blue, 2017). Two aspects of the consumerism are indicated in particular. The first is related to the sphere of emotions during shopping, which become a source of pleasure or happiness. The second is marketing message which causes the irrationality of the consumption choices made. Unfortunately, increased portfolio resources increase this style of living. The final result is the acquisition of many unnecessary goods which, after a short period of time, are then thrown away and become waste. Municipal solid waste could negatively affect the environment and threaten the health of residents due to increase in waste volume and changes in its composition. Poland’s reported MSW generation has soared from 11.1 million tons to 13.1 million tons over the 2001–2020 period, with an average annual growth rate of over 2%, but a significant increase in the amount of waste has taken place in the last ten years. So the accurate projection of municipal waste quantities is important and plays a vital role in an efficient planning of waste management system. Inadequate forecasts may lead to many problems such as insufficient or excessive waste disposal infrastructure. However, the process of municipal solid waste generation forecasting is not easy, moreover it is challenging by rapidly changing world of economy and unexpected factors (Beigl et al., 2008).

Due to (Abbasi et al 2016) MSW forecasting methods can be classified into five main categories:

- descriptive statistical methods (Sha’Ato et al., 2007),
- regression analysis (Denafas et al., 2014),
- material flow model (Zhang et al., 2012),
- time series analysis (Xu et al., 2013),
- artificial intelligence models (Abbasi et al., 2014).

Initially, conventional and descriptive statistical models of waste generation forecasting with demographic and socioeconomic factors were used widely (Abdoli et al., 2011). Nowadays this method is rarely used due to the dynamic changes in municipal waste generation processes. Other models use multiple regression methods, group comparison, time series analyses or artificial intelligent systems (adaptive neurofuzzy logic, artificial neural network, genetic algorithms). Such a large number of methods causes there is no one optimal model for forecasting of MSW generation. To date, numerous predictive models have been developed for municipal waste generation in various geographical locations. The summary of MSW prediction models used in recent years has been well given by (Kolekar et al., 2016).

The use of time series analysis for municipal waste generation forecasting has advantage that it does not rely on the estimation of social and economic factors, so it overcomes the lack of social parameters or other predictors. Time series of waste generation are dynamic in nature, and in this method it is possible to employ non-linear tools in order to discover relationships within the times series. Owusu-Sekyere et al. (2013) employed ARIMA time series model to predict the MSW generation for Kumasi Metropolitan Area (KMA) of Ghana. Using a range of ARIMA model parameters he was able to predict waste generation with good accuracy. He concluded that ARIMA(1,1,1) model gives him the best results for data of KMA. The ability of SARIMA time series model to predict municipal waste generation was examined by other researches (Xu et al., 2013). Xu et al. focused on the building a hydrid model capable of forecasting MSW generation at multiple time scales (monthly, annual). Results showed that SARIMA model, both in monthly as annual scale, was accurately depicted without considering demographic and socioeconomic factors. The authors concluded that the proposed model could provide comprehensive information on waste generation at three timescales, enabling decision makers to develop integrated polices and measures for waste management over a longer period of time which is of particular importance in terms of matching appropriate waste collection and waste utilisation infrastructure.

The vector autoregression (VAR) model is one of the most successful and flexible models for the analysis of multivariate time series. VAR is a natural extension of the univariate autoregressive model to dynamic multivariate time series. The VAR model has proven to be especially useful for describing the dynamic behaviour of economic and financial time series for forecasting (Drachal, 2021). The VAR model is used also for structural inference and policy analysis (Gupta et al., 2020). The generation of municipal waste using multivariate time series was analysed by Pai et al. (2014). This study investigated the effect of the growing birth rate and immigration on municipal waste. In similar study the residential waste generation per capita was mathematically modelled using variables including education level (Benitez et al., 2008). Khajevand et al. (2019) used multiple variable regression modelling to develop a predictive model for the total waste generation and municipal solid waste disposal. A study in Philadelphia (Pennsylvania, US) analysed the impact of population change, unemployment rate and recycling activities on waste disposal to help the city planners in projecting future waste disposal without extensive time and budget investment in historical and predictive data collection. The VAR model has proven to be especially useful for describing the dynamic behaviour of social, economic time series and for municipal waste generation forecasting.

The main goal of the paper was to develop and check a predictive model for municipal waste accumulation rate (residential waste generation per capita) in relation to personal consumption expenditures in Poland using vector autoregressive model. The connection between these factors seems obvious and the use of VAR method is interesting.

2. Experimental

The data for the analysis was collected from Local Data Bank (LDB) driven by Polish Statistical Office. LDB is Poland's largest database of the economy, society and environment. The database offers more than 40 thousands statistical features grouped thematically. The data presenting municipal waste accumulation rate (MWAR) is given under municipal waste section. MWAR given directly in LDB is from year 2015 till 2020. The earlier data has been calculated as a ratio of total municipal waste generated and the number of inhabitants in Poland for a given year. The municipal waste accumulation rate is given in kilograms per capita per year. The data about personal consumption expenditures (PCE) in PLN was achieved from "The situation of households in 2020 on the basis of results of the Household Budget Survey" report prepared by Social Surveys Department of Polish Statistical Office (Central Statistical Office of Poland, 2021). Municipal waste accumulation rate and personal consumption expenditures data in the last twenty years are given in Figure 1. The statistical description of the data is presented in Table 1.

Table 1. The statistical description of the variables used in the study

Variable	Unit	Mean	Std. dev.	Min	Max
MWAR	kg/Ma	277.0	29.1	245.0	343.0
PCE	PLN	931.3	220.4	599.4	1251.7

In this study data, before model adaptation, simulation and future forecasting, was transformed into time series with yearly frequency. Time series analysis comprises methods that attempt to understand the nature of the series. Past observations are collected and analysed 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. For such cases popular model as autoregressive moving averages (ARMA) and autoregressive integrated moving averages (ARIMA) are applied. However, there are some cases where variables affect each other, here we expect a bi-directional relationship between personal consumption expenditure and municipal waste accumulation rate.

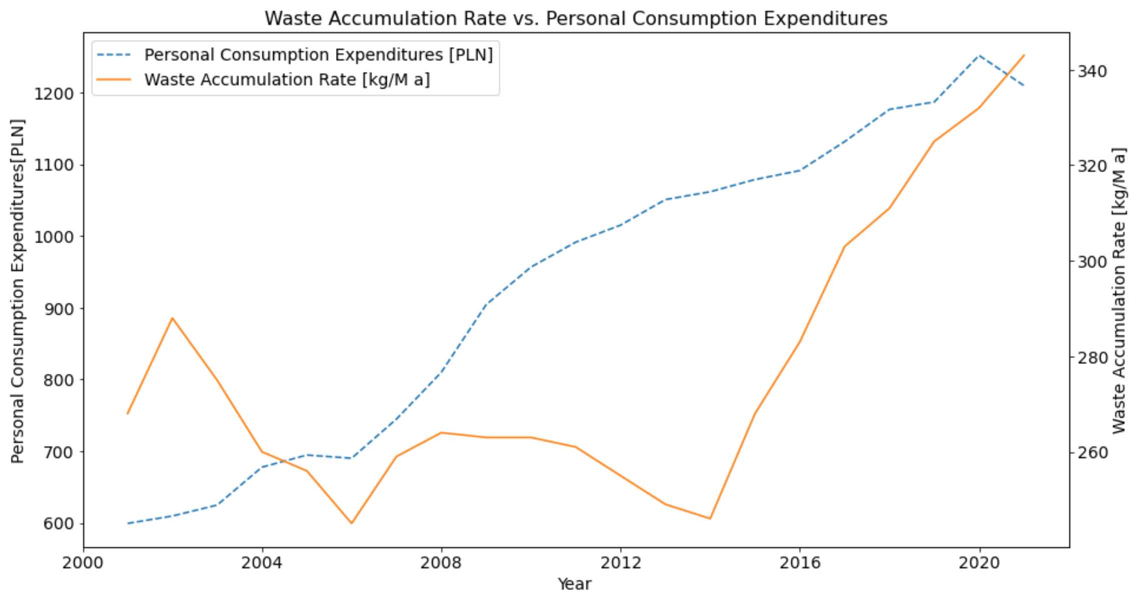

Fig. 1. Municipal waste accumulation rate vs. personal consumption expenditures in the last 20 years

Such feedback relationships are allowed for in the vector autoregression (VAR) model, which is a generalisation of the univariate autoregression model for forecasting (Athanasopoulos et al., 2012). An autoregression AR(p) model is described by the following equation (1):

$$y_t = c + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \dots + \phi_p y_{t-p} + \varepsilon_t \tag{1}$$

where c is a constant, ϕ_1 and ϕ_2 are lag coefficients up to order p, and ε_t is white noise.

A K-dimensional VAR model of order p, denoted as VAR(p)(VAR model of p lag phase), considers each variable y_K in the system. Two dimensional VAR(1) model is described with the following set of equations (2)

$$\begin{aligned} y_{1,} &= c_1 + \phi_{11,1} y_{1,t-1} + \phi_{12,1} y_{2,t-1} + \varepsilon_{1,t} \\ y_{2,} &= c_2 + \phi_{21,1} y_{1,t-1} + \phi_{22,1} y_{2,t-1} + \varepsilon_{2,t} \end{aligned} \tag{2}$$

where the coefficient $\phi_{ii,l}$ captures the influence of the lth lag of variable y_i on itself, the coefficient $\phi_{ij,l}$ captures the influence of the lth lag of variable y_j on y_i, and $\varepsilon_{1,t}$ and $\varepsilon_{2,t}$ are white noise processes. Selecting p parameter for VAR model is achieved using different information criteria, mainly Akaike Information Criterion (AIC) or Bayesian Information Criterion (BIC). Even for VAR models BIC is more preferred because AIC tends to choose large numbers of lags (Hyndman et al, 2021). Forecasts are generated in VAR in a recursive manner. To evaluate the performance of forecasting model in the numerical study first the dataset is splitting into two parts: training and testing data. As a training data set data from 2002 till 2017 were used while data from the 2018-2020 period were used as testing data. The VAR model with estimated parameter of lag phase is then fitted on training data. Next the testing data is compared to predicting data just to evaluate the prediction performance of the proposed forecasting model through statistical metrics. There are many statistical metrics that can be used, such as: Root Mean Squared Error (RMSE), Mean Squared Error (MSE), Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE), coefficient of determination (R^2) (Friedman at al., 2001). RMSE is perhaps the most popular metric used for regression problems because it gives a metric with scale as the target values and is determined by Eqs. (3),

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \tag{3}$$

where N is a number of observations, y_i actual value and y_i hat model output. To compare the results achieved with vector autoregression model, calculations were also done using classic auto regression model separately for municipal waste accumulation rate and personal consumption expenditures. All computations were done in Google Colaboratory environment using statsmodels.tsa library that contains model classes and functions that are useful for time series analysis.

3. Results and discussion

3.1. ADF test

Before starting the modelling process we needed to perform some basic operations on the data. The VAR model requires data to be stationary, so before conducting a simulation analysis the time series has to be changed to stationary sequence, what means that the way the statistical properties of a process generating a time series does not itself change over time. Augmented Dickey Fuller (ADF) test has been used to check the stationarity of municipal waste accumulation rate (MWAR) and personal consumption expenditures (PCE) time series. In case of PCE the result of ADF test showed that there is a strong evidence against null hypothesis and a PCE time series is stationary. However, for the MWAR, the ADF test's result gave a weak evidence against the null hypothesis, MWAR time series was non-stationary. The usual method for changing non–

stationary time series into a stationary series is first–order differencing and this operation was done. However, still MWAR time series was a non-stationary after first-order differencing. It was necessary to apply second order differencing which has just given a positive effect on MWAR time series. As result the further analysis was based on data, in both time series, starting from the 2002 year. They were categorized as follows, the training set of data was constructed on sixteen years history (2002-2017), while the test set of data covered a period of three years (2018-2020).

3.2. VAR model

In VAR model, determining the optimal lag period is an important issue to be resolved. We expected the lag period to be long enough to reflect the dynamic characteristics of the model, but we needed to consider that the longer the lag period the lesser the degree of freedom the model has. We expected not only a sufficient lag period, but also a model with sufficient degree of freedom. Using AIC and BIC criterions it was found that optimal lag period of this model was p=2 (Table 2).

Table 2. Optimal lag-length choice in VAR(p) model

lag	AIC	BIC
0	11.97338	12.06995
1	11.90005	12.18327
2	11.32349*	11.77996*
3	11.88379	12.49219
4	12.15551	12.88287

Note: * indicates optimal lag length selected by the criterion

Figure 2 shows the results of the VAR(2) model based on training set of data. It indicates that most of the variables passed the significance test. .

```
  Summary of Regression Results
==================================
Model:                         VAR
Method:                        OLS
Date:           Fri, 31, Dec, 2021
Time:                     16:54:59
--------------------------------------------------------------------
No. of Equations:         2.00000    BIC:                    11.7800
Nobs:                     14.0000    HQIC:                   11.2812
Log likelihood:          -108.995    FPE:                    88375.9
AIC:                      11.3235    Det(Omega_mle):         47982.5
--------------------------------------------------------------------
Results for equation PCE
==========================================================================
             coefficient       std. error           t-stat            prob
--------------------------------------------------------------------------
const           0.197006         5.773798            0.034           0.973
L1.PCE          0.058238         0.215090            0.271           0.787
L1.MWAR        -0.127539         0.568705           -0.224           0.823
L2.PCE         -0.282636         0.211805           -1.334           0.182
L2.MWAR         1.485612         0.438078            3.391           0.001
==========================================================================

Results for equation MWAR
==========================================================================
             coefficient       std. error           t-stat            prob
--------------------------------------------------------------------------
const           2.917747         3.191158            0.914           0.361
L1.PCE         -0.105179         0.118880           -0.885           0.376
L1.MWAR        -0.471389         0.314321           -1.500           0.134
L2.PCE         -0.108488         0.117064           -0.927           0.354
L2.MWAR        -0.117811         0.242124           -0.487           0.627
==========================================================================

Correlation matrix of residuals
             PCE      MWAR
PCE     1.000000  0.446092
MWAR    0.446092  1.000000
```

Fig. 2. The results of VAR(2) model

The causal relationship tested by Granger causality test allowed to confirm that all time series in the system were interchanged causing each other what makes a system of our multi time series a good candidate for using VAR model. In order to forecast the future data VAR model had to be replenished with lag order number of observations from the past data. It was two observations in our case. The VAR model generates the forecasts on the scale of the training data. It means that we needed to de-difference the modelling results twice because previously we differenced the original input data also twice. The forecasts after de-differencing for three years are presented in Table 3.

Table 3. Optimal lag-length choice in VAR(2) model

Year	Personal Consumption Expenditures [PLN]	Municipal Waste Accumulation Rate [kg/Ma]
2018	1222.73	323.49
2019	1249.68	337.56
2020	1281.75	355.15

Forecasts against the actual data from test data of municipal waste accumulation rate and personal consumption expenditures are given in Figure 3a,b respectively

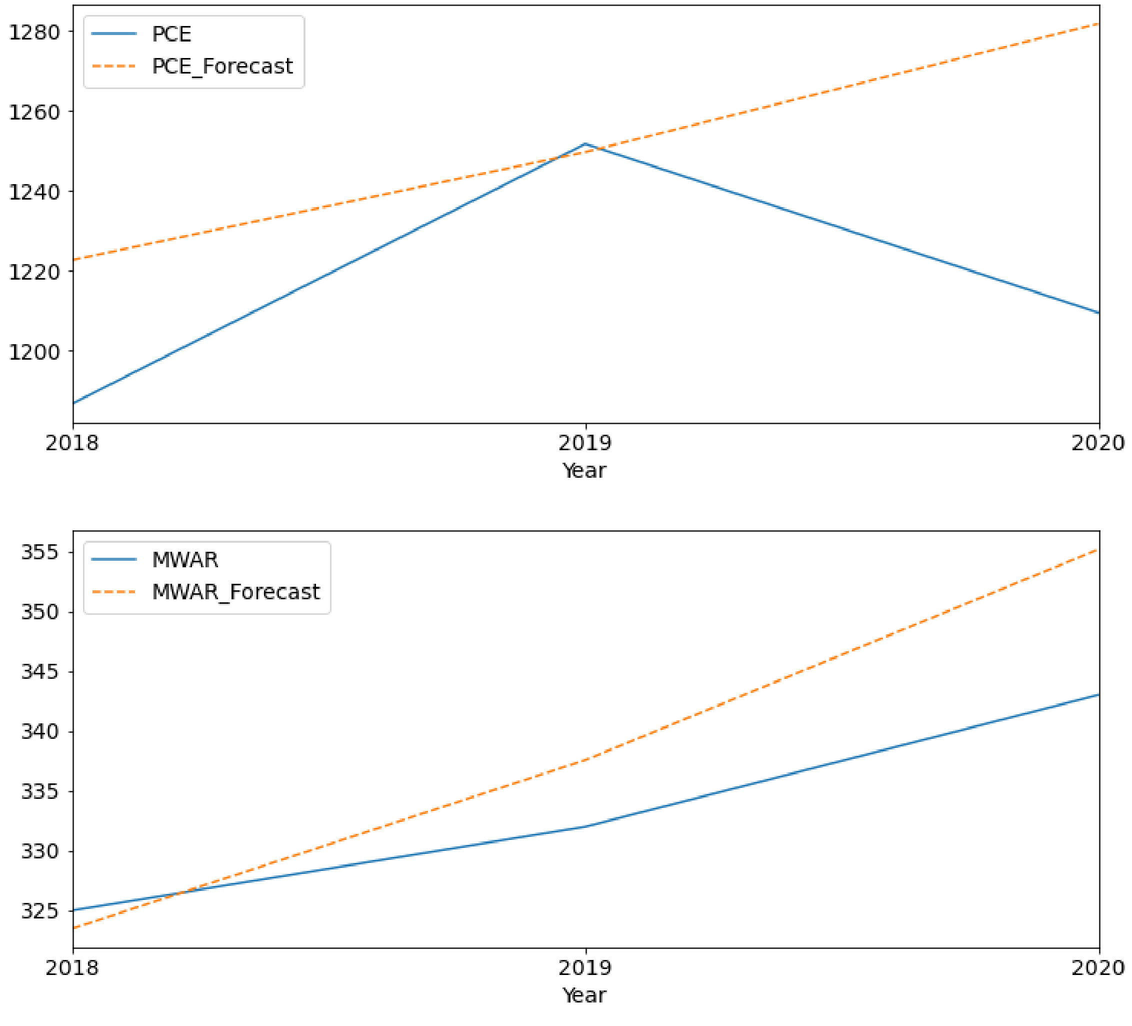

Fig. 3. Forecast vs actuals comparison of VAR(2) model. a) personal consumption expenditures (PCE) b) municipal waste accumulation rate (MWAR)

To evaluate the forecasts computation of a comprehensive set of metrics: MAPE, MAE, and RMSE were done and are presented in Table 4. The mean value in test dataset for personal consumption expenditures is 1216 PLN, and for municipal waste accumulation rate is 333 kg/Ma.

Analysing the obtained values of statistical metrics, in particular RMSE in relation to mean values, it can be concluded that the obtained prognostic model is acceptable for future forecasting.

Table 4. Statistical metrics for VAR(2) model evaluation

Metrics	Personal Consumption Expenditures	Municipal Waste Accumulation Rate
MAPE	0.0305	0.0190
MAE	36.697	6.4105
RMSE	46.546	7.7679

3.3. Future forecasting

Using the developed VAR(2) model, a forecast for the next three years was made for both time series representing the municipal waste accumulation rate and personal consumption expenditures. Forecasts obtained from the developed model are presented in the table 5.

Table 5. Future forecasts of PCE and MWAR time series

Year	Personal Consumption Expenditures [PLN]	Municipal Waste Accumulation Rate [kg/Ma]
2021	1222.73	323.49
2022	1249.68	337.56
2023	1281.75	355.15

3.4. Comparison to autoregressive AR(2) model

Additionally to evaluate the quality of VAR(2) model applied for time series with bi-directional relationship between waste accumulation rate and personal consumption expenditures an autoregression model AR(2) was used separately for both variables. AR(2) model follows the formula given by Eqs. (4).

$$y_t = c + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \varepsilon_t \tag{4}$$

Prior to modelling, the time series of municipal waste accumulation rate as well as personal consumption expenditures were prepared in accordance with the procedure described in chapter 3.1. After modelling, the forecasts needed to be de-differenced to basic values. The results of forecasting are given in Table 6 for personal consumption expenditure (PCE) and in Table 7 for municipal waste accumulation rate (MWAR). The data on RMSE metrics has also been included in these tables.

Table 6. Comparison of personal consumption expenditures (PCE) forecasts in VAR(2) and AR(2) models

Year	VAR(2)	AR(2)
2018	1222.73	1217.36
2019	1249.68	1260.21
2020	1281.75	1305.49
RMSE	46.54	58.31

Table 7. Comparison of municipal waste accumulation rate (MWAR) forecasts in VAR(2) and AR(2) models

Year	VAR(2)	AR(2)
2018	323.49	322.97
2019	337.56	335.07
2020	355.15	346.89
RMSE	7.768	3.093

It is stated that VAR(2) model performs better forecasting then AR(2) model in case of PCE, while in case of waste accumulation rate time series the situation is different. It is therefore worth to conduct an additional analysis using basic methods of autoregression for time series in order to get a broader picture of analysed phenomenon.

4. Summary and conclusion

Accurate projection of municipal solid waste quantities is important for planning of an efficient waste management system. A lot of conventional and descriptive statistical methods of forecasting municipal solid waste generation has been developed over the last thirty years. However, this method is no longer effective due to dynamic changes in municipal waste generation processes. New methods were needed, especially the ones where artificial intelligence models are used. Developing machine learning techniques and its application for prediction result in a wide interest in its applicability to forecast municipal solid waste generation on local, regional or country level. Regression analysis is a widely used modelling technique because of the well-developed mathematical and statistical theory.

This study investigates the future relationship between municipal waste accumulation rates and personal consumption expenditures based on the yearly data, achieved from Local Data Bank (LDB) driven by Polish Statistical Office. The effect of personal consumption expenditures on the municipal waste accumulation rate has been analysed by using the vector autoregressive model, and the following main conclusions are obtained:

Firstly, based on training data the optimal lag period using AIC and BIC criterions for vector autoregressive (VAR) model has been determined. It has been found that optimal lag period for this model is 2.

Secondly, the Granger causality test of endogenous variables in VAR model shows personal consumption expenditures and waste accumulation rate time series are interchanged causing each other what makes the system a good candidate to use the VAR model for forecasting.

Thirdly, the evaluation of VAR model using statistical metrics MAE, MAPE, RMSE shows that the obtained prognostic VAR model is acceptable for future forecasting. The results of the forecasting show that the further growth is to be expected on personal consumption expenditures and municipal waste accumulation rate.

Finally, the comparison to other regression models confirms that it is worth to perform some additional tests to have a wider picture and greater confidence that the model will predict future values with increased probability.

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使用向量自回归（VAR）模型预测城市垃圾堆积率和个人消费支出

關鍵詞
废物堆积率
消费支出
预测
时间序列分析
多元时间序列
向量自回归模型

摘要

城市固体废物（MSW）产生量的准确预测对于城市垃圾管理系统的规划、运营和优化具有重要意义。然而，由于废物量、其成分或不可预测因素的动态变化，这并非易事。最初，主要使用具有人口和社会经济因素的废物产生预测的常规和描述性统计模型。多年来，基于机器学习或人工智能的方法已广泛用于城市垃圾预测。本研究根据波兰统计局驱动的地方数据库（LDB）获得的年度数据，调查城市垃圾堆积率的趋势及其与个人消费支出的关系。采用向量自回归模型（VAR）分析了个人消费支出对城市垃圾堆积率的影响。结果表明，这种方法可以成功地用于此目的，其近似水平为 2.3% 均方根误差（RMSE）。