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Forecasting Landfilling Indicators Of Municipal Waste In Greece Using Univariate Time-series Model

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ABSTRACT

Implementation of environmental policies, is one of the European Commission's key priorities, as confirmed by its proposal for the 7th Environment Action Programme and the Roadmap to a resource-efficient Europe. Subsequently, the European Union revised its waste legislation to address these challenges more adequately. As a result, the EU's Waste Framework Directive and Landfill Directive set binding targets for recycling municipal waste and diverting biodegradable municipal waste from landfills. This paper deals with the monitoring of municipal waste management operations in Greece, in terms of technical content and ability to reach the targets of the initiatives. In addition, a more detailed report on waste indicators published by Eurostat will be based on an Exploratory Data Analysis and on a Univariate time-series prediction model. Finally, the overall aim of this study is to gain maximum insight into the data and understand its underlying structure through graphical representation, to achieve the most accurate forecast for the landfilling operation.

1. Introduction

1.1 Definition and background concept

Over the last decade, European countries have increasingly concentrated their attention on municipal waste from disposal methods to prevention and recycling. The ‘waste hierarchy’ prioritizes waste prevention, followed by preparing for reuse, recycling, other recovery and finally disposal as the least desirable option (European Parliament 2008). Also, it aims to extract more value from resources while lessening the pressure on the environment and creating new jobs.

The definition of ‘municipal waste’ used in different countries varies, reflecting diverse waste management practices. For national yearly reporting of municipal waste to Eurostat, municipal waste is defined as follows (Eurostat 2021):

“*Municipal waste is mainly produced by households, though similar wastes from sources such as commerce, offices and public institutions are included. The amount of municipal waste generated consists of waste collected by or on behalf of municipal authorities and disposed of through the waste management system*”

In this sense, municipal waste is understood as waste collected by or on behalf of municipalities. However, the definition also includes waste from the same sources and other waste similar in nature and composition that is collected directly by the private sector (business or private non-profit institutions), not on behalf of municipalities (mainly separate collection for recovery purposes) (Eurostat 2012).

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Even though municipal waste represents only around 10 % of total waste generated in the European Union (Eurostat 2021), its heterogeneous composition makes environmentally sound management challenging. Prevention of this waste has the potential to reduce its environmental impact not only during consumption but also throughout the whole life cycle of the products consumed. Countries that have developed efficient municipal waste management systems, generally perform better in overall waste management (European Commission 2015).

1.2 EU policies and targets

Waste policies and targets set at the EU level include minimum requirements for managing certain waste types. The most related targets for municipal waste are the Landfill Directive (European Parliament 1999), the Packaging and Packaging Waste Directive (European Parliament 1994) and the Waste Framework Directive (European Parliament 2008). Countries can choose between four different methods to monitor their progress towards the last target (European Commission 2011). These methods for the calculation of the target on municipal waste are:

- Preparation for reuse and recycling of paper, metal, plastic and glass household waste
- Preparation for reuse and recycling of paper, metal, plastic, glass household waste and other single types of household waste or similar waste
- Preparation for reuse and recycling of household waste
- Preparation for reuse and recycling of municipal waste

In addition, the European Commission published 'Closing the loop - An EU action plan for the circular economy (European Commission 2015), also known as the Circular Economy Package. The package sets out many initiatives and led to the adoption of new targets: 55% of municipal waste to be recycled and prepared for reuse by 2025, 60% by 2030 and 65% by 2035 (European Parliament 2018).

2. Literature Review

The increasing volume and complexity of waste associated with the modern economy are posing a serious risk to ecosystems and human health. The world generates 2 billion tonnes of municipal waste annually, with at least 33% of that, extremely conservatively, not managed in an environmentally safe manner (World Bank 2021). Of all the waste streams, e-waste containing new and complex hazardous substances presents the fastest-growing challenge in both developed and developing countries. According to Solving the E-waste Problem Initiative (United Nations 2014):

"E-waste is a term used to cover items of all types of electrical and electronic equipment (EEE) and its parts that have been discarded by the owner as waste without the intention of re-use"

It can be concluded that there is a necessity for proper and comprehensive sorting of waste before disposal. According to Zhang et al. (2012), contaminants of contaminated soils by heavy metals and organic compounds, are transferred to the food chain, especially via rice growing in China. Furthermore, the study of Saida et al. (2019), revealed that the pollution brought by the municipal waste caused significant changes in some of the physicochemical characteristics of the soil. Consequently, the separation of organic waste for biological treatment and the diversion of inorganic waste for various treatment processes will lead to heavy metal contamination reduction in the soils (Azeez et al. 2011).

Arbulú et al. (2015), concluded that tourism and municipal waste generation are strongly correlated by examining the relationship between municipal waste generation, per capita income and tourism, using the framework of the Environmental Kuznets Curve hypothesis. In addition, a linear relationship between the Gross Domestic Product (GDP) of the countries and the amount of e-waste generated was found by Kumar et al. (2015). Therefore, it is obvious that has not been placed particular emphasis on the prediction of the future values of MSW indicators. So, this paper aims to fill this gap by using state-of-the-art technologies of Machine Learning (Exploratory Data Analysis and Univariate Time-

Series model), to understand the underlying structure of the datasets and to forecast future values of the municipal waste operations management.

3. Methods and Data

To analyze the municipal waste indicators of the present work have been used the fundamental techniques of Exploratory Data Analysis and an ARIMA model. Data have been retrieved from Eurostat (Eurostat 2021). The programming language used is Python and the project was implemented in Jupyter Notebook. Below is a brief description of them.

3.1 Exploratory Data Analysis (EDA)

EDA was promoted by John Tuckey in 1977 to encourage statisticians to explore the data, to detect outliers, to discover the relations between the variables and to understand the patterns within the data (Tukey 1977). Furthermore, EDA brings to light hidden motifs about the content without making any underlying assumptions while data scientists use this process to understand what type of modelling and hypotheses can be formulated. The main components of exploratory data analysis include summarizing data, statistical analysis, and visualization of data (Mukhiya & Ahmed 2020).

3.2 “Autoregressive Integrated Moving Average” Model (ARIMA)

ARIMA is a generalized model of Autoregressive Moving Average (ARMA) that combines Autoregressive (AR) process, Moving Average (MA) processes and builds a composite model that uses time-series data to either better understand the dataset or to predict future trends. As the acronym indicates, ARIMA (p, d, q) captures the key elements of the model (Hyndman & Athanasopoulos 2018):

AR: Autoregression. A regression model that uses the dependencies between observation and several lagged observations (p).

I: Integrated. To make the time series stationary by measuring the differences of observations at a different time (d).

MA: Moving Average. An approach that takes into account the dependency between observations and the residual error terms when a moving average model is used to the lagged observations (q).

The AR(p) model is written:

$$y_t = c + a_1 y_{(t-1)} + \ldots + a_p y_{(t-p)} + u_t \qquad (1)$$

Where: $a_1 \ldots a_p$ are parameters; c is a constant, and the random variable u_t is white noise.

The MA(q) model is written:

$$y_t = \mu + u_t + m_1 u_{(t-1)} + \ldots + m_q u_{(t-q)} \qquad (2)$$

Where: $m_1 \ldots m_q$ are the parameters of the model; m is the expectation of y_t (often assumed to equal 0); u_t, $u_{(t-1)} \ldots u_{(t-q)}$ are white noise error terms.

The ARMA (p, q) model refers to the model with p autoregressive terms and q moving-average terms. This model contains the AR(p) and MA(q) models, and is written:

$$y_t = c + a_1 y_{(t-1)} + \ldots + a_p y_{(t-p)} + u_t + m_1 u_{(t-1)} + \ldots + m_q u_{(t-q)} \qquad (3)$$

ARIMA forecasting models, also known as Box and Jenkins (Box et al. 2015), are capable of dealing with non-stationary time series data because of their ‘Integrate’ step. The ‘Integrate’ component involves differencing the time series to convert a non-stationary time series into a stationary. The general form of an ARIMA model is denoted as ARIMA (p, d, q).

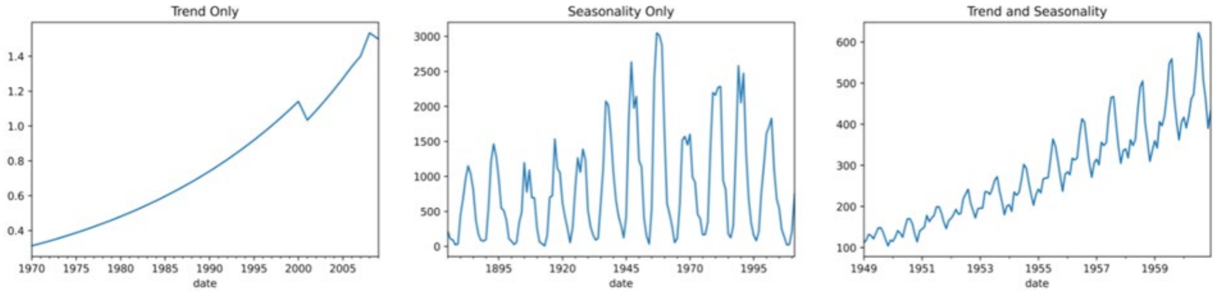

Figure 1. Examples of Trend and Seasonality in the Time Series

A stationary time series is one whose properties do not depend on the time at which the series is observed. Thus, time series with trends, or with seasonality, are not stationary. A trend is observed when there is an increasing or decreasing slope observed in the time series. Whereas seasonality is observed when there is a distinct repeated pattern observed between regular intervals due to seasonal factors. It could be because of the month of the year, the day of the month, weekdays or even times of the day (Figure 1). However, It is not mandatory that time series must have a trend and/or seasonality. A time series may not have a distinct trend but have a seasonality. The opposite can also be true.

3.3 Jupyter Notebook

It is an open-source web application that allows data scientists to create and share live code, equations, visualizations, narrative text or even comprehensive reports. In summary, it is a powerful and versatile online notebook wherein code can be developed, data can be visualized, and the results-outputs can be analyzed without leaving the environment (Jupyter 2021). Also, the Jupyter system supports over 100 programming languages (called 'kernels' in the Jupyter ecosystem) including Python, Java, R, Julia, Matlab, Octave, Scheme, Processing, Scala, and many more. For the project of this paper was used the iPython kernel was. Notebook kernel is a 'computational engine' that executes the code contained in the Notebook. The ipython kernel, referenced in this paper, executes Python 3.8.

4. Empirical Results

Graphical representations are so essential to EDA because the rich information they provide is incomparable in its ability to detect data patterns. Visual examination is the best way to discover hidden motifs and to understand the structure of the data. So, let's jump to the EDA process.

Initially, the libraries must be imported that will be needed to conduct EDA. These libraries are: Pandas is a widely used data analysis library providing numerous functions and methods to work on tabular data. NumPy is a fundamental package for scientific computing with Python. Matplotlib is a plotting library that produces quality figures in a variety of hardcopy formats and Seaborn is also a plotting library that is built on top of matplotlib and allows to create of attractive and informative statistical graphics. Also, the warnings library is used to ignore all the warnings during the interpretation and %matplotlib inline makes plot outputs appear and be stored within the Notebook.

	EU-27	EU-28	Belgium	Bulgaria	Czechia	Denmark	Germany	Estonia	Ireland	Greece	...	Romania	Slovenia	Slovakia	Finland	Sweden
Year																
2015-01-01	127	125.0	4	278.0	166	11.0	8	26	NaN	409	...	178	102	226	57	4
2016-01-01	121	118.0	3	260.0	169	10.0	6	38	149.0	410	...	181	38	228	16	3
2017-01-01	120	115.0	4	269.0	222	8.0	5	75	130.0	403	...	220	48	229	5	2
2018-01-01	120	113.0	4	249.0	229	9.0	5	87	86.0	403	...	219	47	229	4	3
2019-01-01	119	NaN	4	NaN	231	8.0	5	64	NaN	407	...	213	52	219	5	3

Figure 2. Dataframe's structure

After this, data will be loaded and read from four different CSV files into 4 data frames. Each dataset consists of 25 rows and 34 columns. In the output (Figure 2) the columns refer to the countries of the European Union while the dataset's index was set using the column 'Year' (1995-2019). Furthermore, there are empty cells, entries with NaN values, which is a common issue in data analysis and they will be replaced by the mean value of its column. Before any action or change is made to the datasets, copies of the data frames will be made, so that, the initial datasets will be kept intact and secure. Moving forward, municipal waste indicators of Europe and Greece will be analyzed through graphical representation.

The Seventh Environment Action Programme 2020 – 'Living well, within the limits of our planet' contains the objective that waste is safely managed as a resource. This should help Europe to extract more value from the resources, reduce the environmental impacts associated with waste management and create jobs. In this regard, it is important to further increase municipal waste recycling rates. The Waste Framework Directive sets a target of 50% of municipal waste (specific types of household and similar wastes) to be prepared for reuse and recycled by 2020 in the EU Member States. The amount of municipal waste being recycled has been steadily increasing in Europe. The performance of EU Member States on the recycling of municipal waste varies, although the comparability of data is hindered by variation in data collection and definitions. Despite a strong performance from some countries and clear progress being made in nearly all since 2004, in several Member States significant efforts are still needed to achieve the 2020 target.

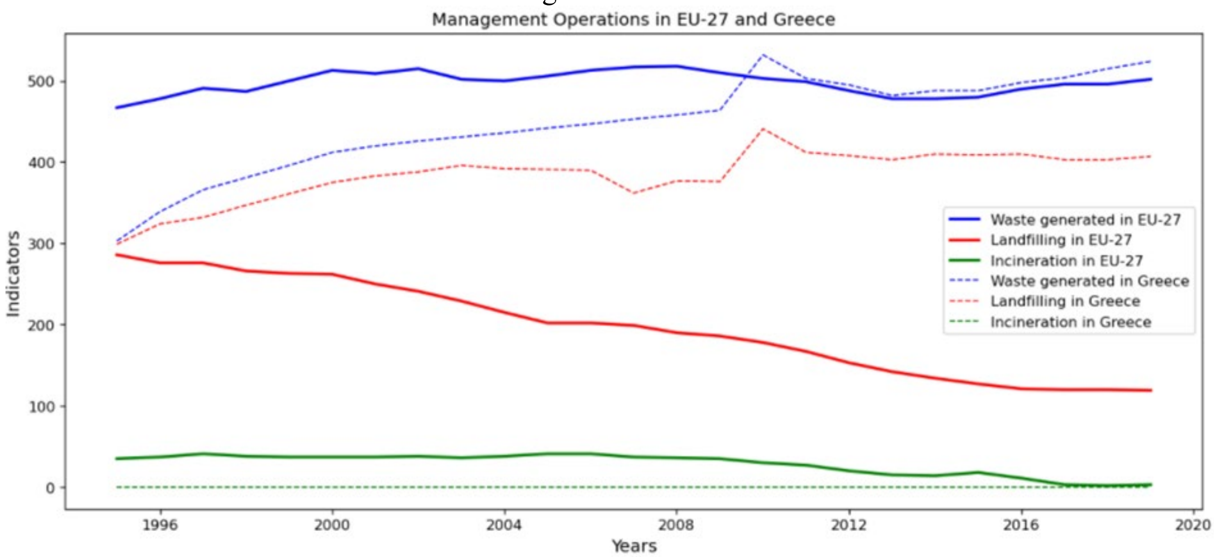

Figure 3. Management Operations in EU-27 and Greece (1995-2019)

Europeans generated on average 502 kg of municipal waste per person in 2019. 47.7% of this amount was recycled or composted, while a quarter was landfilled. In the same year, Greeks generated 524 kg per capita. 77.6% of this amount was landfilled, 1% was incinerated and only 21% recycled (Figure 3). Even though municipal waste represents only around 10% of the total waste generated in the EU, it is one of the most complex streams to manage due to its diverse composition and its large number of producers.

Over the examined period (1995-2019), some countries show high levels of municipal waste recycling and many others show strong improvement. Despite this, the low rates of recycling in some countries, suggest that not every country is likely to achieve the Waste Framework Directive target by 2020. Analysis by the European Commission (European Commission 2018) indicates that 14 EU Member States are at risk of not meeting the 2020 target of 50%. These are Bulgaria, Croatia, Cyprus, Estonia, Finland, Greece, Hungary, Latvia, Malta, Poland, Portugal, Romania, Slovakia and Spain. In addition, scenario modelling was performed and concluded that if no additional policy action is taken, some of the aforementioned countries concerned would probably not even meet the 50% target by 2025.

At this point, the Exploratory Data Analysis has been completed and it is time to build the ARIMA model. Following the necessary processes, it has been determined that p=1, d=2 and q=1.

```
                             ARIMA Model Results
==============================================================================
Dep. Variable:               D2.Greece   No. Observations:                   23
Model:                  ARIMA(1, 2, 1)   Log Likelihood                 -98.483
Method:                        css-mle   S.D. of innovations             16.138
Date:                 Thu, 22 Jul 2021   AIC                            204.966
Time:                         00:44:41   BIC                            209.508
Sample:                     01-01-1997   HQIC                           206.108
                          - 01-01-2019
=================================================================================
                    coef    std err          z      P>|z|      [0.025      0.975]
---------------------------------------------------------------------------------
const            -0.6590      0.379     -1.738      0.082      -1.402       0.084
ar.L1.D2.Greece  -0.2918      0.198     -1.473      0.141      -0.680       0.097
ma.L1.D2.Greece  -1.0000      0.132     -7.590      0.000      -1.258      -0.742
                                    Roots
=============================================================================
                  Real          Imaginary           Modulus         Frequency
-----------------------------------------------------------------------------
AR.1           -3.4267           +0.0000j            3.4267            0.5000
MA.1            1.0000           +0.0000j            1.0000            0.0000
-----------------------------------------------------------------------------
```

Figure 4. ARIMA Model Results

As shown in Figure 4, even though the p-value of ar.L1 is slightly over the significance level while the p-value of ma.L1 is 0, it seems to be a decent ARIMA model. To determine if this model is undoubtedly the optimal one, Out-of-Time Cross-Validation needs to be applied. Following that, the time series has been split into 2 contiguous parts (training - testing dataset) without randomly sampling the training data. This validation method takes a few steps back in time and forecasts into the future as many steps have been taken back. In the case of the present work was used the duration of 3 years (2019 - 2018 - 2017).

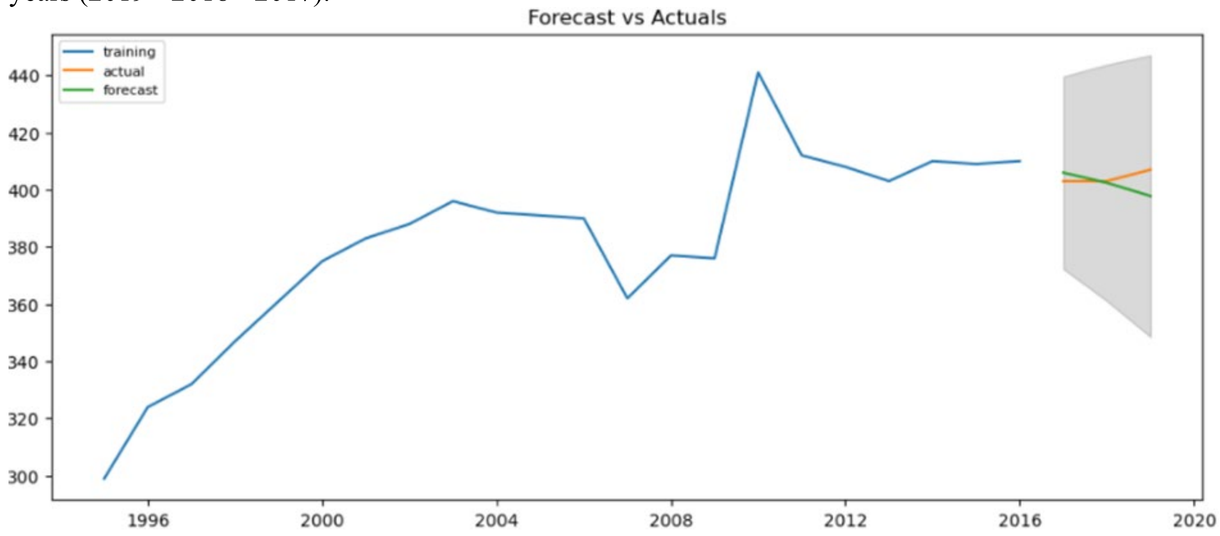

Figure 5. Forecast vs Actual values

According to the chart in Figure 5, the ARIMA (1,2,1) model seems to give a directionally correct forecast for the period 2017-2019. The actual and forecasted values lie within the 95% confidence band. Also, the Accuracy Metrics for this time series forecast represent Mean Absolute Percentage

Error (MAPE) around 1.05%. This implies that the model is about 98.95% accurate in predicting the next 3 in-sample observations (3 years).

Last but not least, is the multi-step Out-of-Sample Forecast. The fact that the Waste Framework Directives were amended in 2018 to include new targets and measures beyond 2020, triggered the need to predict how the municipal waste landfilling would fluctuate over the next 10 years. In Figure 6, the grey section of the chart represents the predicted values for the period 2020-2030 (GitHub Repository 2021).

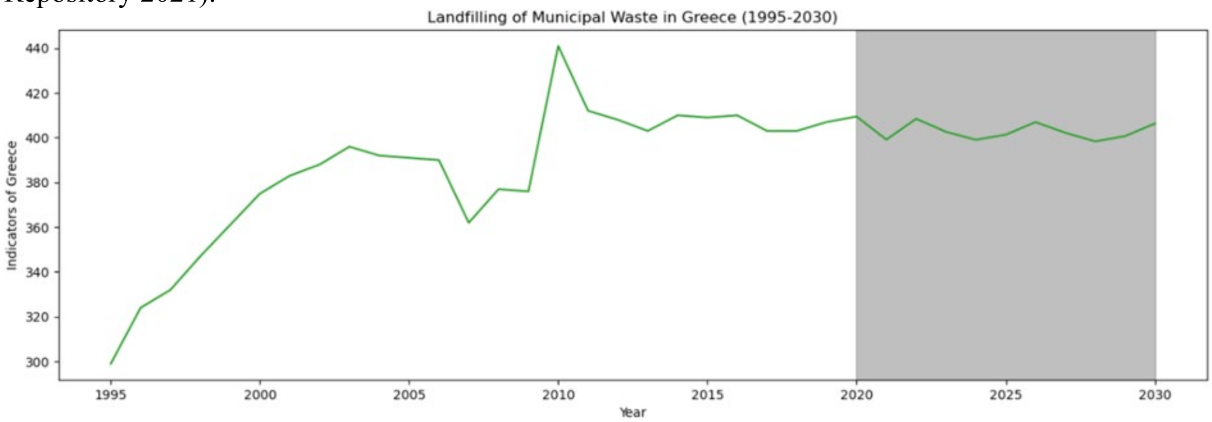

Figure 6. Predicted values (2020-2030)

5. Conclusions

Inappropriate municipal waste management activities are most often sources of huge pollution, affecting all the compartments of the environment and threatening the health of workers and residents. Soils are polluted by various substances, heavy metals and organic compounds, especially when the disposal of such waste in landfilling areas is performed improperly.

Over the examined period (1995-2019), Greece were generated 11.2 tons of municipal waste per person and 85.7% of this amount was landfilled. The Recycling rate of Europe is 34.8% while Greece represents 14.3%. Despite the circumstance that in 2018 Greece has been identified by the European Commission as at risk of missing the 2020 target, no amendments in the national legislation were adopted to improve the recycling of municipal waste.

In 2019, Greece landfilled 407 kg per person of municipal waste and recycled 21%. Based on the predicted values of the ARIMA model, Greece, in 2020, 2025 and 2030, will landfill around 409, 401 and 406 kg per person respectively. Subsequently, the results of this study reinforce the initial scenario of the European Commission that Greece would not even meet the 50% target by 2025 (not even by 2030) if no additional policy action will be taken.

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