Modeling And Simulation Of Plastic Wastes Generation For Operational Planning And Management In The Bonaberi Industrial Region, Cameroon

Ndoh Mbue Innocent[1,*] Bitondo Dieudonne[2]

[1]Energy, Materials, Modeling And Methods Laboratory (E3M)
[2]National Polytechnic School Of Douala (NPSD), University Of Douala, Cameroon
*Corresponding Author:
Email: dndoh2009@gmail.com

***Abstract**.*
A review of waste management literature in use today shows that new techniques are needed in the process of planning strategic goals and objectives to technical goals and objectives. One of these techniques is the method which involves the modeling and simulation of wastes generated in our communities. This study uses the ARIMA (Autoregressive Integrated Moving Average), model to model and simulates plastic wastes generated in the Bonaberi industrial zone, of Cameroon for operational planning and management. Attention was also paid to their composition and uses as important resources for recycling industries. The monthly municipal plastic waste data from 2014 to 2020 was used to create a parsimonious ARIMA model. Different performance measures such as mean absolute deviation (MAD), mean absolute percentage error (MAPE), root mean square error (RMSE) and coefficient of determination (R-squared) were used to evaluate the performance of these models. Following this, ARIMA (1, 1, 1) model showed a superior prediction performance. According to this model, if current production and waste management trends continue, approximately 5468 Kg/month, 95% CI (2843, 9581) could be attained by December 2021.The results contribute to the process of planning strategic goals and objectives to technical goals and objectives in the region. The model developed can help decision-makers to take better measures and develop policies regarding waste management practices in the future. However, technical, environmental, and socio-economic feasibility studies to explore the technical options available, and to determine the factors that are considered important for the economic success of the project, and causing significant environmental problems resulting from improper disposal, namely burning or dumping, could also direct future investors in the region.

***Keywords:** Modeling, Simulation, ARIMA Model, plastic wastes, Bonaberi industrial region*

I. INTRODUCTION

There is a general consensus in literature that the end of plastics is not nigh due to their utilitarian benefits. As a component of solid wastes, plastics have emerged as the most versatile polymer material successfully integrating into our daily lives [1], and their presence in the environment has been on an increase since 1950 [2]. Mounting evidence shows that their generation could double by 2050[3], and could continue to rise to unprecedented levels in the coming decades in the absence of a decision support system. Under the latter scenario, there would be leakages into the environment, where they are believed to slowly release phthalates and biphenyls into the soil, groundwater, and other water bodies [4, 5], with serious negative consequences on the ecosystem. Indeed, the dissociations between economic growth, environmental pressures, and societal sustainability greatly impede SWM technology, which is then pressed to its limits, placing unexpected burdens on society [6]. There is scientific evidence on the bioavailability of plastic pollutants to the ingesting organisms [7], and of their potential transfer along the food chain [8].

Generally, the end of life management of plastics is a global issue, especially in developing countries that have non-existent or ineffective waste management practices. However, this does not mean that plastics are only known for their negative impacts on the environment. Their unique properties, for example, lightweight, strength, durability, affordability, corrosion resistance and low production costs [9], high functionality, and relatively low cost make them suitable for use in different forms for various applications including food packaging, construction, household, and medical products [10].

To close the loop of the circular economy, the old way of doing things following the "make, use and dispose of" model should be abandoned for the sustainable "make, use, reuse and recycle" model [11]. More in-depth studies such as modeling and simulation are necessary to improve waste processes and move towards sustainability, as well as to create a society free from the risk of resource exhaustion, where cities' ecosystems, especially, opportunities and challenges for reuse and recycling, are preserved without being threatened. According to [12], dynamic modeling and simulation (or dynamic system simulation) is "the collective ability to grasp a system and implications of its changes over time together with forecasting." It takes feedback into consideration, which could be a fundamental idea of analytic thinking and is widely used as a modeling and simulation methodology for long-run decision-making analysis of business management issues [13].

Maria [14], states that a model for simulation could be a mathematical model that may be: deterministic or stochastic, depending on the data; dynamic or static, depending on the consideration of time; continuous or discrete, if the time is continuous or considered in discrete points. The selection of the model depends on a trade-off between realism and simplicity. Simulated experimentation accelerates and replaces effectively the "wait and see" anxieties in discovering new insight and explanations of future behavior of the real system. Linear programming, input-output analysis, expert systems, and system dynamics are among the many models that had been applied to aid decision-makers in the designing and management of solid waste management systems [15] in current literature.

Over the past decade, emphasis has been placed on the dynamic capacity of solid waste generation forecasting systems [16, 17]. In the recent past, time series simulations and / or forecasting methods have been identified as one of the most important requirements for solving problems arising in the operation of a production system, providing decision support at the planning and execution level [18], forecasting methods are models capable of providing forecasts on certain phenomena on the basis of what are called "time series", term which designates a chronological sequence of events [19]. Negahban and Smith [20], like [21], report that forecasting is an essential part of decision making related to sourcing, purchasing, manufacturing, inventory, logistics and finance, among others. In the solid waste management literature, there is a wide range of prediction methods, including probable quality distributions [22], Interval Parameter Fuzzy Stochastic Programming Approach [23], Two Stage Interval Stochastic Programming Model [24] and artificial neural network (ANN) models [25].

There are several other cases in the existing literature where integrated simulation and prediction techniques have been used [26, 27], however, there is some paucity in existing literature with regard to the use of these techniques to create a decision support tool. A lot of other applications of parametric univariate time series models such as the Autoregressive Integrated Moving Average (ARIMA) model [28] have been used to simulate demand for domestic consumption-imports-exports of goods in order to adopt adequate solutions [29], in agricultural productions, [30, 31]; predict electricity production [32], and some other products and services [33, 34]. A time series $\{Y_t\}$ is a set of observations always indexed in the temporal order t, and is said to be discrete if the observations are recorded at successive equidistant instants [35]. ARIMA models describe the actual behavior of variables in terms of linear relationships with their past values and have been shown to be relatively robust compared to more sophisticated structural models in terms of short-term forecasting capabilities [36] .

Previous studies on waste management in Cameroon have either focused on waste collection, treatment, and disposal and its impact on the environment[37], the composition and rate of generation [38], or laws and regulations aspects [39] on waste management. Though implicit in operational management and planning, dynamic modeling and simulation have never been the focus of policymakers and waste managers in the past. As a result, often policies are based on rough estimates with little empirical data to support them. The present work attempts to fill this lacuna by exploring the dynamics of plastic wastes generation and to forecast the monthly generations rates using Autoregressive Integrated Moving Averages (ARIMA) time series model. This study contributes to the environmental sustainability debate by addressing the following key objectives:

- Assess the composition and trend in the generation of plastic wastes in the Bonaberi industrial region of Cameroun, and,
- Explore the time series data of plastic wastes generated in the region to build a time series model that can be used to make predictions on the quantities of plastic wastes generated to improve operational planning and management.

The Box-Jenkins type stochastic Autoregressive Integrated Moving Average (ARIMA) process was used because it provides a convenient framework that allows an analyst to find an appropriate statistical model that could be used to answer relevant questions about data, and because it has the capability of dealing with assumptions about system structures in a stringent fashion.

II. MATERIALS AND METHODS

Study Area

Bonabéri, (headquarter of the Douala 4th district, having about 242,847inhabitants, surface area 25,65km^2) is one of the five urban municipalities/districts that make up the Douala city council. It is located at 4.08° North latitude, 9.68° East longitude, at an average elevation of 1-meter above sea level. It is bounded to the North by the Dibombari subdivision of the 'Mungo division, to the East by Douala I, II, III, and V councils, and to the south by the River Wouri (Fig 1)

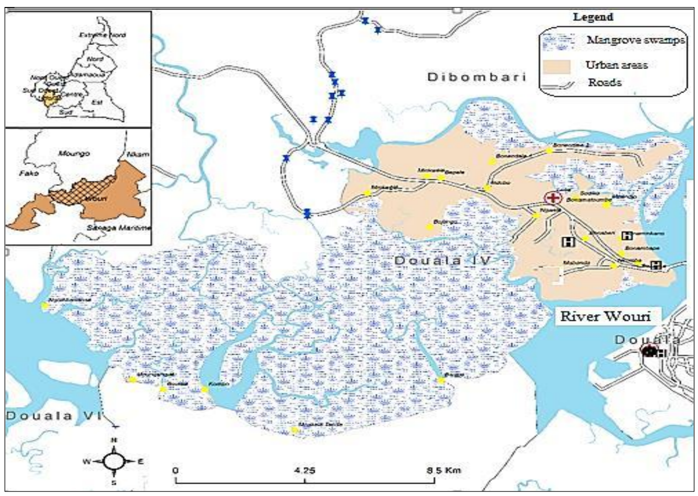


Fig 1. Location of the study area

The subdivision has expanded geographically in terms of industries, human settlement, and population over the years. The unchecked population growth, compounded by poorly planned land-use practices has impacted negatively on the catchment's structural and natural ecological stability over the years. Though there are small private firms in the waste management sector, municipal solid waste management in the area is the main activity of the private operator, "Hygiene et Salubrite du Cameroun" (HYSACAM). HYSACAM operates across the entire municipal solid waste management chain, from collection through to processing.

Sample selection and eligibility criteria

The Bonaberi Industrial Zone, is found in the Douuala 4th district of the Douala urban council, littiral region of Cameroon was selected after an exploratory investigation for their high municipal plastic generation and because, there is proliferation of plastic recycling enterprises in the zone. Two main enterprises (ISOTECH Consulting Sarl and DONG SHENG SULIAO GONSHI) were purposefully selected for the collection of data on plastic wastes generation in the zone because they have been in the business for atleast five years. They were chosen because they are the only ones engaged in the daily collection and transformation of plastic wastes in the region.

Data Collection

Data collection took place between April and May 2021. Both secondary and primary data were exploited. Secondary data was obtained through the screening of potentially relevant articles (February – May 2021). The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) were employed for the review [40]. The purpose was to understand the current state of the art knowledge in the field. This also enabled us to obtain background information that enabled the construction of a conceptual model. Both secondary and primary data were collected.

Next, each of the leading companies in the zone was contacted for monthly historical data of municipal plastic waste (MPW), covering the period from January 2014-December 2020. This period corresponds to the average time these enterprises had been in business. In each of these enterprises, wastes pickers are contracted to pick and transport plastic wastes from dumpsites to them, where they are weighed and paid accordingly. The monthly averages of these daily collections constitute the monthly generation rates for the industrial zone. Primary data was collected using checklists that were designed for the waste collection enterprises. Through observations and focus group discussions with the authorities of the enterprises, insight into the different categories of MPW collected, as well as the properties related to their uses was decoded.

Data Analysis

Classification of MPW generated

The Resin Identification Code system designed for material recycling and recovery by the Society of the Plastics Industry, was used to classify the different MPW generated into their appropriate categories namely: (1) Polyethylene terephthalate (PET), (2) Polyethylene(PE): Low-density polyethylene, LDPE, and High-density polyethylene, HDPE, (3) Polyvinyl chloride (PVC), (4) Polypropylene (PP), (6) Polystyrene (PS), and (7) OTHER (acrylic, nylon, polycarbonate, polylactic acid). After MSW was unloaded, the pile of MSW was flatted and grouped randomly.

Development of ARIMA modeling for plastic wastes modeling

A five – phase ARIMA (p,d,q) building and forecasting algorithm was adopted (Fig. 2)

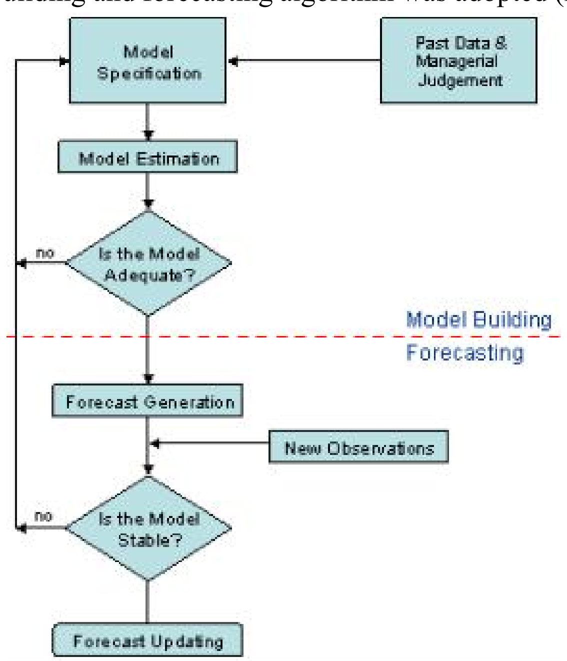


Fig 2. ARIMA (p,d,q) building and forecasting algorithm

In the preliminary phase, the data was explored to identify and eliminate possible cyclical and seasonal behavioral patterns in the plastic waste data, as they frequently exhibit such behaviors. The objective was to find the integer values of p, d, and key questions answered at this stage included:

a) Is there a trend, or on average, do the measurements tend to increase (or decrease) over time?
b) Is there seasonality- a regularly repeating pattern of highs and lows related to calendar time such as seasons, quarters, months, days of the week, and so on?
c) Is there a long-run cycle or period unrelated to seasonality factors?
d) Is there constant variance over time, or is the variance non-constant?, and
e) Are there any abrupt changes to either the level of the series or the variance?

In order to identify the proper *p, d,* and *q* parameters to model and forecast plastic wastes generation, the Box-Jenkins algorithm was adopted as follows: (1) model identification, (2) model estimation, (3) model diagnostics, and (4) forecasting.

In the second phase (model identification) stationery behaviours were eliminated. Model identification involves determining whether a particular model with specific p, d and q parameters is a good statistical fit. This study employed sample autocorrelation function (ACF) and sample partial autocorrelation function (PACF) tests to identify the d parameter. Denoted, $\rho(l)$, the autocorrelation coefficient between a time series, $\{Y_t\}$ and $\{Y_{t-1}\}$ is defined as (Equation 1)

$$\rho(l) = \frac{Cov(Y_t, Y_{t-1})}{Var(Y_t)} \qquad [1]$$

The highly subjective nature of the ACF and PACF methods made alternative objective methods for identifying ARMA models imperative.

For any ARIMA (p, d, q) process, the theoretical PACF has non-zero partial autocorrelations at lags 1, 2...,p and has zero partial autocorrelations at all lags, while the theoretical ACF has non-zero autocorrelation at lags 1, 2, …, q and zero autocorrelations at all lags. The non-zero lags of the sample PACF and ACF are tentatively accepted as the p and q parameters. The following techniques were used to stationarise the time series:

a) *Detrending:* This is simply the removal of the trend component from the time series:

$$X_t = (mean + trend * t) + \varepsilon \qquad [2]$$

Where,

The part in the parentheses was removed and the rest was used to build an appropriate model for the data.

X_t= plastic waste generated at time t, and

ε = error term or uncorrelated process: $\varepsilon \sim N(0, \sigma^2)$,

b) *Seasonality:* Because data is likely to exhibit a kind of seasonal pattern that is not stable over time, considerations were made for the possible addition of sAR term to the model in case the autocorrelation of the appropriately differenced series becomes positive at lag s, where s is the number of periods in a season. It is worth mentioning that if the autocorrelation of the differenced series is negative at lags, an sMA term should be added to the model. This situation is likely to occur if a seasonal difference has been used, which should have been done in this analysis if the data had a stable and logical seasonal pattern.

c) *Differencing*: This technique was used to remove non-stationarity in the data. Non-stationary stochastic process is indicated by the failure of the estimated autocorrelation functions to die out rapidly. To achieve stationarity, a certain degree of differencing (d) is required. In this paper, this was done by fitting the first order AR model to the raw data to test whether the coefficients φ is less than one. The objective was to identify an appropriate sub-class of the model from the general ARIMA family (Eqn. 3).

$$\emptyset(B)\nabla^d Z_t = \theta(B)\alpha_t. \ [3]$$

The degree of differencing (d), necessary to achieve stationarity is attained when the autocorrelation functions (Eqn 4) die out fairly quickly.

$$X_t = (1 - \mathrm{B})^d = \nabla^d Z_t \qquad [4]$$

The autocorrelation function of an AR (p) process tails off, while its partial autocorrelation function has a cut off after lag p. Conversely, the ACF of a MA (q) process has a cut off after lag q, while its partial autocorrelation function tails off. However, if both the ACF and PACF tail off, a mixed ARMA (p,q) process is suggested. The ACF of a mixed ARMA (p,q) process is a mixture of exponentials and damped sine waves after the q-p lags. Conversely, the PACF of a mixed ARMA (p,q) process is dominated by a mixture of exponentials and damped sine waves after the first p-q lags. In this paper, the time series was differentiated until a rapidly decaying Autocorrelation Function (ACF) compatible with that of an ARIMA process was obtained (Brockwell and Davis, 2002) [40].

Once a stationary series was been obtained, an optimal model was built in phase 3 (Model Estimation) by comparing the sample ACF (aka Autocorrelation Function) and PACF (aka Partial Autocorrelation Function) plots to the theoretical ACF and PACF for the various ARIMA models. The Auto here simply means we are taking the correlation of the variable to itself, but with a lag version of it. Partial autocorrelation, on the other hand, measures the correlation of the variable after removing the effects of previous time lags. For example, the PACF value at lag k is the net effect of y(t) and y(t+k) which is not explained by the lag from 1 to k-1. The principle of parsimony was employed for the final model selection. A parsimonious model is desirable because including irrelevant lags in the model increases the coefficient standard errors and therefore reduces the t-statistics. Models that incorporate large numbers of lags, tend not to forecast well, as they fit data specific features, explaining much of the noise or random features in the data.

In the fourth phase, the model was assessed to see how well it fits the data (Model diagnosis). The objective was to find optimal parameters for the model. We assess this through ACFs and PACFs. Several (p,d,q) combinations were explored to ensure that values found in previous section were not just approximate estimates. The Bayesian Information Criterion, BIC, was employed for model selection among the finite set of models under test (Equation 5):

$$BIC = n\left[ln\left\{\frac{1}{n-1}\sum_{i-1}^{n}(x_i-\bar{x})^2\right\}\right] + k[\{\ln(n)\}] \quad [5]$$

Where,

n = The number of data points/observations, or the sample size;

k = The numbers of free parameters to be estimated,

$\hat{\sigma}^2{}_e = \frac{1}{n-1}\sum_{i-1}^{n}(x_i-\bar{x})^2$ = The error variance, and

x = The observed data (here, MSW generated)

To test the overall randomness of the model (or independence of residuals), the Ljung-Pierce Q-statistics (Ljung and Box, 1978) was employed:

$$Q = T(T+2)\sum_{k=1}^{s}\frac{r^2{}_k}{T-K} \quad [6]$$

Where

T= number of observations

s = length of coefficients to test autocorrelation

r_k = Autocorrelation coefficient (for lag k)

If the sample value of Q exceeds the critical value of a χ^2 distribution with *s* degrees of freedom, then at least one value of *r* is statistically different from zero at the specified significance level.

As a general rule, given any set of estimated models, the model with the lower value of BIC is the one to be preferred. In addition to the residual plots and Ljung-Pierce Q-statistics, the R-squared, Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE) were used to check on the efficiency of the model. Usually the fitting process is guided by the principal of parsimony, by which the best model is the simplest possible model – the model with the fewest parameters that adequately describes the data.

Once the final ARIMA model was found, it was then used in a final phase (phase 5) to make predictions on the future time points for plastic wastes generated. Prediction intervals based on the forecasts were also constructed. ARIMA modeling was developed using the Statistical Package for the Social Sciences (SPSS) version 20 software and Eview version 12. To make 12 monthly forecasts, the data were divided into two parts, comprising 84 sample observations from January 2014 to December 2020 and 12 out-of-sample observations from January 2021 to December 2021. According to [41], statistical forecasting methods are extremely useful when it comes to short- and medium-term forecasting. The first part is considered as historical period (for fit) and the second part is named validation period (for forecasting) to verify the out-of-sample accuracy and adequacy of the model for the data.

Theory/calculation

Plastic generation per month is a continuous variable, and it is measured once per month without gaps for 7 years. The data was modeled using Autoregressive Integrated Moving Average (ARIMA) stochastic model. The model takes into account historical data and decomposes it into an Autoregressive (AR) process, where there is a memory of past events; an integrated (I) process, which accounts for stabilizing or making the data stationary, making it valid for forecast; and a Moving Average (MA) of the forecast errors, such that the longer the historical data, the more accurate the forecast will be, as it learns over time.

ARIMA model therefore have three model parameters, one for the AR(p) process, one for the I(d) process, and one for the MA(q) process, all combined and interacting with each other and recomposed into the ARIMA(p,d,q) model. These models are fitted to time series data either to better understand the data or to predict future points in the series:

- A *p*th-order autoregressive model, or AR(p), takes the form:

$$Yt = \alpha_1 Y_{t-1} + \ldots + \alpha_p Y_{t-p} + \epsilon_t \quad [7]$$

Where:

Y is a response variable,

α is a constant and

ϵ is the uncorrelated random error term with zero mean and constant variance, that is, $\epsilon \sim N(\mu = 0, \delta = 1)$.

The equation demonstrates that the forecast value of Y at time t depends on its value in the P previous time period and a random term at time t. A useful property of an AR (p) process is that it can be shown that the partial ACF is zero at all lags greater than. This means that the sample partial ACF can be used to help determine the order of an AR process (assuming the order is unknown as is usually the case) by looking for the lag value at which the sample partial ACF 'cuts off' (meaning that it should be approximately zero, or at least not significantly different from zero, for higher lags).

- *d* is the number of differences. ARIMA (p, 0, q) = ARMA (p, q). A model with autoregressive terms can be combined with a model having moving average terms to get an ARMA (p, q) model (equation 8):

$$Y_t = \phi_0 + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \ldots + \phi_p Y_{t-p} + \varepsilon_t - \omega_1 \varepsilon_{t-1} - \omega_2 \varepsilon_{t-2} - \ldots - \omega_q \varepsilon_{t-q} \quad [8]$$

ARMA (p,q) models can describe a wide variety of behaviors for stationary time series.

- A *qth*-order moving average model, or MA (q), takes the form:

$$Y_t = \mu + \varepsilon_t - \omega_1 \varepsilon_{t-1} - \omega_2 \varepsilon_{t-2} - \ldots - \omega_q \varepsilon_{t-q} \quad [9]$$

Where:

Y_t = response variable at tie t

$\mathscr{M}$ = Constant mean of the process

w_q = regression coefficients to be determined, and

ϵ_{t-q} = error in time *t-k,* and constitute a white noise.

In addition to the non-seasonal ARIMA (p, d, q) model, is the seasonal ARIMA (P, D, Q) parameters for the data were also identified**42**:

- Seasonal autoregressive (P),
- Seasonal Differencing (D) and
- Seasonal moving average (Q).

The general form of the above model describing a current value X*t* of a time series by its own past is:

$$Xt = (1-\emptyset_1\beta)(1-\propto_1\beta^{12})(1-\beta^{12})X_t = (1-\theta_1\beta)(1-\gamma_1\beta^{12})\epsilon_t \quad [10]$$

Where:

$1-\emptyset_1\beta$ = Non seasonal autoregressive of order 1

$1-\propto_1\beta^{12}$ = Seasonal autoregressive of order 1

X_t = The current value of the time series examined

$1-\theta_1\beta$ = Non-seasonal moving average of order 1

β = The backward shift operator $\beta X_t = X_{t-1}$ and $\beta^{12}X_t = X_{t-2}$

1- β = First order non-seasonal difference

$1-\beta^{12}$ = Seasonal difference of order 1

$1-\gamma_1\beta^{12}$ = Seasonal moving average of order 1

III. RESULT AND DISCUSSION

Composition and characteristics of plastic wastes generated

Based on self-reported levels of inadequate disposal, the study revealed that on average, 16477.143Kg/month of municipal plastic wastes of all categories are generated in the Bonaberi Industrial Region, with polyethylene (49.85%) dominating. This is closely followed by, PP (24.95%), and PVC (7.95%).

Table 1. Categories and average quantities of plastic wastes generated in the district

ID	Type of Plastic waste	Quantity generated (Kg/month)	Parentage composition(%)
1	Polypropylene	4110.714	24.95
2	Polyethylene	8214.286	49.85
3	Polystyrene	953.571	5.79
4	Polycarbonate	739.286	4.49
5	Polyvinyle chloride	1148.571	7.95
6	Polyamides	1310.714	6.97
	Total	16477.143	100

According to the collection centers, these plastics wastes can be put into varying uses based on their characteristics or a combination of properties.

Table 2. Characteristics And Uses Of Thermoplastics Generated At The Bir

Name, abbreviation	Characteristics	Use
Polyethylene (PE)	Translucent, inert, easy to handle, cold resistant. There are two families: - LDPE (low density polyethylene) good chemical resistance, olfactory,taste and chemically neutral, easily processed and welded. - HDPE (high density polyethylene)	LDPE: flexible products: bags, films, sachets, cans, containers and flexible bottles (sauces, shampoo, creams ...) HDPE: rigid objects (bottles, flasks, waste bins, pipes, toys, household utensils, boxes storage, plastic bags
Polypropylene (PP)	Semi-rigid, Translucent, Good chemical resistance, Tough, Good fatigue resistance, Integral hinge property, Good heat resistance.	Polypropylene (PP) is one of the most commonly used thermoplastics in the world. Polypropylene uses range from plastic packaging, plastic parts for machinery and equipment and even fibres and textiles.

Polystyrrene (PS)	Unmodified polystyrene is clear, rigid, brittle and moderately strong. Its electrical properties are good, though it has relatively low heat resistance	Packaging, Household appliances. Consumer electronics products. Building and construction, for example insulation foam, panels, bath and shower units, lighting and plumbing fixtures.
Polycarbonate (PC)	Polycarbonates are strong, stiff, hard, tough, can maintain rigidity up to 140°C and toughness down to -20°C or special grades even lower.	PC is commonly used for plastic lenses in eyewear, in medical devices, automotive components, greenhouses, Digital Disks (CDs, DVDs,…), and exterior lighting fixtures.
Polyethylene terephthalate (PET)	Hard, stiff, strong, dimensionally stable material that absorbs very little water. It has good gas barrier properties and good chemical resistance except to alkalis (which hydrolyse it). Its crystallinity varies from amorphous to fairly high crystalline	PET is a clear, strong, and lightweight plastic that is widely used for packaging foods and beverages, especially convenience-sized soft drinks, juices and water.
Polvinyl cholride(PVC)	Density: PVC is very dense compared to most plastics (specific gravity around 1.4) Economics: PVC is readily available and cheap. Hardness: Rigid PVC ranks well for hardness and durability. Strength: Rigid PVC has excellent tensile strength	PVC is a versatile material that offers many possible applications, these include; window frames, drainage pipe, water service pipe, medical devices, blood storage bags, cable and wire insulation, resilient flooring, roofing membranes, stationary, automotive interiors and seat coverings, fashion and footwear, packaging.
Polyamides (PA)	High Abrasion Resistance – Higher levels of resistance to wear by mechanical action. Good Thermal Resistance – Special grades of nylon can have a melting point of almost 300°C.	Often features in the production of items that require both strength and flexibility, including fishing line, electrical connectors, gears, guitar picks and strings and medical implants.

The mean monthly quantities generated show a constant increasing trend.

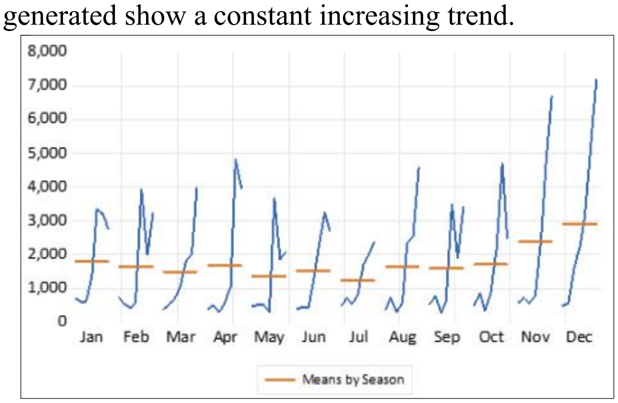


Fig 2. Residual plot of plastic wastes generated by season (white noise)

There is a clear opportunity for Bonaberi industrial region of Cameroon to develop local capacities for recycling PET bottles.

Physical analysis and determination of exact waste materials compositions are key factors in designing a management strategy in terms of considering recycling, reuse, transformations and final disposal [43, 44]. Though there is the potential for these wastes to be transformed into finished products, collection centers in the region are currently interested in transforming them into granules. The granules are packed in bags of 25kg for sale to manufacturing companies elsewhere.

The participation of the general public is important in waste management yet they are neglected as was observed in the Bolgatanaga Municipality and by [45] in Kenya. For instance in Ghana where the only medium scale recycling company, Blowplast Limited operates, it engages about 100 people in collecting plastic waste sachets [46]. These people therefore form a link between the sources of plastic waste including the households and recycling companies. [35] emphasize the importance of the general public by explicitly putting it that, "Without the public's conscious, collective decision to support an alternative route to their waste, there will be no material for the post-consumer waste recycling industries."

Description of original series

While the polypropylene showed increasing exponential trends, the rest generally portrayed cyclical patterns with the polyethylene dominating.

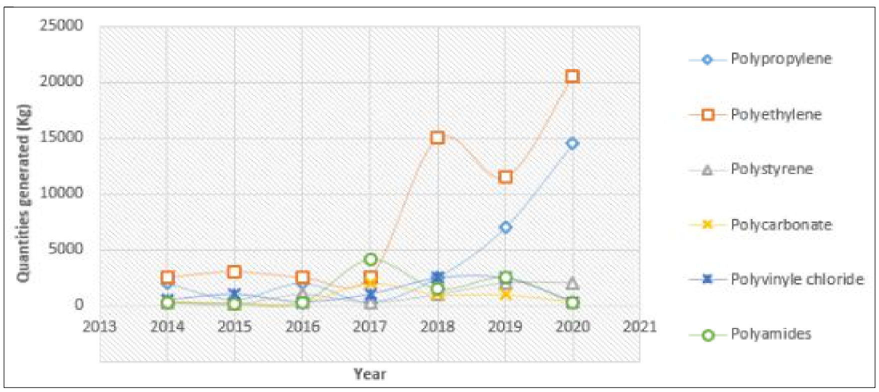


Fig 3. Annual patterns of plastics wastes generated in the district

Exploring the Plastic waste data for a pattern

It can be further inferred from the correlogram (Fig. 4) that: (1) the month to month trend clearly shows that plastic waste generations have been increasing without fail, (2) there seem to be the presence of trend in the mean since the left hand side of the plot is lower than the right hand side. The fluctuation differences also suggest trend in variance, and (3) there is no evidence of seasonal components since no regular peaks and troughs are observed.

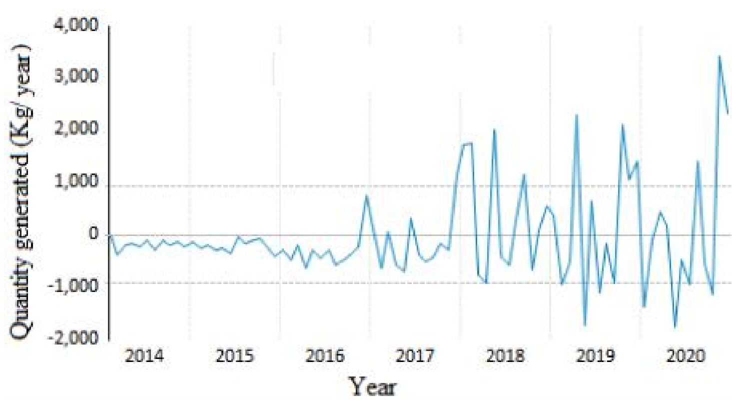


Fig 4. Variation in original series X, of pastic wastes (2014-2020)

Autocorrelations of the original series die out slowly at high lags, with significant Ljung-Box Q statistic at each lag, suggesting the non-stationarity behaviour of the series, a weak ARIMA model, and that the model as such does show a lack of fit.

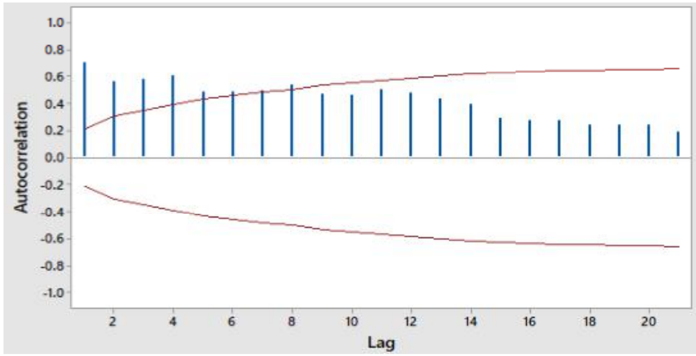


Fig 5. Residual plot of ACF for plastic wastes generated, ARIMA (0, 0, 0) with a constant

Seasonality usually causes the series to be nonstationary because the average values at some particular times within the seasonal span (months, for example) may be different than the average values at other times. This syndrome was treated by using both difference and logarithmic methods of transformations. Firstly, the series was transformed using the first order difference method (d = 1) and a near stationary series was obtained, however, variation in the plot is increasing as we move towards the right of the chart. Consequently, the series was transformed by taking the second differences of the natural logarithms of the values in the series so as to attain stationarity in the second moment:

$$X_t^{new} = log_e(X_t) = log_e(X_t) - log_e(X_{t-1})$$

Where $X_t = \phi_0 + \phi_1 X_{t-1} + \phi_2 X_{t-2} + ... + \phi_p X_{t-p} + \varepsilon_t$

Following this transformation, the data became stationary on both mean and variance (Fig 6).

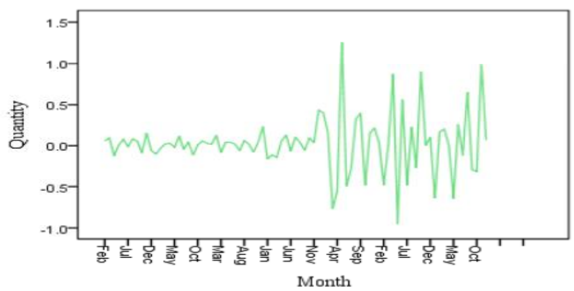


Fig 6. Transforms:Natural log, Difference (1)

The pattern displayed in the figure suggests that the integrated part of our ARIMA model will be equal to 1 as first difference is making the series stationary. The autocorrelation and partial autocorrelation functions of the log, differenced series indicated no need for further differencing as they tend to be tailing off rapidly. They also indicated no sign of seasonality since they do not repeat themselves at lags that are multiples of the number of periods per season.

Model Identification

For the first log differenced series, ARIMA (p, 1, q) are considered where d=1 is the order of differencing. The patterns of the ACF and partial autocorrelation function (PACF) plots of the differenced series were examined for the tentative determination of the components of the autoregressive (p) and moving average orders (q) in ARMA(p,q) model(Fig. 7 a & b).

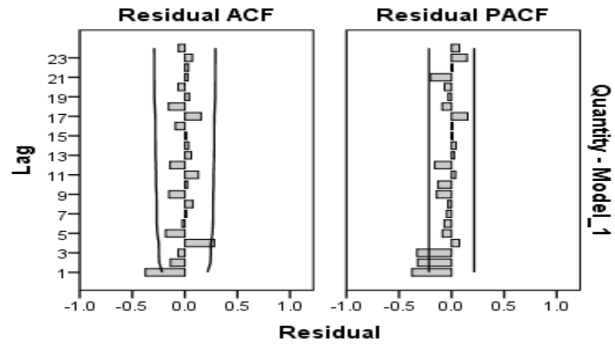


Fig 7. Sampled ACF (a) and PACF (b) for differenced (1) Solid Waste Data

We infer from Fig. 7 that there are partial autocorrelations at lags 1, 2 and 3 as the spikes exceeded the significance bounds. Clearly, these patterns suggest a variety of ARIMA models including ARIMA (1,1,1), ARIMA(2,1,1), ARIMA(1,1,2), ARIMA (3,1, 1), ARIMA (3,1, 4) as potential fits for data. Considering that the judgment is very subjective, to establish a more accurate model, the range of values of p and q is appropriately relaxed, and multiple ARMA (p, q) models are established.

Model Diagnosis and Selection

The efficiencies of the models to forecast plastic waste generation in the municipality were assessed using the R-squared, Root, Mean Squared Errors (RMSE), Mean Absolute Percentage Error (MAPE), the normalized BIC and the Ljung-BoxQ statistics (table 3).

Table 3. Evaluation of various ARIMA models

Model	Model statistics				Ljung-BoxQ(18)			Outliers
	R^2	RMSE	MAPE	Normalized BIC	Statistics	df	Sig.	
ARIMA(1,1,1)	*.654*	*940.743*	*36.977*	*13.853*	*12.757*	*16*	*.690*	*0*
ARIMA(3,1,1)	.603	1008.301	40.439	13.992	17.085	16	.380	0
ARIMA(1,1,2)	.654	946.356	39.076	13.918	12.758	15	.621	0
ARIMA(2,1,1)	.654	946.579	39.084	13.919	12.761	15	.621	0

It can be inferred from the table that all the estimated coefficients are significantly different from zero and the root mean square errors (RMSE), MAPE, R-squared and BIC are similar for all models, except ARIMA (3, 1, 1). This suggests that the errors are exactly the same and that there are no programming mistakes in the model. In addition, there were no white noises at 5% significance limit for all models as there were no spikes outside the insignificant zone for both ACF and PACF plots. Furthermore, all residuals were independent, identically distributed and were therefore adequate for the observed data. Therefore, either model is adequate and provides nearly the same three-step-ahead forecasts.

Parsimonious Model

The aim of this type of modelling is to produce a model that is parsimonious as possible, whilst passing the diagnostic checks. Following this, the simpler AR (1) model was selected to forecast future readings. More so, ARIMA (1, 1, 1) outperformed other potential models in terms of MAPE, and RMSE and BIC measures. The low value of RMSE (940.743) indicates a good fit for the model. Also, the high value of the R-Square (.654) and MAPE (36.977) indicate a perfect prediction over the mean. A further look at the plots of the residual, ACF and PACF plot (Fig. 8) for the ARIMA (1, 1,1) model show a random variation- from the origin (0), the points below and above are all uneven, hence the model fitted is adequate.

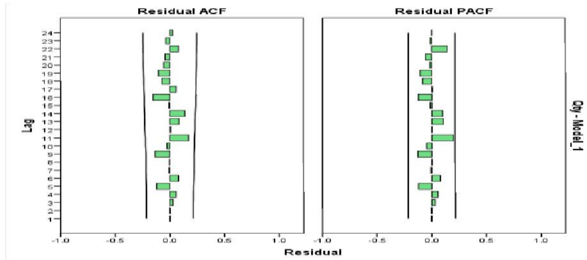


Fig 10. Autocorrelation & Partial Autocorrelation Functions of the Residuals

Reading from the bottom up, both figures show no pattern in the correlations reported among the residuals nor do any of the correlations extend beyond the vertical 95% confidence intervals included in the plots. This, combined with the Ljung-Box Q statistic, and the Normalized Bayesian Information Criterion (BIC), suggests that the ARIMA (1, 1,1) model appropriately modeled the dynamics for this time series. Table 4 summarizes the statistical significance of the terms in the forecasting model.

Table 4. ARIMA (1) model parameters

Variable	Estimate	SE	t	Sig.
Constant	.028	.012	2.370	.020
AR(1)	.309	.156	1.983	.001
MA(1)	.842	.106	7.911	.000

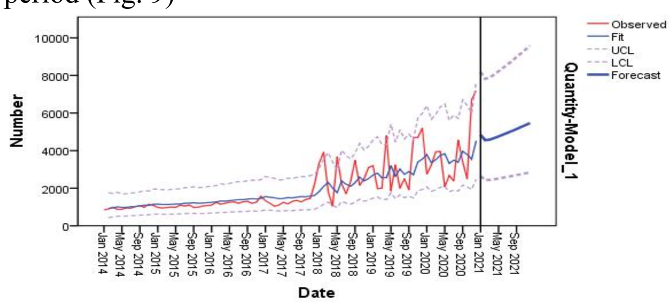
The p values of the associated with the parameters are less than 0.05, so the terms are significantly different from zero at the 95.0% confidence level. The developed model is given by the following equation

$$y_t = 0.028 + 0.309.\, y_{t-1} - 0.842\varepsilon_{t-1} + \varepsilon_t$$

The model residue is stationary and follows a white noise process in the range of ±30. The residues that distribute relatively normal around zero with a relatively low dispersion at a 5% risk.

Accuracy/stability of ARIMA (1, 1, 1) model

The accuracy of the developed model was evaluated by comparing the experimental and the simulated generation rates in the same period (Fig. 9)



Because of higher forecasting accuracy, ARIMA (1,1,1) was applied to estimate the municipal plastic wastes

Fig 9. Holt-Winters Additive prediction for tons of plastic wastes generated

MPW) generated in the industrial zone from December 2021 to 2022. Figure 9 shows the future prediction for municipal plastic wastes generation using time series and residual plots for ARIMA (1,1,1) model. Plastic waste values (in Kg) are shown by the thicker red sinusoidal curve, the forecasted values are shown by the thick blue line, whilst the bounded light pink shaded region areas show 80% and 95% prediction intervals respectively. We infer from the figure that the selected model has a high accuracy and ability to simulate the dynamic behavior of the quantifies generated. The model is validated since the predicted quantity fluctuates around the fit. Furthermore, the predicted quantities stayed between the upper limit and the lower confidence limits. In addition to this, it was observed that, the estimated model is covariance stationary: inverse AR roots should lie inside the unit circle; and the estimated process is invertible: inverse MA roots should lie inside the unit circle (Fig. 10).

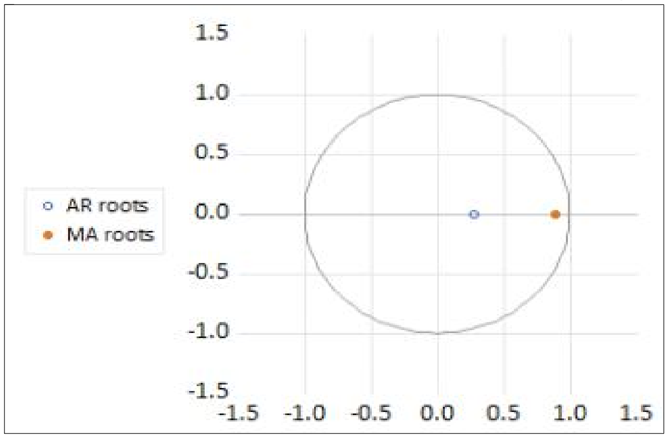


Fig 10. Test for the stability of the model

We can see in the figure above that all the inverse roots lie inside the unit circle. Hence, our ARIMA (1, 1,1) satisfies the stability conditions and the error terms are white noise. We are in a good spot now to forecast future values of the MPW generation.

It can be inferred from Table 5 that the total amount of plastic waste in Bonaberi Industrial Region showed a relatively stable rising trend in the following twelve months, and could reach approximately 5468 Kg/month, 95% CI (2843, 9581).

Table 5. Three-step forecast of the ARIMA (1) Model

Model		Jan 2022	Feb 2022	Mar 2022	Apr 2022	May 2022	Jun 2022	Jul 2022	Aug 2022	Sep 2022	Oct 2022	Nov 2022	Dec 2022
Quantity-Model_1	Forecast	4840	4558	4582	4662	4754	4850	4948	5048	5150	5254	5360	5468
	UCL	8174	7820	7889	8045	8219	8401	8587	8778	8972	9171	9374	9581
	LCL	2644	2438	2440	2475	2517	2561	2606	2652	2698	2746	2794	2843

For each model, forecasts start after the last non-missing in the range of the requested estimation period, and end at the last period for which non-missing values of all the predictors are available or at the end date of the requested forecast period, whichever is earlier.

Forecasting MPW generation is paramount for effective operational planning in the sector. That is, the information is not only important for determining the size of storage facilities and cost, but also the number and type of collection equipment, and future treatment and disposal capacity needs. The forecasts obtained after modeling can help managers make real time decisions on the type investments, the resources needed and therefore, the cost of investment, thereby minimizing potential losses.

Being a human inhabited industrial ecological system, the Bonaberi Industrial Region has seen a massive surge in population in recent years following the current Anglophone crises that started in 2016. The increasing population implies that much more MPW will be generated in the coming years. Therefore, research on a suitable model that explains MPW generation data is a significant step for ensuring successful MPW management in metropolitan cities such as Bonaberi. For this purpose, a combination of statistical tools was employed to select the most parsimonious ARIMA model to evaluate forecasting performances for future trends. Based on the principle of parsimony, ARIMA (1,1,1) model was considered, and was used to estimate the future MPW generation amount.

IV. CONCLUSION

The paper assesses models and forecasts plastic wastes generation for operational planning and management in the Bonaberi industrial region of Cameroon. The simulation model that underlies the information subsystem of management support for plastic solid municipal waste management has been developed. A statistical, ARIMA, was used in learning time series data of plastic wastes generated. Several diagnostic tests were performed to select the p, d, q parameter that best fit the series for the chosen period. On the basis of the BIC, the mean squared errors, Mean absolute deviation, mean percentage error. ARIMA (1,1,1) model was found to be most efficient in modelling time series dataset related to plastic waste quantity generated in the region. The model was validated and could be adequate for forecasting solid waste generation in the foreseeable future. The forecasting model allow municipal plastic wastes managers to predict at least a month within a mean relative error less than 10%, being these predictions very useful to optimize the resources needed for effective MPW management.

We therefore recommend the promotion of a circular economy focusing on ecological modernisation, plastic waste modeling, sustainable plastic waste manufacturing and recovery strategies such as recycling as a long-term strategies.The results of the study can help potential investors and authorities to create a reliable MPW prediction model, which can be an important source of information for the region. Furthermore, accurate prior knowledge about the amount of MPW generated can fine tune both the planning and design of future facilities. ARIMA has been successfully applied to solve many optimisation problems in existing literature. Some of these techniques have been discussed. This could be an interesting area of research in the future. In addition, technical, environmental, and socio-economic feasibility studies to explore the technical options available, and to determine the factors that are considered important for the economic success of the project, and causing significant environmental problems resulting from improper disposal, namely burning or dumping, could also direct future investors in the region.

V. ACKNOWLEDGMENTS

The authors are grateful to the Head of State, His Excellency President Paul Biya of Cameroon, for research modernization allowance, which has tremendously assisted in accomplishing this task. Many thanks also go to the enterprises for accepting to cooperate with the research team

REFERENCES

[1] J. Payne, P. McKeown, M.D Jones. *A circular economy approach to plastic waste.* ***Polym. Degrad. Stab***., 165, 2019, pp. 170–181.

[2] United Nations Environment Programme, Marine Plastic Debris and Microplastics – ***Global Lessons and Research to Inspire Action and Guide Policy Change***, United Nations Environment Programme, Nairobi, 2016.

[3] J. Zheng and S. Suh. Strategies to reduce the global carbon footprint of plastics. ***Nature Climate Change***, 9(5), 2019, p. 374

[4] R. Verma, K.S Vinoda, M. Papireddy and ANS Gowda. Toxic pollutants from plastic waste- a review ***Procedia Environmental Sciences***, 35, 2016, pp. 701-708.

[5] H. Ren, W. Zhou, Y. Guo, L. Huang, Y. Liu, Y. Yu and T. Ma. A GIS-based green supply chain model for assessing the effects of carbon price uncertainty on plastic recycling. ***International Journal of Production Research***, 58(6), 2020, 1705-1723.

[6] D. Karlaite. The importance of responsible production and consumption to overcome the plastic paradox. ***Social Transformations in Contemporary Society*** 4: 2016, 151–163.

[7] Q. Chen, J. Reisser, S. Cunsolo, C. Kwadijk, M. Kotterman, M. Proietti, B. Slat, FF. Ferrari, A. Schwarz, A. Levivier, D. Yin, J. Hollert Contreras, R. Espinola, F.J. Nogales, A.J. Conejo. ARIMA Models to Predict Next day Electricity Prices, ***IEEE Transactions on Power Systems***, Vol. 18, No. 3, 2003, pp. 1014-1020.

[8] L.S, Au, S. Ahn, & T.W. Kim. System Dynamic Analysis of Impacts of Government Charges on Disposal of Construction and Demolition Waste: A Hong Kong Case Study. ***Sustainability***, 10(4), 2018, 1077.

[9] WC Li, HF Tse, & L. Fok. Plastic waste in the marine environment: A review of sources, occurrence, and effects. ***Science of the Total Environment***, 566, 2016, pp. 333-349.

[10] V. Guillard; S. Gaucel; C. Fornaciari; H. Angellier-Coussy; P. Buche; N. Gontard. The next generation of sustainable food packaging to preserve our environment in a circular economy context. ***Front. Nutr***. 2018, 5, 121.

[11] M. Yaacob; M.H Ibrahim; Z.M. Nasir. Solid Waste Management in Malaysia: The Perspectives of Non-governmental Organizations (NGOs) and Youths on Consumers' Commitment. In Environmental Sustainability and Education for Waste Management; Springer: Heidelberg/Berlin, Germany, 2019; pp. 27–41.

[12] G. Bellinger. Modeling & simulation: An introduction. 2004. Retrieved February 9, 2006, from http://www.systems-thinking.org/modsim/modsim.htm.

[13] N. Kollikkathara, H. Feng, D. Yu. "A system dynamic modeling approach for evaluating municipal solid waste generation landfill capacity and related cost management issues," ***Waste Management***, Volume 30, 2010, pp. 2194-2203.

[14] Maria. Introduction to modeling and simulation. In S. Andaradóttir et al. (Ed.), 29th Winter Simulation Conference , 1997, pp. 7-13. Atlanta, GA: ACM Press.

[15] Z.G. Ming, Y.X. Zhong, Z.P. Yue, G.H. Cheg, H.G.G. He, L. Hemelaar, (2000) "Environmental input–output model and its analysis with a focus on the waste management sectors," ***Journal of Environmental Science***, Volume 12(2), pp. 178-183.

[16] B. Dyson, N.B. Chang. "Forecasting municipal solid waste generation in a fast-growing urban region with system dynamics modeling," ***Waste Management***, Volume 25, 2005, pp. 669-679.

[17] M.A. Sufian, B.K. Bala. "Modeling of urban solid waste management system: The case of Dhaka city," ***Waste Management***, Volume 27, 2007, pp. 858–868.

[18] R. Beregi, A. Szaller, & B. Kádár. Snergy of multi-modelling for process control. IFAC Papers OnLine, 51(11), 2018, 1023-1028. http://dx.doi.org/10.1016/j.ifacol.2018.08.473.

[19] D.C. Montgomery, C.L. Jennings, & M. Kulahci. Introduction to Time Series Analysis and Forecasting (1st ed.). New Jersey, 2008: John Wiley & Sons.

[20] Negahban, & J.S. Smith. Simulation for manufacturing system design and operation: literature review and analysis. ***Journal of Manufacturing Systems***, 33(2), 2014, 241-261. http://dx.doi.org/10.1016/j.jmsy.2013.12.007.

[21] M. Arvan, B. Fahimnia, M. Reisi,E. Siemsen. Integrating Human Judgement into Quantitative Forecasting Methods: A Review. ***Omega***, Volume 86, 2019, pp. 237–252.

[22] B.G. Wilson; B.W. Baetz. Modeling Municipal Solid Waste Collection Systems Using Derived Probability Distributions I: Model Development; ***ASCE J. Environ. Eng***. 2001; 127, 1031-1038.

[23] Y.P. Li, and G.H Huang. Minimax regret analysis for municipal solid waste management: An interval-stochastic programming approach, ***J. Air Waste Manage. Assoc.*** 2006a; 56, 931-944.

[24] Maqsood; G.H. Huang. A Two-Stage Interval-Stochastic Programming Model for Waste Management under Uncertainty; ***J. Air & Waste Manage. Assoc***. 2003; 53, 540-552.

[25] F. Karaca. and B. Özkaya, NN-LEAP: A neural network-based model for controlling leachate flow-rate in a municipal solid waste landfill site. ***Environ. Model. Software***. 21, 2006, 1190-1197.

[26] J.R. Rego, & M.A. Mesquita. Demand forecasting and inventory control: a simulation study on automotive spare parts. ***International Journal of Production Economics***, 161, 2015, 1-16. http://dx.doi.org/10.1016/j.ijpe.2014.11.009.

[27] P. Sharma, M.S. Kulkarni, & V. Yadav. A simulation-based optimization approach for spare parts forecasting and selective maintenance. ***Reliability Engineering & System Safety***, 168, 2017, 274-289. http://dx.doi.org/10.1016/j.ress.2017.05.013.

[28] GE. Box, GM. Jenkins, GC. Reinsel, GM. Ljung. Time series analysis: forecasting and control. John Wiley & Sons, 2015.

[29] Sohail, A. Sarwar and M. Kamran. Forecasting total food grains in Pakistan. ***J. Eng. Appl. Sci***., Department of Mathematics and Statistics, University of Agriculture, Faisalabad, 13: 1994, 140-146

[30] I.B. Najeeb, M. Khuda, M. Asif and S.A. Abid. Use of ARIMA model for forecasting wheat area and production in

[31] W. Rachana, M. Suvarna and G. Sonal. Use of ARIMA models for forecasting pigeon pea production in India. ***Int. Rev. Bus. Financ***., 2(1), 2010: 97-107.

[32] J.E. Contreras, H.A. Sanchez, E.A Eugenin, D. Speidel M. Theis, K. Willecke,F.F. Bukauskas, M.V.L. Bennett, & J.C. Sáez. Proc. Natl. Acad. Sci. USA 99, 2002, 495–500.pmid:11756680.

[33] Q. Liu, and H. Wang. Research on the forecast and development of China's public fiscal revenue based on ARIMA model. ***Theor Econ Lett*** ,2015; 5: 482–493.

[34] S. Shen, Y. Shen. ARIMA model in the application of Shanghai and Shenzhen stock index. ***Appl Math*** 2016; 7: 171–176.

[35] P.J. Brockwell and R.A. Davis. Introduction to Time Series and Forecasting. Springer. 2002.

[36] R.B. Litterman. Forecasting with Bayesian Vector Autoregressions-five Years of experience. ***Journal of Business & Economic Statistics***, 1986; 25-38.

[37] E. Ngnikam. Evolution Environmentale et Economique du system de gestion des dechets solides municipaux : Analyse du cas de Yaounde au Cameroun. LAEPSI, Lyon. Institute National des Sciences Applique de Lyon; 2000.

[38] NI. Mbue, D. Bitondo, RA. Balgah. Municipal Solid Waste Generation, Composition, and Management in the Douala Municipality, Cameroon. ***Journal of Environment and Waste Management***. 2015; 2(3): 091-101.

[39] VE. Manga et al., Waste management in Cameroon: A new policy perspective?, ***Resources Conserv Recycl*** (2007), doi:10.1016/j.resconrec.2007.07.003.

[40] D. Moher, A. Liberati, J. Telzlaff, DG. Altman, P. Group. Preferred reporting items for systematic reviews and meta-analyses: the PRISMA statement. ***PLoS Med***. 2009; 6(7).

[41] C.C. Zhao, Z.Y. Shang. Application of ARMA Model on prediction of Per Capita GDP in Chengdu City. ***Ludong University Journal (Natural Science Edition)***. 28 (2012) 223-226.

[42] S. Aparcana. Approaches to formalization of the informal waste sector into municipal solid waste management systems in low-and middle-income countries: Review of barriers and success factors. ***Waste management,*** 61, 2017, 593—607.

[43] JY. Park. Assessing determinants of industrial waste reuse: The case of coal ash in the United States. ***Resources, Conservation and Recycling,*** 92: 2014, 116–127.

[44] L. Oyake-Ombis, BJM. van Vliet and APJ. Mol. Managing plastic waste in East Africa: Niche innovations in plastic production and solid waste. ***Habitat International*** 8: 2015, 188–197.

[45] N.M. Wienaah. Sustainable Plastic Waste Management: A Case of Accra, Ghana, 2007, Arkitektur och samhällsbyggnad, Kungliga Tekniska högskolan. Available at, http://www2.lwr.kth.se/Publikationer/PDF_Files/LWR_EX_07_10.PDF; retrieved: 14/07/2021.

[46] S. McDonald. and R. Ball. Public participation in plastics recycling schemes. ***Resources, Conservation and Recycling,*** 22: 1998. 123-141