FUZZY LOGIC MODELLING OF MUNICIPAL SOLID WASTE GENERATION

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Abstract
The amount and factors that affect generation of municipal solid waste are important for solid waste management. This paper presents a model for the estimation of municipal solid waste using fuzzy logic. Fuzzy logic is a multivalued logic developed to deal with imprecise or vague data. Several parameters of waste generation were taken into consideration. A weighting system was used in analyzing all the aspects and this ensured an integrated and interrelated classification method. The obtained results established the success of the designed system in the evaluation technique of the best number of waste bins in each area.

Keywords: *Fuzzy logic, modeling, municipal solid waste, waste generation*

Introduction

Fuzzy logic is a form of multivalued logic derived from fuzzy set theory to deal with reasoning that is approximate rather than precise. The fuzzy logic variables may have a membership value of only 0 or 1, or between 0 and 1. In fuzzy logic, the degree of truth of a statement can range between 0 and 1 and is not constrained to the two truth values {true (1), false (0)} as in classic predicate logic (Novák et al, 1999). Fuzzy logic allows for partial membership in a set, values between 0 and 1, and introduces the concept of the fuzzy set. When the approximate reasoning of fuzzy logic is used with an expert system, logical inferences can be drawn from imprecise relationships.

The term "fuzzy logic" emerged as a consequence of the development of the theory of fuzzy sets. Fuzzy logic is used to optimize automatically the wash cycle of a washing machine by sensing the load size, fabric mix, quantity of detergent and has applications in the control of passenger elevators, household appliances, cameras, automobile subsystems, and smart weapons.

Municipal solid waste (MSW) generation data are used in the planning of waste management systems (Ogwueleka, 2003), including personnel and truck utilization (Matsuto and Tanaka, 1993); land demand for facilities (Leao et al, 2001) etc. They serve as a basis for further improvements and optimization in terms. The estimation and the prediction of municipal solid waste generation play an important role in solid waste management. The population growth and migration, underlying economic development, household size, employment changes, as well as the impact of waste recycling are factors that influence solid waste generation interactively. The design and development of a fuzzy model for calculating and forecasting the aggregate impact of economic trends, population changes, and recycling impact on solid waste generation was noted to be very useful in the application of solid waste management.

The issue of determining a suitable procedure of analysis for municipal solid waste quantities has been investigated in many research approaches. Certain aspects of MSW management and policies are found in the literature based on the correlation among socioeconomic data, solid waste composition and quantities. The main objective in these cases is to simulate the multivariate problem of MSW in a mathematical form by using deterministic models (mostly regression models) and trend analysis (Karadimas et al, 2005). Matsuto and Tanaka (1993) have normalized values of waste amounts and subsequently have estimated moving averages. Several studies have documented the use of time series on an annual (Beigl et al, 2004), monthly (Chang and Lin, 1997), or daily (Navarro-Esbri et al, 2002) basis using waste data, census and economics data in addition to waste management related information. Sircar et al (2003) proposed horizontal and vertical factors for the prediction of waste management quantities. Horizontal factors describe the processes of interchanges between different waste types. Vertical factors are due to change of the total sum of all waste streams depending on demographic, economic, technical and social developments. Parfitt et al (2001) used five collection infrastructure related variables as cluster criteria for a successive group comparison. Skovgaard et al (2005) provided forecasts for all necessary predictors for MWS forecasts to potential users. Chen and Chang (2000) proposed a grey fuzzy dynamic model without the use of any independent variable.

The main objective of these models is to provide a prediction tool. Most of these models are often unusable due to the lack of underlying data for the model parameters. These traditional forecasting methods need a complete socioeconomic and environmental database to build an essential mathematical model. Many cities may not have sufficient budget and manpower to perform such a long term and large scale sampling and analysis program (Liu and Yu, 2007). Nearly all statistical estimation models, such as the least-squares regression method and the curve extension method are designed based on the configuration of semi-empirical mathematical models but the fuzzy logic modeling handles the estimation issues under uncertainty.

Study Area

Abuja is the capital city of Federal Republic of Nigeria. Abuja lies between longitude 6^0 $45^/$ to 7^0 $38^/$E and latitude $8^0 25^/$ to $9^0 29^/$N. The study area is located on the North-eastern quadrant of Federal Capital Territory (FCT). Abuja has an area of 250 km^2 with population of about 450,000 by 2006.

Abuja phase 1 has central business area and residential districts with few businesses: Garki, Wuse, Asokoro and Maitama. The Garki District is the area in the southwest corner of the city, having the Central Area District to the north and Asokoro District to the east. The District is sub-divided into units called Areas. The District is numbered Areas 1-11 and Garki II. Wuse District is the northwestern part of the city, with Maitama District to its north and Central District to its south. The District is numbered Zones 1-8 with Wuse II. Maitama District is to the north of the city, with Wuse and Central District lying to its southwest and southeast respectively Maitama is mainly residential district with few commercial activities. Maitama has about 310 waste bins. The collection trucks must visit all bins in order to complete its collection. Asokoro is located on the east of Garki District and south of Central District.

The average waste generation rate in Abuja is 0.55-.58 kg per person per day (Solid Waste Audit Report, 2004). Abuja Environmental Protection Board (AEPB) is responsible for collecting waste from municipalities, and has made containers (120-L and 240-L plastic bins, and 1.1 m^3 metal bins) available to every household (Imam et al, 2007). There is no sanitary landfill in Abuja. Solid waste is transported to a dumpsite at Mpape.

Fuzzy set theory defines fuzzy operators on fuzzy sets. As there may be a problem of not getting the appropriate fuzzy operator, fuzzy logic rules of IF-THEN was used in this study. The rules was expressed in the form of IF *variable* IS *property* THEN *action,* as seen in the sample of the collection program which determines the level of waste bin collection in the study area.

Fuzzy reasoning is the process of deriving conclusions from a set of IF–THEN fuzzy rules using an inference procedure. Through fuzzy reasoning, the truth of the consequent is inferred from the degree of truth of the antecedent. The concept of fuzzy set theory, IF–THEN rules, and fuzzy reasoning together constitute a computing framework usually called fuzzy inference system (FIS). In this study, the FIS is made up of the rule base, a database and a reasoning mechanism.

Factors considered during the evaluation of the whole solid waste generation process in an area under study are land use, real-estate commercial values, are of study in square meters, maximum building density factor, and electricity bills. These factors are grouped into two main groups of estimation of the daily residential waste generation and commercial-industrial generation of solid waste in the study area. The residential waste coefficients include real estate commercial values (RECV), maximum building density factors (MBDF), size of area in square meters (SAS) and electricity bills of each residential property (EBRP); while the commercial coefficient includes factors related to commercial traffic (CCT), land use (LU), size of area in square meters (SAS) and the electricity bills (EBCP) of each commercial property.

This study aims to develop prediction model based on fuzzy logic to estimate municipal solid waste generation and consequently to the calculation of the optimal number of waste bin as well as their position in a pre-defined area. The model was applied to Maitama district, whose urbanistic structure is similar to that of the whole town.

Materials and Methods

This study developed a system that uses the fuzzy sets in describing uncertainties in the different factors involved in solid waste estimation. These factors were individually denoted by a variable representing the required values for both the residential and commercial property. The fuzzy based design methodology first step was to understand and characterize the system behaviour by using our knowledge and experience. The second step was to directly design the control algorithm using fuzzy rules, which describe the principles of the controller's regulation in terms of the relationship between its inputs and outputs. The last step was to simulate and debug the design. If the performance was not satisfactory during testing and implementation, then there will be need to modify some fuzzy rules and re-try. This fuzzy-based methodology substantially simplifies the design loop and this resulted in some significant benefits, such as reduced development time, simpler design and faster time to market.

The fuzzy rule base drives the inference system. The designed rule base consists of rules that describe the various supports of these factors on the study area total solid waste generation as shown in Figure 1.

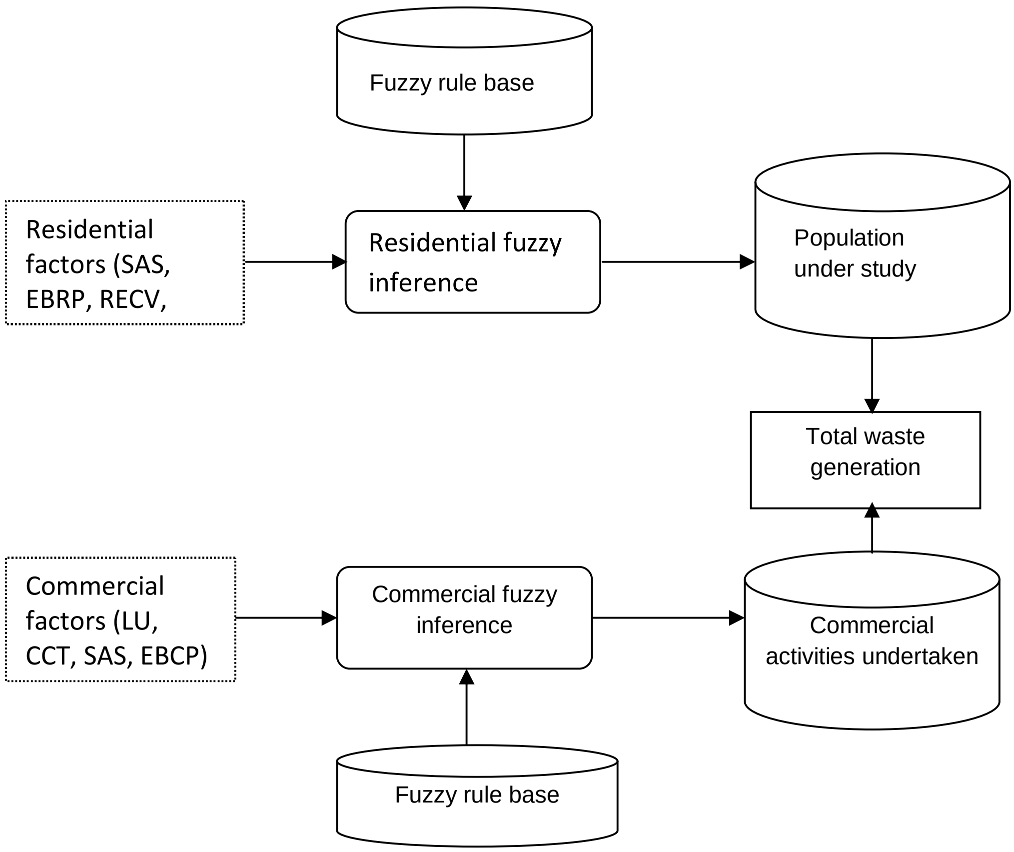

Figure 1: Fuzzy inference system (FIS) for solid waste estimation

The fuzzy inference system (FIS) that was modeled maps input characteristics to input membership functions; input membership functions to rules; rules to a set of output membership functions; and a decision associated with the output. This FIS is shown in Figure 2.

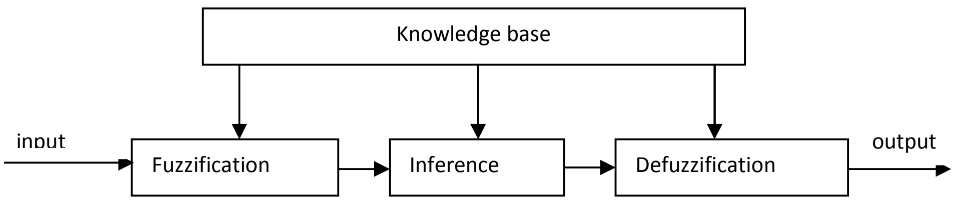

Figure 2: FIS model

The stages taken in the modeling approach used are: first, hypothesizes of a parameterized model structure relating inputs to membership functions to rules to outputs to membership functions; collection of input/output data in a form that will be usable for training; training of the FIS model to emulate the training data presented to it by modifying the system training the membership function parameters according to a chosen error criterion; and validation. A validation data set was used to check and control the potential for the model overfitting the data. After presenting the checking and training data to the system, the FIS model was selected to have parameters associated with the minimum checking data model error.

The structure of the designed fuzzy inference system consists of three major parts, namely a rule base that holds the fuzzy IF–THEN rules used in the inference process; a database that contains the membership functions that characterize the fuzzy sets, and a reasoning mechanism that performs the inference procedure and derives conclusions depending on a set of rules and facts. The fuzzy inference process consists of five steps including fuzzification, application of the fuzzy operators, fuzzy implication, fuzzy aggregation, and defuzzification. The last step uses a defuzzification method to produce a single crisp number for each output variable. These procedural steps are shown in Figure 3.

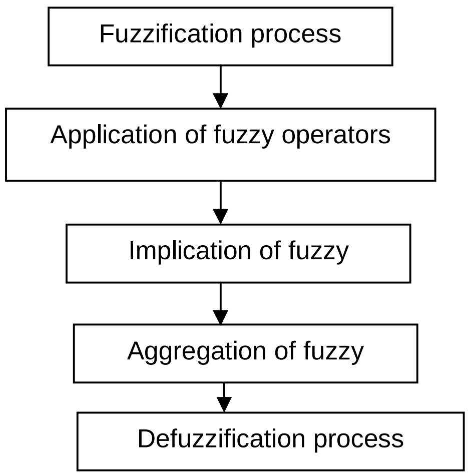

Figure 3: Steps in fuzzy inference process

The total solid waste generation was expressed as a weighted sum of all the listed factors. Linguistic values were used for the residential waste coefficient as well as for the commercial coefficient. Due to the kind of required representation of the fuzzy rules used in this study, Mamdani model was used in the system development. The Mamdani model was proposed by Mamdani in 1975 to control a steam engine and boiler combination.

The designed model was represented by the consequents of its rules using fuzzy sets. The aggregation of the outputs of all rules generated a single fuzzy set output. The defuzzification process was performed to extract a value from the output fuzzy set. The final output was given after defuzzification of the aggregated outputs, for both residential and commercial fuzzy inference, using the centroid method as described in Equation (1).

$$\mathrm{Def}_y = \frac{\int_y \mu_{B'}(y)\, y\, d(y)}{\int_y \mu_{B'}(y)\, d(y)} \qquad 1$$

After the defuzzification of each group of the coefficients the equation (2) was used to calculate the final solid waste generation. The equation was able to calculate the total solid waste generation on a given area, based on the population, the waste generation coefficient of the pre-defined area, the number and waste generation of the industrial and commercial activities accurately.

$$Total\ waste = \sum_{i=1}^{m} (a_i\, x_i + \sum_{j=1}^{n} b_{ij}\, y_{ij} \qquad 2$$

where a_i is the population of the examined area i, x_i is the value of the daily waste generation per person in the area i, produced by the defuzzification method. Also, b_{ij} is the total area (in m^2) of every commercial activity j in the particular segment area i, and y_{ij} is the coefficient related to waste generation of the commercial activity j in the area i produced by the defuzzification method. The m stands for the distinct set of areas, used for the calculation of the total solid waste generation, while n is the total number of commercial activities in each predefined area. The estimates, that is, x_i and y_{ij} coefficients was used to construct the prediction equation waste production and to generate predicted scores on a variable for analysis.

In this study, fuzzy logic rules were programmed using the fuzzy logic programming (FLP) language. The multi-adjoint logic program (FLP) was made up of the fuzzy logic and the logic programming. In the prototype tool, the system was implemented with the appropriate Prolog clauses. The generated Prolog code was also asserted in the system and saved into a

".pl" file. Both the fuzzy and Prolog are listed and have options of clean, stop and quit. The program provided two implementation techniques, namely compilation to Prolog code (run), which led to its simplicity, transparency, and complete evaluation of goals; and low-level representation (debug) where it gives the detailed data and other powerful manipulations.

Results and Discussion

Fuzzy logic is a paradigm for an alternative design methodology, which can be applied in developing both linear and non-linear systems for embedded control. By using fuzzy logic, designers can realize lower development costs, superior features, and better end product performance. With fuzzy logic, rules and membership functions can be used to approximate any continuous function to any degree of precision. Fuzzy sets and fuzzy logic deal with the concept of uncertainty.

The linguistic values used are ≠310, >310, <310, and normal. The linguistic values and the universe field of discourse on which these values are defined are called linguistic variables. The three basic operations on a classical set of union, intersection and complement were used. Through fuzzy reasoning, the truth of the consequent was inferred from the degree of truth of the antecedent.

The input variables in the designed fuzzy control system are mapped by sets of membership functions known as the fuzzy sets through the process of converting the crisp input value to a fuzzy value called fuzzification. This control system have the "0-1" and "ON-OFF" types of switch, which also have inputs of a truth value equal to either 1 or 0. With the given mappings of the input variables into membership functions and truth values, the microcontroller then makes decisions for what action to take based on the set of "rules", each of the form:

IF waste bin IS > 310 THEN stop collection program

The system decision was based on a set of rules:

(i) All the rules that were applied are invoked, using the membership functions and truth values obtained from the inputs, to determine the result of the rule.

(ii) This result was then mapped into a membership function and truth value controlling the output variable.

(iii) These results are combined to give a specific answer through the procedure of defuzzification.

The fuzzy controllers used consist of an input stage, a processing stage, and an output stage. The input stage mapped all inputs to the appropriate membership functions and truth values. The processing stage invoked each appropriate rule and generated a result for each, then combines the results of the rules. Finally, the output stage converted the combined result back into a specific control output value. The processing stage was based on a collection of logic rules in the form of IF-THEN statements, where the IF part is called the "antecedent" and the THEN part is called the "consequent". The fuzzy rule sets have several antecedents that are combined using fuzzy operators, such as AND, OR, and NOT, where AND uses the minimum weight of all the antecedents; OR uses the maximum value; while the NOT operator subtracts a membership function from 1 to give the complementary function.

There are different ways to define the result of a rule, but the "max-min" inference method, in which the output membership function is given the truth value generated by the premise, was used in this study. The centroid method in which the center of mass of the result provides the crisp value was also used instead of the height method, which takes the value of the biggest contributor. The centroid method favoured the rule with the output of greatest area.

The fuzzy control system design was based on empirical methods known as trial and error. The process used was:

1. Documentation of the system's operational specifications and inputs and outputs.
2. Documentation of the fuzzy sets for the inputs.
3. Documentation of the rule set.
4. Documentation of the defuzzification method.
5. Running through test suite to validate system and adjust details as required.
6. Completion of documentation and release to production.

The design of a fuzzy controller for the waste generation has rule set of

Rule 1: IF waste bin IS $\neq$310 THEN speed up waste collection

Rule 2: IF waste bin IS $<$310 THEN continue waste collection

Rule 3: IF waste bin IS $>$ 310 THEN stop collection program

Rule 4: IF waste bin IS normal THEN maintain collection rate

The controller accepts the inputs and maps them into their membership functions and truth values. These mappings are then fed into the rules. If the rule specifies an AND relationship between the mappings of the two input variables, the minimum of the two was used as the combined truth value and if an OR is specified, the maximum was used. The appropriate output state was selected and assigned a membership value at the truth level of the premise. The truth values are then defuzzified through centroid defuzzification.

The model error for the checking data set tend to decrease as the training takes place up to the point where over fitting begins and then the model error for the checking data suddenly increases. During training, back propagation was used. It was noted from the error tolerance used to create the training stopping criterion, which is equally related to the error size, that the training will stop after the training data error remains within the tolerances, which was left set to 0 as there is no prediction of how the training error will behave. The training was run 38 times.

Two experimental examples are used in checking and training of the data. Two identical data sets are used for checking and training. It was observed that the checking data set was corrupted by a small amount of noise and so the fuzzy inference system was used with the checking data to reduce the effect of model overfitting. The training data set that was presented to fuzzy inference system was different from the applied checking data set.

Checking data helps model validation so by examining the checking error sequence over the training period, it was clear that the checking data set was not good for model validation purposes. The fuzzy inference system graphical user interface was used to compare the data sets using the MATLAB. The training and checking data sets are loaded into the MATLAB workspace.

```
load fuzex1trnData.dat
load fuzex2trnData.dat
load fuzex1chkData.dat
load fuzex2chkData.dat
```

Data set fuzex1trnData for training was loaded from the workspace. The training data appeared in the plot in the center as a set of circles. The horizontal axis was marked data set index, which indicates the row from which that input data value was obtained. Checking data fuzex1chkData was loaded from the workspace. The data appeared as pluses superimposed on the training data. This data set was used to train the fuzzy system by adjusting the membership function parameters that best model this data. An initial fuzzy inference system was specified for training. Figure 4 shows the fuzzy inference system plotted against training data

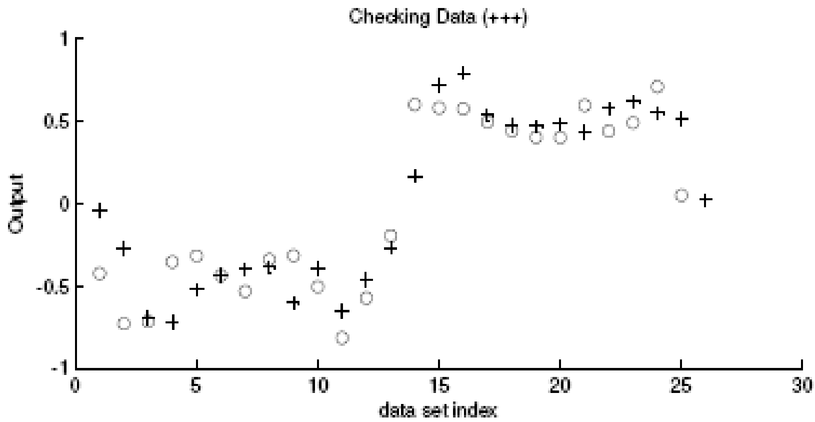

Figure 4: Fuzzy inference system plotted against training data

The number of inputs used is 1, number of outputs is 1 and number of input membership function is 3. Number of check data pairs is 26. The checking data was loaded and the fuzzy inference system grid partition was generated. The fuzzy inference system was trained using the optimization method. The observed error tolerance was 0 and the epochs are 3. The fuzzy inference system was tested and plotted against the training data.

During the fuzzy inference system training, two parameter optimization method options were made available. These are the hybrid and backpropagation. The error tolerance was used to create a training-stopping criterion, which was related to the error size. The training stops after the training data error remain within this tolerance, which was set to 0. The training was run for 40 epochs. The checking error decreases up to a certain point in the training and then it increases. This increase represents the point of model overfitting. The fuzzy inference system chooses the model parameters associated with the minimum checking error. Figure 5 shows the plotting of error against epochs.

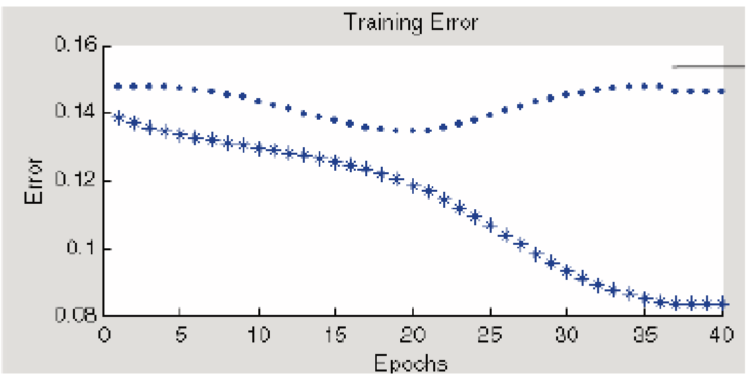

Figure 5: Error plotted against epochs

The training error is represented with *** and checking error with …. The number of input is 1, number of output is 1 and the number of input membership functions is 4. The training will stop after the training data error remains within the error tolerance. The number of training epochs is up to 40.

The checking error decreases up to a certain point in the training and then it increases. This increase represents the point of model overfitting. The fuzzy inference system chooses the model parameters associated with the minimum checking error.

In testing the fuzzy inference system against the checking data, the result is obtained shown in Figure 6.

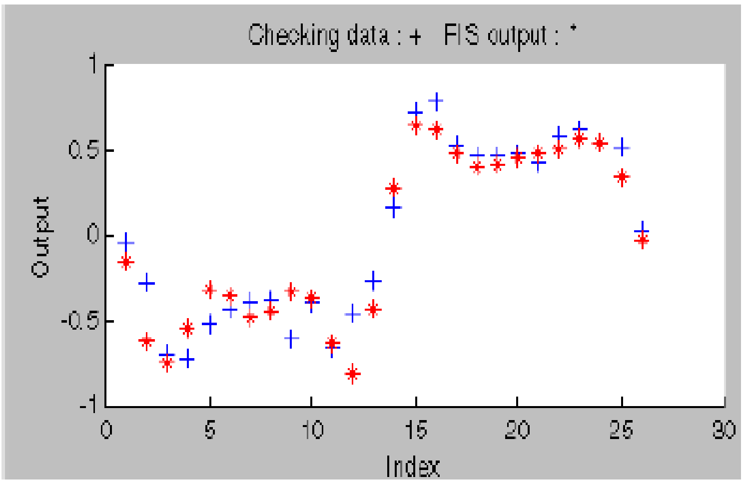

Figure 6: Fuzzy inference system against checking data

The number of input is 1, the number of output is 1 and the number of input information is 4. The checking data is loaded and the grid fuzzy inference system generated. The inference system is trained using the optimization hybrid method. Error tolerance is 0 and the epochs are 40. The fuzzy inference system is then trained and tested by plotting against the checking data. The average testing error is 0.15.

Loading the checking data, it was examined to make sure it does not validate the model. The result obtained is shown in Figure 7.

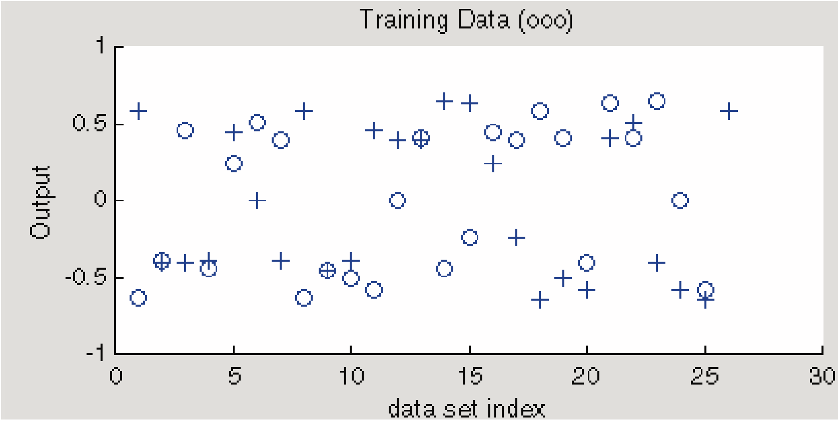

Figure 7: Fuzzy inference system plotted against the checking data in loading check data

The training data was loaded. Checking data was represented using '+' and training data 'o'. The number of inputs was 1, the output was 1, and the input membership function was 4. The number of train data pairs was 25.

Training for 60 epochs gives the observation was that the checking error was quite large. It appears that the minimum checking error occurs within the first epoch. The checking error was sufficiently large to indicate that either more data needs to be selected for training, or there is need to modify the membership function choices, that is, both the number of membership functions and the type, otherwise the system can be retrained without the checking data, if the training data captures sufficiently the features being represented. The training error plotted against epochs is shown in Figure 8.

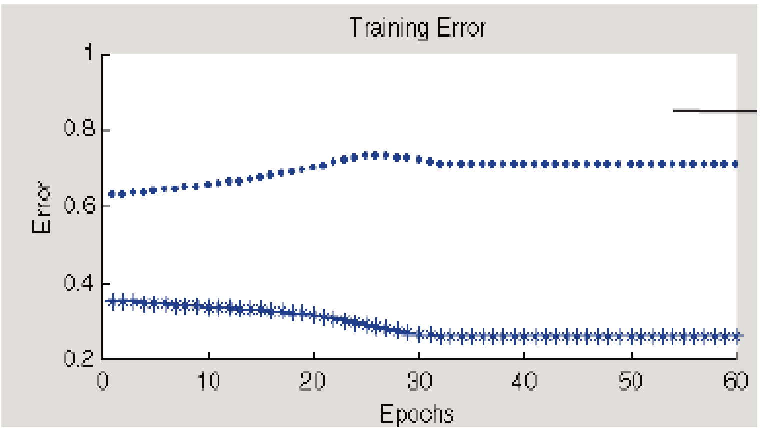

Figure 8: Training error against epochs

The result of approximating the data is shown in Figure 9.

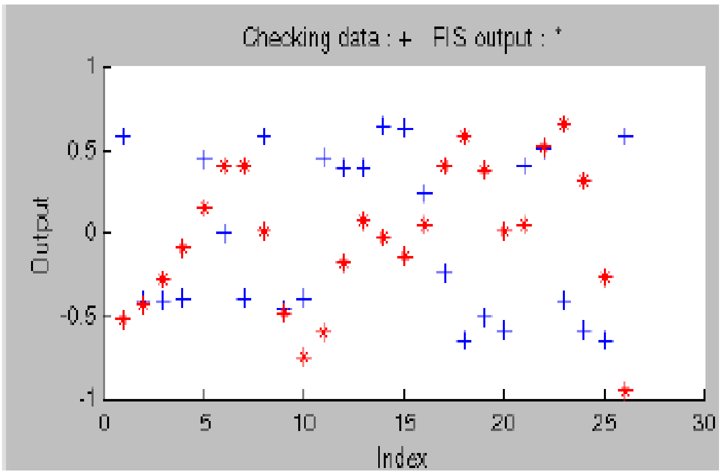

Figure 9: Plot against checking data

The number of input is 1, output is 1 and input membership functions are 4. The error tolerance is 0 and the epochs are 60. The fuzzy inference system is plotted against the checking data. The average testing error is 0.7

Conclusion

The non-linearity of fuzzy logic was solved through rules, membership functions, and the inference process, which resulted in improved performance, simpler implementation, and reduced design costs. This study was basically for municipal solid waste generation modeling using fuzzy logic, the design and the implementation of the developed model for accurate estimation of urban solid waste. The model was able to take into consideration the available data.

The system uses a fuzzy inference system that was able to encode the knowledge obtained and this was adapted by adjusting the knowledge base. Results obtained after analysis showed the efficiency and effectiveness of the system

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