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A Robust Electricity Demand Forecasting of Rajshahi Metropolitan City of Bangladesh

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ABSTRACT
Analysis of electricity demand serves as a foundation to understand the trend of demand and related variability which helps to plan for the distribution of electricity to a region. Fuzzy linear regression uses fuzzy parameters to represent ambiguous and imprecise relationships between dependent and independent variables which omits the limitations of conventional linear model. In this paper, robust optimization has been used to increase the feasibility while working with uncertainty in input data. A combined Interval-Ellipsoidal Robust Counterpart of the fuzzy linear regression model is used to analyze the data. To formulate the Robust Fuzzy Linear Regression model (RFLR), the quantity of customers and the average yearly temperature have been regarded as independent variables, while the consumption of electricity has been regarded as a dependent variable. The proposed method has been applied to forecast electricity demand of Rajshahi City. The optimal solution of the linear model has been obtained using the Lingo software. The results show the capability of the RFLR to analyze data uncertainty with more accuracy and it is demonstrated that the inaccuracy in forecasting and estimated fuzzy bands grow as the data perturbation increases.

Keywords: Fuzzy linear regression; Robust optimization; Robust Fuzzy Linear Regression; simplex method; forecasting.

1. Introduction

Forecasting of the electricity demand has been crucial to the effective design, planning, and upkeep of a power generation and management. The understandings of the demand trends and its associate variables for a region can be obtained by analyzing the historical data of electricity demand of that region. Numerous of them, including moving average, exponential smoothing, regressive models are based on the concepts of time series analysis and stochastic processes. These models can only be used if the distribution of the data in accordance with a statistical model and there is a clear relationship between X and Y is the crisp. The question is when there is no statistical data, then how can we predict or forecast an expected output with ensuring robustness that depends on different independent inputs? A fuzzy regression model would help to answer this question. Fuzzy regression, an extension of traditional regression that has been developed to get around these constraints. It is used to estimate the associations between variables when the quantity and quality of the data are very constrained and the way that the interaction of the variables is unpredictable. Additionally, if the nominal data is somewhat skewed, optimal solutions to the problems of the linear programming may become extremely infeasible. Robust Optimization (RO) is one of the modeling methodologies which have association to the different types of tools where computational tools is one of them. RO is specially used to the problems of the optimization of different process where the data collection is uncertain or belong to some uncertain set. In this research, a simple robust fuzzy linear regression (RFLR) model has been proposed for predicting the consumption of electricity. The robust optimization (RO) method developed by Ben-Tal and Nemirovski is used in our RFLR model [1]. The model has been applied for the estimations of the consumption of electricity of a city of Bangladesh. Our objective is to find electricity demand of Rajshahi city using robust optimization to cope with uncertainty in input data.

2. Literature Review

Power systems are more secure and have lower generation costs when the load is forecasted with high precision. The nonlinear and random behavior of system loads as well as the fluctuating nature of the economic environment and the weather that make the task of forecasting of the electric power load more challenging. In order to increase the prediction accuracy, numerous studies on load forecasting have been conducted thus far utilizing a variety of traditional methodologies, including deterministic, knowledge-based, stochastic, and artificial neural network (ANN) methods. J. Lee suggested that the preferable method is the one which fits the scenario of the organization [2].

M. A. Monne & K. S. Alam developed a fuzzy linear regression model for electric load forecasting. In that research, the algorithm like min-max and the fuzzy set theory were also employed to address the uncertainty associated with meteorological variables and statistical model error [3]. Short-term electric load forecasting based on cuckoo search algorithm was completed by Xiabo Zhang, Jianzhou wang and Kequan Zhang [4]. Also, in that year two different methods had been used to forecast the demand of electricity of an isolated island situated in Bangladesh by A. Islam et al. [5]. The forecasting was made by the calculation of inverse matrix and the analysis of linear regression. Another approach for the prediction of the short-term loads using Fuzzy Logic and Similarity had been created by E. Srinivas & A. Jain in India [6]. This research makes a contribution to the forecast of short-term load because it demonstrated how meteorological variables like temperature and humidity might affect the forecast.

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A specialized and relatively new methodology for dealing with optimization issues with unclear data is basically known as robust optimization. In order to solve the associated explicitly stated convex Resilient Counterpart (RC) program and provide robust solutions to an uncertain LP problem, A. Ben-Tal and A. Nemirovski created analytical and computational optimization techniques [7]. They showed that the robust counterpart of an LP with ellipsoidal uncertainty set is computationally tractable since it produces a conic quadratic program that is polynomial time-solvable. They also surveyed the main results of robust optimization (RO) as applied to uncertain linear, conic quadratic and semi definite programming. In electricity market, a robust optimization approach was built by Marco Zugno & Antonio J. Conejo to analyse the energy and reverse dispatch [8]. They used robust optimization for designing antennas. A basic robust fuzzy linear regression model was proposed by H. Omrani et al. for the forecast the consumption of electricity in Iran [9]. The effectiveness of the suggested methodology was demonstrated using a numerical example and used to project of the residential sectors of Iran. X. Lin et al. addressed the problem of scheduling under bounded uncertainty [10]. They provide a new robust optimization approach when used to solve mixed-integer linear programming (MILP) issues, yields "robust" solutions that are essentially impervious to limited uncertainty.

Form the above, it is seen that forecasting model choice is a crucial thing. Different forecasting models gives different predictions in varying situations. As Rajshahi is a developing city and demand pattern is varying significantly, a robust model is needed to predict electricity consumption. Thus, the contribution of this study is twofold: (1) to develop a robust fuzzy linear regression model to predict electricity demand; (2) to conduct a case study on the Rajshahi Metropolitan City of Bangladesh to validate the model

3. Model Formulation

The extrapolation of trends from historical data to derive an approximation of the future demand over a time horizon is referred as time-series based forecasting. Numerous forecasting techniques have been developed using various mathematical and statistical techniques. Although using mathematical techniques to predict demand can be accurate in some situations that extrapolate recurring patterns alone to foretell specific and finite events might result in inaccurate projections. In the recent past, the energy area has heavily utilized intelligent techniques like fuzzy regression ([11]-[14]). The fuzzy regression approach, where a little perturbation could have a significant impact on parameter estimate that has drawn significant criticism. Ben-Tal and Nemirovski shown the investigation in a survey on a few benchmark issues that even slight data perturbation could result in implausible solutions. On the other side, Developments of the recent time in robust optimization that have made it possible to the design of the models of robust FLR which are capable of the prediction of the parameters that are relatively more dependable and cannot be affected by slight changes in input and output data. In order to represent optimization issues with the uncertainty of the data and produce a guaranteed solution to be correct for all or the majority of potential realizations of the parameters which is uncertain, this process is known as robust optimization.

3.1 Fuzzy Linear Regression (FLR) Model

Tanaka et al. have proposed Fuzzy linear regression for the purpose of solving the numerous problems [15]. This approach is frequently used in many areas such as management, marketing forecasting of sales. It can also be used to solve issues with energy forecasts. This section presents a formulation for the estimation problem for fuzzy linear regression. The outputs of this model are connected to the observations which are non-fuzzy. The inputs are not fuzzy, either. The basic model is taken to be the following fuzzy linear function:
These variables are introduced while using fuzzy regression:

y_j: yearly electricity demand
x_1: Rajshahi's average annual temperature
x_2: Average number of consumers

This section presents a formulation for the estimation problem for fuzzy linear regression. The basic part of the model is taken to the considerations for the following fuzzy linear function:

$$y = f(x, \tilde{A}) = \tilde{A}_0 + \tilde{A}_1 X_1 + \tilde{A}_2 X_2 + \cdots$$

Where, A_i (i =1,2,3 ,...) are the fuzzy parameters that are represented with (p_i, c_i) where p_i is centre value and c_i is in the spread. Fig-3.1 shows the membership function required for the coefficient of fuzzy A_i.

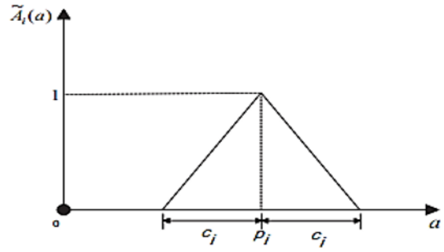

Fig-3.1: Fuzzy coefficient of the membership function.

We find the parameters $(\tilde{A}_i)$ = (p_i, c_i) that reduce the fuzzy output's distribution across all sets of data.

The following is the linear programming paradigm for minimizing the spread:

$$\text{minimize} \sum_{i=1}^{n}\sum_{j=1}^{m} c_i x_{ij}$$

Subject to,

$$y_j \geq \sum_{i=1}^{2} p_i x_{ij} - (1-h)\sum_{i=1}^{2} c_i x_{ij}$$

$$y_j \leq \sum_{i=1}^{2} p_i x_{ij} + (1-h)\sum_{i=1}^{2} c_i x_{ij}$$

$$p_i \geq 0, \quad c_i \geq 0$$

where, y_j be the future predictions in MW

p_i be the centre value of prediction

c_i be spread of prediction

h is used to express the level of confidence that the decision-maker chooses, and it ranges from 0 to 1. Therefore, the parameter can be understood as the decision-optimism maker's or flexibility level.h is the level of confidence that the decision-maker chooses, and it ranges from 0 to 1. Therefore, the parameter can be understood as the decision-optimism maker's or flexibility level.

3.2 Robust Optimization (RO) Model

RO is a highly effective method for modelling data disruption. Frequently, the parameters of the problem relate to quantities that can only be approximated at the time of formulation of the problem and addressed or that will only be realized in the future. RO is one of the most modern methods for dealing with optimization with data uncertainty. When one seeks a solution that performs well for every possible implementation of the ambiguous data, one uses RO. Uncertainty sets which include all (or the majority of) the various values that the uncertain parameters could take, are used to characterize parameter uncertainty. Modelling data uncertainty can be done in a variety of ways.

Interval Uncertainty: A linear constraint was considered which was represented as,

$$l <= \sum a_j x_j <= u$$

The a_j coefficients are erratic and fluctuate in the intervals $a_j \pm \sigma_j$. Uncertainty set is,

$$B = \{a = (a_1, a_2 \dots . a_n)^T \colon a_j^n - \sigma_j \leq a_j \leq a_j^n + \sigma_j\}$$

This is used to express the worst-case-scenario model for the interval uncertainty.

Ellipsoidal Uncertainty: In some circumstances, it appears that the robust counterpart based on the interval model of uncertainty is too cautious. The *ellipsoidal* model of uncertainty provides a less cautious approach. Coefficients can be calculated using the nominal value a_{ij} as follows-

$$\tilde{a}_{ij} = (1+\varepsilon\xi_{ij})\, a_{ij}$$

where ε = Data perturbations percentage/uncertainty level

ξ_{ij} = symmetrically distributed random independent variables in the range $[-\sigma_j, \sigma_j]$.

Considering that the random variable's value of a never exceeds its mean plus Ω times the value of standard deviation, gives the ellipsoidal robust counterpart.

$$\Omega \sqrt{\sum\nolimits_{1}^{n} {\sigma_j}^2 {u_j}^2}$$

Ω is called safety parameter. The uncertainty set is,

$$B = \{a = (a_1, a_2 \dots . a_n)^T \colon \sum (a_j^n - a_j)^2 \leq \Omega^2\}$$

Combined Interval-Ellipsoidal Robust Counterpart: The interval uncertainty model ignores the ellipsoidal uncertainty model takes into consideration the stochastic nature of the data as well as the stochastic nature of the perturbations. The combined interval-ellipsoidal uncertainty is still given by a system of linear and conic quadratic inequalities. The robust counterpart is

$$\left[\sum_{1}^{n} \sigma_j y_j + \Omega \sqrt{\sum\nolimits_{1}^{n} {\sigma_j}^2 {u_j}^2}\right] - t \leq 0$$

We take into account the uncertainty in various input parameter in the FLR model.

3.3 Robust Fuzzy Linear Regression (RFLR) Model

Uncertainty is added in the objective function and the constraints. Following is an expression of the resilient RFLR model based on the Ben-Tal and Nemirovski approach. Combined Interval-Ellipsoidal Robust Counter part of fuzzy linear regression model is-

Minimize, t

Subject to,

$$\sum_{i=1}^{2}\sum_{j=1}^{14} c_i x_{ij} - t + \varepsilon\left[\sum_{1}^{n} \sigma_j k_j + \Omega \sqrt{\sum\nolimits_{1}^{n} {\sigma_j}^2 {u_j}^2}\right] \leq 0$$

$$\sum_{i}^{n} p_i x_{ij} - (1-h)\sum_{i}^{n} c_i x_{ij} + \varepsilon\left[\sum_{1}^{n} \sigma_j l_j + \Omega \sqrt{\sum\nolimits_{1}^{n} {\sigma_j}^2 {v_j}^2}\right] \leq y_j$$

$$\sum_{i}^{n} p_i x_{ij} + (1-h)\sum_{i}^{n} c_i x_{ij} - \varepsilon\left[\sum_{1}^{n} \sigma_j m_j + \Omega \sqrt{\sum\nolimits_{1}^{n} {\sigma_j}^2 {w_j}^2}\right] \geq y_j$$

$$\geq y_j - k_j \leq x_j - u_j \leq k_j$$

$$-l_j \leq \quad x_j - v_j \leq l_j$$

$$-m_j \leq \quad x_j - w_j \leq m_j$$

$$j = 1, 2 \dots . n$$

3.4 Auto Regressive Model

The Auto Regressive (AR) model, in which value is regressed from previous values from time series. The explanation of the model produces response variable over a period of time, along with how it relates to predictor variables and errors. The model is given by-

$$x_t = \alpha x_{t-1} + \varepsilon$$

Where, x_t express the value of this year, x_{t-1} be value of previous year and error term is indicated by ε.

4. Data Collection

Different variables that are related to the economic and cultural circumstances of each country are utilized to forecast the consumption of electricity. In this paper, the number of customers, annual temperature has considered as the variables which are independent, and the consumption of electricity has considered as another variable which is dependable. The required data for our study- annual temperature of Rajshahi metropolitan city, annual number of consumers and annual electricity demand previous 14 years was taken from PDB (Power Development Board), Rajshahi and BMD (Bangladesh Meteorological Department), Dhaka.

Table 1 Data of annual average temperature, number of consumer and annual electricity consumption.

Year	Temperature (℃)	No. of Consumer	Electricity Consumption (MW)
2005	25.54	72990	45
2006	25.55	80457	48
2007	25.03	86502	52
2008	25.10	91193	54
2009	25.53	96692	54
2010	25.78	93912	56
2011	25.92	97912	58
2012	26.61	112671	60
2013	26.32	106659	65
2014	26.66	136867	70
2015	26.78	146595	74
2016	26.50	159738	82
2017	26.91	170454	92
2018	26.88	182544	102

5. Result Analysis

The demand of electricity in Rajshahi is increasing day by day due to increased population and industrial zones. Lot of markets, small industries and Hi-Tech Park is establishing in Rajshahi. Also, weather is changing in Rajshahi. Some research shows that Rajshahi is going towards desertification. Data of Table 1 has been used to find the coefficient of AR model as shown in Table 2.

Table 2 Coefficient of AR model

Variable	α	ε
Temperature, x_1	0.8753737	3.3650932
No. of consumer, x_2	1.0692558	688.4680538

The annual number of consumer and temperature from 2019 to 2025 has been forecasted using the AR model shown in Table 3.

Table 3 Forecasted value of average temperature and annual consumer.

Year	Temperature (℃)	No. of Consumer
2019	26.895	195869
2020	26.908	210116
2021	26.919	225350
2022	26.930	241639
2023	26.939	259055
2024	26.947	277677
2025	26.954	297588

The optimized parameter for RFLR has calculated using Lingo Software. The Lingo Software uses the exact method that presents optimal value of the objective function. Thus, the result is well justified. Using the FLR and RFLR model, the consumption rate of electricity is forecasted for years 2019-2025. Table 4 shows the upper bound, lower bound of projection of the consumption of electricity in MW. The estimated fuzzy bands are expanded with the increment of the perturbation. The safety parameter Ω has been taken as 5. The choice of safety parameter may affect the results. In RFLR model is applied with 0.05, 0.1 and 0.3 perturbations in data.

Table 4 Forecasting result for FLR and RFLR model

Year	**FLR**	**RFLR ε = 0.05**	**RFLR ε = 0.10**	**FLR ε = 0.30**
2019	(99.9, 103.5)	(98.6, 103.78)	(98.27, 103.89)	(97.86, 104.2)
2020	(106.5, 110.0)	(106.32, 110.65)	(105.93, 111.23)	(105.63, 111.58)
2021	(113.5, 117.0)	(113.23, 117.0)	(113.11, 117.63)	(112.87, 118.20)
2022	(121.0, 124.5)	(120.5, 124.78)	(120.23, 124.89)	(119.65, 125.10)
2023	(129.0, 132.6)	(128.7, 132.85)	(128.0, 133.50)	(127.41, 133.89)
2024	(137.6, 141.1)	(137.2, 142.3)	(136.62, 143.0)	(135.2, 144.1)
2025	(146.7, 150.3)	(146.0, 151.1)	(145.2, 151.92)	(146.3, 152.64)

7. Conclusion

Most nation's socioeconomic progress depends heavily on electricity. Accurate models required for the forecasting of the load of electric power are highly essential to the supplier's operations and planning. A non-traditional technique represented by this study - Robust Fuzzy Logic approach based on Ben-Tal and Nemirovski (2000) to forecast the demand of electricity. In this model, the variables influencing electricity demand are temperature and the number of consumers. However, the robust technique used for the new proposed robust method which finds the optimized fuzzy parameters. For the examination of the impact of data uncertainty, the model with 0.05, 0.1 and 0.3 perturbations have applied to that. This finding demonstrates that the study's objectives were fully attained. The outcomes demonstrated that the error and spread of electricity grows as the perturbation increases. For the industrial perspective, electricity demand forecasting is crucial. The consumption of electricity is highly correlated with industrial production. The more electricity demand can be predicted, the better the production rate.

8. Future Research

For the next investigations based on the methodology of RO, other models of the fuzzy regressions can be established. Additionally, the development of fuzzy linear regression may be applied using a reliable method based on Bertsimas and Sim [16]. The suggested model can also be applied in other demand forecasting, such as for gas and water.

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