

Machine Learning Based Prediction of Energy Consumption

Sayan Chatterjee¹, Saruk Chand Sk¹, Manish Kumar Singh¹, Judhajit Sanyal²

Student, Department of EE, Techno International New Town, Kolkata, India¹

Assistant Professor, Department of ECE, Techno International New Town, Kolkata, India²

Abstract: The prediction of energy consumption on a national or regional scale has become extremely important to researchers in recent years, especially in the light of the rate of depletion of primary energy sources combined with the rate of increase in the demand of the same resources on a global scale. The present paper deals with a simple machine learning based approach, using regression, for accurate prediction of energy consumption using the fossil fuel and energy consumption data of India as a representative country.

Keywords: Energy Consumption, National Scale, Machine Learning, Regression, Prediction, Consumption Data

I. INTRODUCTION

There are enormous direct benefits to demand prediction of energy on a national and regional scale, as evidenced by the sheer amount of research that has gone into the development of economic and heuristic models for that purpose. The thrust on this area of research has also increased in the light of the economic growth of countries and an overall global initiative to reduce energy wastage and overproduction while meeting the needs of growing economies worldwide.

The current work aims to develop a relatively simple yet accurate machine-learning model using regression, to accurately predict the power demands in a national economy. Section II surveys some of the recent research in the domain of energy consumption prediction. Section III describes the current approach and the results obtained by it. Section IV concludes the paper with a brief deliberation on future research in this area.

II. LITERATURE SURVEY

Machine-learning based prediction models using Decision Trees and Random Forest algorithms have been investigated by researchers for predicting the energy demand in regions [1].

Data mining techniques have also been used by researchers to design prediction models for future energy demand estimation [2].

Long-term prediction models using linear and non-linear regression have also been proposed by scholars [3].

Artificial Neural Network based models have also been constructed and tested by some researchers to predict energy demand in post-disaster situations [4].

Long-term models using Bayesian Networks have also been used by many researchers for demand estimation [5].

Most of the proposed are complex, and, although the results obtained by them are by and large good, their computational complexity is quite high and the computationally simple approaches such as linear regression are, in general, able to predict local fluctuations less effectively. Thus the authors have endeavoured to present a machine-learning based model which uses linear spline regression for accurate prediction.

III. PROPOSED SOLUTION AND RESULTS

The authors have used a dataset containing the energy demand of India from 1971 to 2014, as well as the percentage fossil fuel energy consumption for the same period. The authors have applied linear regression to get a predicted consumption to compare against the actual energy consumption using the percentage fossil fuel energy consumption as the independent regression variable. The corresponding Table 1 follows.

Table 1: Actual and Predicted Energy Consumption by Linear Regression

Year	Power Consumption (kWh per capita)	Estimated Power Consumption (kWh per capita)	Error %
1971	98.056	47.738	51.316
1972	100.595	49.31	50.982
1973	100.923	50.687	49.776
1974	104.293	67.633	35.151
1975	114.891	74.542	35.119
1976	124.487	88.049	29.27
1977	126.630	93.565	26.112
1978	136.326	78.709	42.264
1979	136.156	100.63	26.092
1980	142.149	110.68	22.138
1981	152.362	140.735	7.631
1982	158.614	164.444	-3.676
1983	166.238	176.649	-6.263
1984	183.923	196.176	-6.662
1985	194.202	226.455	-16.608
1986	208.704	241.623	-15.773
1987	221.000	262.741	-18.887
1988	240.883	285.854	-18.669
1989	257.964	308.96	-19.769
1990	273.047	322.981	-18.288
1991	291.954	342.166	-17.199
1992	305.536	357.03	-16.854
1993	321.711	370.118	-15.047
1994	342.462	385.733	-12.635
1995	360.047	414.866	-15.225
1996	361.093	427.226	-18.315
1997	376.801	441.223	-17.097
1998	387.197	444.804	-14.878
1999	393.373	466.13	-18.496
2000	394.964	470.072	-19.016
2001	395.105	468.899	-18.677
2002	411.967	478.956	-16.261
2003	431.841	481.762	-11.56
2004	453.010	497.477	-9.816
2005	469.454	503.471	-7.246
2006	510.752	515.516	-0.933
2007	543.359	531.427	2.196
2008	562.899	547.987	2.649
2009	600.202	579.555	3.44
2010	642.112	583.412	9.142
2011	698.548	584.401	16.341
2012	724.791	598.387	17.44
2013	765.564	596.414	22.095
2014	805.599	615.481	23.6
		Mean	2.702
		RMSE	3.36

The authors have then used classification to split the total time period into five-year data clusters and have carried out linear spline regression to improve the accuracy of prediction. The results are shown in Table 2, which follows.

Table 2: Actual and Predicted Energy Consumption by Linear Spline Regression

Year	Power Consumption (kWh per capita)	Estimated Power Consumption (kWh per capita)	Error %
1971	98.056	98.695	-0.651
1972	100.595	99.471	1.118
1973	100.923	100.149	0.766
1974	104.293	108.5	-4.034
1975	114.891	111.904	2.6
1976	124.487	131.291	-5.466
1977	126.630	132.932	-4.977
1978	136.326	128.511	5.732
1979	136.156	135.034	0.824
1980	142.149	138.025	2.901
1981	152.362	149.825	1.665
1982	158.614	162.364	-2.364
1983	166.238	168.819	-1.553
1984	183.923	179.147	2.597
1985	194.202	195.161	-0.494
1986	208.704	206.526	1.043
1987	221.000	223.197	-0.994
1988	240.883	241.442	-0.232
1989	257.964	259.683	-0.666
1990	273.047	270.751	0.841
1991	291.954	293.455	-0.514
1992	305.536	307.88	-0.767
1993	321.711	320.583	0.351
1994	342.462	335.737	1.964
1995	360.047	364.012	-1.101
1996	361.093	366.138	-1.397
1997	376.801	376.359	0.117
1998	387.197	378.974	2.124
1999	393.373	394.546	-0.298
2000	394.964	397.424	-0.623
2001	395.105	396.26	-0.292
2002	411.967	417.311	-1.297
2003	431.841	423.183	2.005
2004	453.010	456.077	-0.677
2005	469.454	468.625	0.177
2006	510.752	511.952	-0.235
2007	543.359	538.381	0.916
2008	562.899	565.887	-0.531
2009	600.202	618.324	-3.019
2010	642.112	624.729	2.707
2011	698.548	700.946	-0.343
2012	724.791	747.649	-3.154
2013	765.564	741.062	3.2
2014	805.599	804.731	0.108
		Mean	-0.04
		RMSE	0.32

Thus, there is improvement of the error by an order of magnitude and the superiority of the proposed model is well established.

**IV. CONCLUSION**

The current work accomplished in this paper can be improved upon by investigating other computationally simple methods such as k-means clustering in conjunction with spline smoothing techniques to further improve prediction.

REFERENCES

- [1]. S. Nallathambi, "Prediction of electricity consumption based on DT and RF: An application on USA country power consumption," 2017 IEEE International Conference on Electrical, Instrumentation and Communication Engineering (ICEICE), Karur, 2017, pp. 1-7.
- [2]. N. Karimtabar, S. Pasban and S. Alipour, "Analysis and predicting electricity energy consumption using data mining techniques — A case study I.R. Iran — Mazandaran province," 2015 2nd International Conference on Pattern Recognition and Image Analysis (IPRIA), Rasht, 2015, pp. 1-6.
- [3]. N. H. M. Vu, N. T. P. Khanh, V. V. Cuong and P. T. T. Binh, "Forecast on vietnam electricity consumption to 2030," 2017 International Conference on Electrical Engineering and Informatics (ICELTICs), Banda Aceh, 2017, pp. 72-77.
- [4]. A. Kwangkaew, V. Sornlertlamvanich, I. Kumazawa and S. Skolthanasarat, "ANN approach for predicting economic trends based on electric energy consumption during natural disaster period," 2016 11th International Conference on Knowledge, Information and Creativity Support Systems (KICSS), Yogyakarta, 2016, pp. 1-5.
- [5]. C. R. Rivero, V. Sauchelli, H. Daniel Patiño, J. A. Pucheta and S. Laboret, "Long-term power consumption demand prediction: A comparison of energy associated and Bayesian modeling approach," 2015 Latin America Congress on Computational Intelligence (LA-CCI), Curitiba, 2015, pp. 1-6.