An Improved Model for Short Term load forecasting and Price Forecasting using Novel Machine learning for various areas of Lahore Pakistan

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***Abstract*— The economy relies on accurate projections of power usage. Accurate predictions of power consumption are essential for supply-side policymakers. In contrast, when there is a lack of data and considerations, it might be difficult to make accurate predictions. Consequently, using the original data sequence, we developed the DCOGM forecasting model, which combines data transformation with background value interpolation optimization (1,1). To test the accuracy of DCOGM (1,1) in simulation and prediction, two case studies are conducted. Most existing enhanced grey models do not do as well in forecasting as DCOGM (1,1) does, according to the data DCOGM is used to estimate Pakistan's Lahore City's overall energy consumption from 2017 to 2021. (1,1). According to the DCOGM (1,1) model, Lahore's demand for energy will increase over the next four years, comparing to those other grey adjustment models and the regular GM (1,1). It is possible to employ DCOGM (1,1) as a short-term forecasting approach in addition to other forecasting challenges with a limited number of data points.**

Index Terms — **DCOGM, GM, ANNs, SVMs, SVR**

I. INTRODUCTION

As the global economy continues to develop at an unprecedented rate, so too is the demand for electricity. Our daily life and economic prosperity depend heavily on the availability of electricity. Planning for the present and the future necessitates knowing how much electricity a country or region will demand over the long term [1]. Accurate and reliable electricity consumption forecasting models are critical to power system management.

For electricity, it is becoming increasingly difficult to keep up with the supply. This could lead to inaccurate or unworkable electricity consumption projections over the long term. According to Lee and Tong, data on energy usage deviates from statistical estimates on a frequent basis. When it comes to enhancing the accuracy of electricity consumption projections in real-world models, models that perform well with a limited sample size are critical.[2][3] According to the findings, predictive effects are more prominent when data is collected closer to the predicted period of interest. Another strategy for improving forecast accuracy is to use the most up-to-date data that is currently available [2].

As the global economy continues to develop at an unprecedented rate, so too is the demand for electricity. Our daily life and economic prosperity depend heavily on the availability of electricity. Planning for the present and the future necessitates knowing how much electricity a country or region will demand over the long term [1]. Accurate and reliable electricity consumption forecasting models are critical to power system management.

All of these factors have an impact on the accuracy of energy consumption predictions, resulting in highly nonlinear and stochastic data sequences that fluctuate over time and are unexpected. With the increasing demand for electricity, it is becoming increasingly difficult to keep up with the supply. This could lead to inaccurate or unworkable electricity consumption projections over the long term. According to Lee and Tong, data on energy usage deviates from statistical estimates on a frequent basis. When it comes to enhancing the accuracy of electricity consumption projections in real-world models, models that perform well with a limited sample size are critical [2], [3]. According to the findings, predictive effects are more prominent when data is collected closer to the predicted period of interest. Another strategy for improving forecast accuracy is to use the most up-to-date data that is currently available [2].

II. MATERIALS AND METHODS

Numerous projection models have been devised to predict the future because of the critical role energy plays in human civilization. It is possible to predict the outcome of a wide range of events by using grey forecasting models that combine statistical study, machine intelligence, and artificial intelligence techniques. Multivariate regression and operationally state space modelling, and also multiple linear regression, geographic modelling, Markov chain modelling, and Kalman filter modelling, have been increasingly popular during the past few years in the statistical analysis of data sets (KF). Due to their complexity and need on a large number of samples, forecast models' parameters are heavily dependent on these variables in order to become a good predictor. Assumptions that must be met for the appropriate statistical model to work effectively, such as the normal distribution of data used, are constrained [5], [6]. Two of the most used AI models in computer science nowadays are artificial neural networks (ANNs) and support vector machines (SVMs) (SVR). Even though training sample data is often no smaller than 30 samples in size, the accuracy of evolutionary computing models' projections may be related to the quantity of training sample data, according to this study [6].

Advanced analytical intelligence models cannot always accurately estimate power usage since the source data sequences is frequently small and does not always conform to the specified statistical distributions. You should be aware that not every time it's this way, though Deng's Grey systems approach, first stated in 1982 and now widely accepted, can be used to provide more accurate short-term electricity use projections [1]. Deng's Grey system theory. It's still unclear how the Grey system's various components are connected or how much data has been recovered from them. Unexplainable information (black), concept is applicable (white), and incomplete information (yellow, green) are all sorts of knowledge according to this theory (grey). The conclusion is that all systems are grey systems, which take into consideration the fact that there will always be unknowns. Investigatory information is always going to be incomplete and erroneous because it must consider both internal as well as external factors [11].

When you have a small amount of information and a data source that is both incomplete and fragmented, you might turn to the grey system for help. Grey prediction models are a common type of forecasting model, although there are many others [7]. Using n differential equations and m variables, a grey prediction model can be constructed using the grey systems theory, expressed by the GM (m,n) theory of the greyish networks GM (1,1) multivariate regression is perhaps the most often used of the greyish systems. now due to its processing efficiency. GM (1,1) is already being used in economic, environmental, tourist, education, infrastructure, and energy applications [9],[10]. Wang et al. constructed the PRGM (1,1) grey model, which was used in this study to predict Pakistan's tertiary industry. To improve the effectiveness of the algorithm established by Li and colleagues, Pakistani scientists fabricated and tested a more accurate GM (1,1) model. To make projections, Hu and his colleagues were using the MCGM to predict the number of passengers from eight key nations (1,1). To anticipate how many automobiles will be manufactured in Lahore, Li and his collaborators used GM (1,1). The amount of power used in a specific location is determined by the population and the state of the economy [3],[6]. The structure of the sector and environmental legislation, for example, have a significant impact on the functioning of the industry. Even though data collection is at an all-time low, power consumption in developing countries like Pakistan is expanding at an alarming rate. GM (1,1) is a great choice to consider due to the difficulty in calculating power usage. At this moment, the high rate of forecast error in the GM (1,1) model makes it unsuitable for real-world use. Interest in power consumption estimating methods has skyrocketed recently. This is according to Ding and coworkers (Ding et al.) who have predicted Pakistan's electricity consumption from 2015 to 2020. The NoGM (1,1) model is one of the most recently produced GM (1,1) models because of its innovative and optimized starting condition and rolling mechanism [19].

III. Participants were able to contribute the following after the investigation was over

Data modification and interpolation were used to create a more accurate GM (1,1) model. A better interpolation was achieved using the model as a result than with the original data set. Compression and interpolation optimization are used to make the data more helpful in this model (1,1) [17]. As a result, Grey's method for predicting future electricity usage has been improved. Statistical and machine learning models of intelligence, but also seven other grey-alteration models, were all rejected in our analyses. Using the DCOGM (1,1) model improved prediction accuracy. For relatively brief estimates in a variety of fields, such as GDP or desire for tourists, this approach could be used evaluation, as well as artificial gas consumption estimations, even though there are no major source data available [18].

A. GM (1,1) Model

It is a "first order" model when the first modeling in a series has a measured value of 1. This model's optimum effectiveness is dependent on a modest rate of increase and an exponentially growing pattern. A single parameter is all that is required to fit the model, which improves computer performance (1,1). The following step-by-step tutorial will walk you through modelling the GM (1,1) model. Data sequences must contain no negative values and therefore should not surpass four numbers [14]. When x (1) is added to x (1), the Accumulated Generation Operator [30] produces the new incremental data sequence (k). Because of this, it is possible to misinterpret how random data sequence x (1) appears. An initial grey second derivative of the GM (1,1) model is accessible here [12].

DCOGM (1,1) is compared to short-term electricity consumption projections from APEC and Pakistan [6] to evaluate its ability to simulate and predict the future of electricity consumption. (1,1). This is followed by a comparison with other, previously published, superior GM (1,1) models. A Windows 64-bit PC with 2GB of RAM and 4GB of computing power was utilized to execute the tests in this post using R [15].

Grey difference equations (GM (1,1)) are used to discretize the formula (1). There are two ways to look at the Z (1) (k) background value in the GM (1,1) model. If n is less than 1, then K will be bigger than 1. Grey developed coefficients (GM (1,1) model) and grey controlled variables (GM (1,1) model) are used to represent independent variables. Least squares can be used to estimate A and B in two ways:

B. Methodology of the Combined Optimized

An Illustration of the GM-1 in 3-D. Both altering the original sequence and optimising the backdrop calculation can improve the model's ability to anticipate outcomes [1],[4]. Many newer GM (1,1) models have been developed by focusing on these two domains. Tien's study led to the development of the FMG (1) model, which integrates the original series' first-entry messages and shows that FGM (1) is more effective than the current GM at extracting data's messages. The Tien source says that (1,1). An enhanced version of a previously reported background value estimated model was employed to predict Chung's background valuations. The Rolling-ALO-GM (1,1) modeling approach by

Table 1 APEC's power consumption is displayed using APE and MAPE.

City	AGM	BPN	SVR	DCOGM (1,1)
Lahore	1.75	1.56	1.34	1.12
Karachi	6.78	2.65	1.87	0.98
Multan	1.56	1.23	1.59	0.78
Islamabad	2.65	1.44	0.76	1.2
Bahawalpur	4.65	2.34	0.987	1.76
Raheemyar khan	5.87	1.26	1.67	0.19
Khanewal	0.98	1.43	0.93	0.23
MAPE%	3.23	5.98	7.98	3.12

Zhao and Guo improved Pakistan's annual electricity consumption estimate. Particle swarm optimization (PSO) was used by Li and colleagues to build a better greyish model (PGM (1,1) models) than the traditional grey model (PSO). Based on a genetic algorithm, Hsu developed an efficient inverted grey model (ITGM (1,1)) that increased predicting performance both within and outside of a sample. However, there is still room for improvement before they grow and thrive [12],[15]. Using data transformation and backdrop value optimization, the DCOGM prediction algorithm is improved in this study by using combination interpolation (1,1). The following image depicts yet another way in greater detail. We can utilize combined extrapolation optimization to expand the number of elements in the backgrounds after the original data has been converted to enhance the foreground value [5].

C. 3 Indicators that measure a company's performance.

The evaluation indices used to evaluate the performance of the improved GM (1,1) models must be able to distinguish

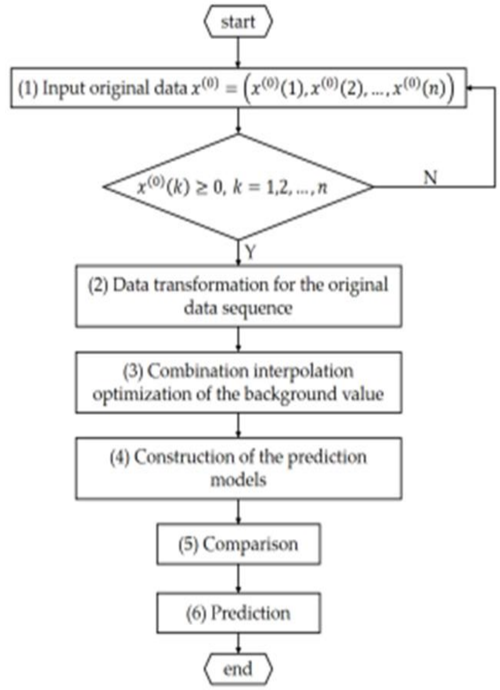

Figure 1: flow chart of combined optimized [5].

between real and anticipated values. MAPE and RMSE are two commonly used statistical assessment indicators that will be used in this inquiry (RMSE). all of Equation, the RMSE, as well as the MAPE, are defined in this way [18].

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{\hat{x}^{(0)}(i) - x^{(0)}(i)}{x^{(0)}(i)}\right| \times 100\% \quad (1)$$

$$RMSE = \sqrt{\frac{1}{T}\sum_{i=1}^{T}\left(\hat{x}^{(0)}(i) - x^{(0)}(i)\right)^{2}} \quad (2)$$

Table 2: Methods for Calculating yearly consumption

Year	Actual value	MAED	GPRM	BPN	RBFN	NNGM (1‘1)	DCOGM (1”1)
2012	63.35	9.33	6.02	3.72	2.85	2.156	1.65
2013	69.60	11.26	2.79	2.49	4.10	2.76	1.98
2014	75.38	10.47	4.28	5.05	16.27	3.23	1.32
2015	80.68	9.25	0.44	4.63	16,54	4.98	1.76
2016	85.87	10.87	3.56	0.63	4.76	5.87	1.87
2017	93.70	16.08	5.37	3.39	11.86	6.87	1.85
2018	97.25	17.46	2.34	3.42	15.62	3.45	1.34
2019	95.40	28.52	7.04	5.89	2,41	2.87	1.23
2020	103.20	29.92	1.73	2.66	9.35	4.76	1.62
2021	113.37	29.05	6.92	6.48	4.56	3.65	1.92
2022	123.42	30.68	2.76	6.97	3.45	2.34	1.83
MAPE (%)		18.74	3.87	3.65	3.87	2.32	3.16

Table 3 Methods for calculating industrial power consumption are shown (APE and MAPE)

Year	Actual value	MAED	GPRM	BPN	RBFN	NNGM (1‘1)	DCOGM (1’1)
2012	73.35	9.33	6.02	3.72	2.85	2.156	1.65
2013	59.60	11.26	2.79	2.49	4.10	2.76	1.98
2014	74.28	10.47	4.28	5.05	16.27	3.23	1.32
2015	80.68	9.25	0.44	4.63	16,54	4.98	1.76
2016	85.87	10.87	3.56	0.63	4.76	5.87	1.87
2017	93.70	16.08	5.37	3.39	11.86	6.87	1.85
2018	97.25	17.46	2.34	3.42	15.62	3.45	1.34
2019	95.40	28.52	7.04	5.89	2,41	2.87	1.23
2020	103.20	29.92	1.73	2.66	9.35	4.76	1.62
2021	113.37	29.05	6.92	6.48	4.56	3.65	1.92
2022	123.42	30.68	2.76	6.97	3.45	2.34	1.83
MAPE (%)		17.84	4.85	4.65	3.67	3.32	3.16

Table 4:Consumption of electricity in Lahore

Year	2010	2011	2012	2013	2014	2015	2016
Value	1278	1300	1345	1476	1387	1423	1487

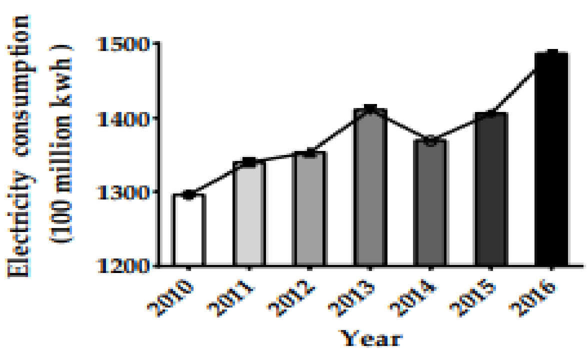

Figure 2: Electricity Consumption yearly wise

D. Analyses of the GMS Improvements

An experiment is being carried out using annual electricity use data from the years 2000-2007. Based on years 2000-2003, we developed and evaluated several prediction models using the same data as Li et al. AGM (1,1) models are used to predict future regional energy consumption based on a single dataset of APEC power consumption [20]. Expected outcomes are summarized in Table 1.

Table 1 shows MAPEs of 3.23 percent, while Table 1 shows MAPEs of 5.98 percent and Table 1 shows MAPEs of 3.12. DCOGM (1,1) reduces error by about 11% when compared to the AGM model, even though other models show less error in this case study (1,1). As predicted, DCOGM (1,1) outperforms other predictive models, including AGM, BPN, and SVR, when it comes to predicting problems (1,1) [6].

E. Predicted Lahore Electricity Use in Case 2

We conducted a second experiment to find out how much electricity Lahore consumes on a yearly basis. Here, we'll teach you how to estimate Lahore's electricity usage. All these models were created using the same data as our DCOGM (1,1) model in order to project Lahore's total power consumption and industrial electricity consumption between 2012 and 2020 and make relevant comparisons. Two and three tables summarize the findings [8][10].

F. Estimated Lahore, Pakistan, electricity consumption.

A major city in Pakistan, Lahore is also the country's financial and economic centre and the largest metropolitan. Therefore,

Table 5 For Lahore City in Pakistan, illustrates the forecasts of five distinct models. Electricity (kWh): 100,000,000.

Year	DCOGM	GM	DGM	FGM	RGM	TGM	LR
2015	3.45	3.95	3.48	3.55	3.49	3.75	4.45
2016	3.43	3.009	3.45	3.32	3.67	3.74	3.80
MAPE	3.12	1.12	4.52	6.18	3.44	2.22	3.19
RMSE	3.11	3.5	3.8	3.65	3.43	3.57	3.1

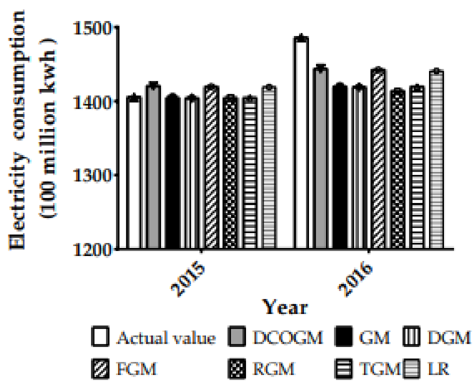

Figure 3: Electricity consumption in KWH

Pakistan's Lahore City must estimate and analyze its electricity consumption in order to be economically and practically feasible. DCOGM has calculated how much electricity Lahore will use (1,1) [11].

1. Estimation of Lahore's electricity usage

Raw statistics about Pakistan's energy usage can be found on the official website of the Lahore City Bureau of Statistics (http://www.stats-sh.gov.cn/). From 2010 to 2016, Lahore City, Pakistan's annual electricity usage is shown in Table 4 and Figure 2. Figure 2 depicts the seven-year nonlinear growth in Lahore, Pakistan's total power usage. It's possible that prices will fluctuate briefly. To get an idea of how much electricity Lahore consumes daily, follow these simple steps. It was possible to create DGM (1,1), FGM (1,1), RGMS , TGMS, and the linear regression (LR) model utilizing data from Lahore City's annual overall electricity consumption from 2010 to 2014. To arrive at a final prediction, each of these models must be evaluated and compared to historical data from the year 2021 [12],[19].

G. Accuracy of Forecasting by Predictive Models

A comparison of actual and expected data for 2015 and 2016 is provided in Figure 3 by seven different models (Table 5). A few common measures for assessing the forecasting accuracy of predictive models are RMSE and MAPE (see Table 5). Table 5 shows that all seven of the study's predictive models meet Lewis' accuracy requirement (MAPE 10 percent) [6],[8].

Table 5 shows that DCOGM (1,1) surpasses the other six models when it comes to estimating overall electricity consumption. In comparison to the LR model and other grey forecasting techniques, DCOGM (1,1) surpasses them all. An improved grey forecasting model (DCOGM (1,1)) is used to anticipate energy usage. The electricity usage of Lahore City from 2017 to 2021 may be projected using this new model [5].

Pakistan's Lahore City is predicted to need 159.85 billion megawatt-hours of energy by 2021. (MWh). Power usage in Lahore City, Pakistan, is expected to rise by 11.25 billion kilowatt hours between 2016 and 2021. Considering the current global electricity scarcity, Lahore's electrical demand strategy has a significant challenge, and the relevant authorities must take adequate measures to deal with the future lack of electricity

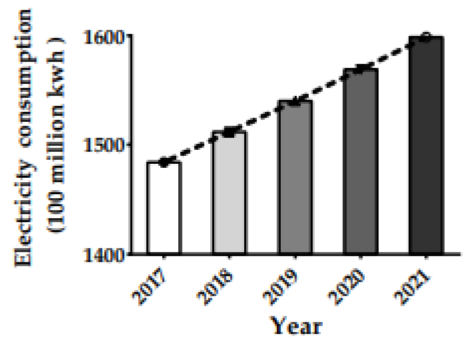

Figure 4: Electricity Consumption Yearly wise

demand immediately [16].

It is vital to accurately predict a country's (regional) electricity consumption for a variety of economic and policy reasons. In the event of a power outage, it may be possible to avert financial losses if correct calculations are made in advance. On the other hand, the data that is used to compute power consumption is frequently limited in scope and subject to wide fluctuations. Considering this, the most accurate technique to estimate power consumption is to utilise a grey prediction model, which is often used and takes only a small number of data to develop an appropriate model. In this work, the DCOGM (1,1) model was presented as an upgraded version of the GM (1,1) model, which was previously proposed. By comparing DCOGM (1,1) to statistical and computational models (LR and MAED), researchers have been able to get insight into its modelling and prediction abilities (1,1) [17].

Table 2 shows the lowest MAPEs for AGM (1,1) and DCOGM (1,1), whereas the greatest MAPEs are for MAED, BPN, and RBFN. (1,1). In several investigations, grey forecasting methods outperformed statistical and computational models. It's possible that the first information is then stored was widely circulated. If you start with an exponential distribution, you can use the GM (1,1). Comparing this to actual data, we see an uneven pattern of expansion, as illustrated in the chart below. Accuracy is diminished when underlying values are inaccurately estimated, including in the GM (1,1) model. When estimating the background value of the model, a DCOGM technique was employed (1,1). The DCOGM (1,1) grey modification model outperforms both the statistical analysis model and the computational intelligence model in three of the four scenarios [16].

With DCOGM, it may be easier to forecast short-term electricity consumption (1,1). The accuracy of this model's predictions can be improved by employing coupled optimization in a variety of different situations. Short-term forecasting, on the other hand, is more accurate than DCOGM(1,1long-term) and should be taken into consideration [9],[5]. The usage of grey modification models in the GM (1,1) model might possibly be beneficial to the model. However, as shown in Table 5, the prediction performance of the DGM (1,1) and RGM (1,1) models falls short of that of the regular GM (1,1) model from Case 3. This is since the DGM (1,1) and RGM (1,1) models are more complex. In some circumstances, the use of modification models, which can improve model precision, may not be appropriate due to their complexity. As a result, when adapting a model to a new environment, extra caution must be exercised [19],[20].

V. Conclusions

For both energy finance and organizational growth, effective predictive estimates are critical. While attempting to better the GM (1,1) model's predictive performance and predictability, we discover that the original data distribution and the ambient value are two of the most essential elements to take into consideration. We then proceed to create an even better model by using an improved GM (1,1) model called DCO (1,1), which incorporates both data transformations and foreground interpolated minimization for the original input sequences. The DCOGM (1,1) model beat both its original and modified GM (1,1) counterparts in terms of exploration and utilization, as well as overall performance. Overall power consumption in Lahore, on the other hand, can be projected using DCOGM (1,1), which reveals that demand for electricity will increase over the next five years, indicating that the model can make accurate predictions (1,1). Actual evidence suggests that a system such as DCOGM (1,1), which can foresee with more precision, may one day prove to be advantageous in certain situations.

Among the many applications are projecting GDP (for example), tourist demand, peak load (for example), business forecasting, and natural gas use, to name a few (for example). Accuracy of improved GM (1,1) models diminishes rapidly when input data sequences change significantly or violently, although more improvements are also necessary in this situation, as previously stated. The beginning condition and the rolling mechanism of the conventional GM (1,1forecastaccuracyforecast) can be optimized in order to improve the accuracy of the conventional GM. By combining DCOGM (1,1) with initial circumstances and rolling mechanism optimization, it is feasible to anticipate energy consumption. By including more known approaches into the grey prediction model, you can increase the accuracy of the model. It is possible that these topics will receive greater attention in the future.

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