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AN INTELLIGENT SHORT TERM LOAD FORECASTING FOR SOLAR PLANT

M.R.Sathya[1], G Kiruthiga[2]

Assistant Professor, Department of Electrical and Electronics Engineering, Government College of Engineering-Srirangam, Tiruchirapalli, India, mrsathyaa@gces.edu.in[1]

UG Scholar, Department of Electrical and Electronics Engineering, Government College of Engineering-Srirangam, Tiruchirapalli, India, kiruthiga0614@gmail.com[2]

Abstract: Precise estimating of solar energy is a key issue for an expressive incorporation of the solar power plants into the lattice. It is know that the solar dynamism is very asymmetrical so the result output of Solar Photovoltaic Systems (SPV) unfocussed by the distinctive nature like high temperature, moisture, wind swiftness, solar irradiance and supplementary climatological facts. It's compulsory to prediction of astrophysical energy is most important to minimalize hesitation in power connect from solar photovoltaic system. The day-ahead Short Term Load Forecasting (STLF) is an obligatory daily task for power report of unit obligation, commercial allocation of group, maintenance plans. This work offerings a solution organization with the proportional investigation with Fuzzy Logic and k Nearest Neighbor algorithm for short term consignment forecasting. From the experimentation and analysis, load prediction is predicted for 4 days of readings taken from the given data set of BHEL in the year 2018-19, where 5th day load estimating is predicted with the above-mentioned algorithms. From the assessment Fuzzy logic approach provides better optimal result for weather penetrating data and historical load data for forecasting the consignment.

Keywords —*Fuzzy Logic, k Nearest Neighbor Algorithm, Optimal Solution, Renewable Dynamism, Solar Photovoltaic System, Short Term Load Forecasting (STLF), Solar Energy.*

I INTRODUCTION

The solar radiation is an indispensable parameter for solar energy investigation but is not present for most of the location due to uncertainty in environment of solar radioactivity calculating apparatus at the climatological stations. Therefore, it is essential to prognosis solar radiation for an individual location using numerous climatic limitations. This parameters are brightness duration, wet-bulb temperature, comparative humidity, wind velocity/speed, daily clear sky global radiation etc. like all impressive condition that affects solar power influences on the earth's surface. The sunshine interval, maximum and minimum malaises are easily obtainable and measured at most of the position so it is generally used for showing of solar radiation. There are numerous researchers which have industrialized experimental reproductions of solar power prediction.

The solar energy prediction develops to be precise with unhurried data. It is estimated with mean absolute percentage error (MAPE) i.e. MAPEr10% resources high anticipating accuracy, 10%rMAPEr20% means good forecasting, 20%rMAPEr50% means judicious forecasting. Now a days collective crude the prices of crude oil highlights the mistreatment of renewable energy sources submissions is a best alternate. The energy from solar is among the most appropriate energy performance due to its less emanation of CO_2 and eco-friendly nature. In the other hand, attentiveness of huge amount of solar energy for the peer group of energy storage faces several difficulty levels to the power system's trainers, severely because of the erraticism of solar radiation fall in surface. So, the energy generated from the SPV organization is changed with the solar radioactivity and the infection and relative clamminess, wind speed unexpected vicissitudes of the SPV system power harness may raise price of functioning for the electricity storage system due to augmented operation and organization price based with cycling existing compeers. The Optimal location assortment for harness of energy from the solar energy is strong-minded based on the obtainable solar irradiance data at that position. The Solar irradiance data are significant for design, sizing, process and commercial calculation of solar energy. However, in India, only IMD canter gives substantiates data for quite few positions or users which is occupied as the raw data for research determinations.

Forecasting is described as the prediction of next future trends data by examining historic previous year or month data. Due to renewable sources like solar supremacy changes with time, atmospheric infection, solar radiations, wind speed/velocity, moisture, etc., experimenting and predicting output gain by solar is an indispensable part. It is the fact that final output solar power is asymmetrical in behaviour, so that to assimilate this final output of generation with the grid or to consume distribution generation (DG), proper energy administration system is needed. Now a day numerous numbers of applications can be employed for short term solar energy calculation such as physical approaches, statistical methods and artificial intellect methods among this three group of method reproduction intelligence approaches are widely used.

II REVIEW OF LITERATURE

In power system load forecasting is very significant part of energy management system for process and planning purpose. Load forecasting means that the methods for predication of electrical load [1]. Load forecasting is integral and fundamental process in the planning and procedure of electric energy organization system [2]. In power structures the next day's supremacy group must be programmed every day, day ahead Short-term load forecasting (STLF) is a compulsory daily task for power communication. In a power system network short term load predicting play important in non-competitive to renewable dynamism system[3].STLF is also used for prevention of congestion, in reduce occurrence of apparatus of failure. STLF is a very useful tool for basic group scheduling functions, measuring the safekeeping of power system at any time, timely correspondent information [4]. The types of prediction are classified into three groupings Short-term predicting, Medium-term predicting and Long-term predicting. In this paper, it is discussed about short term load predicting where short term predicting is limited to less than one month gaining [5].

Load forecasting is very significant in part of the electric industry for the decontrolled market. It has many of the application in energy acquiring and generation, substructure development. Load forecasting is also significant for energy supplier and electric energy group, transmission, circulation, and markets [6]. There are so many techniques used for short term load predicting. Time series, multiple linear deterioration and expert system are used for short term load predicting. The time series method indulgences the load pattern as a time sequence signal with known recurrent, inadequately and daily periodicities [7]. The difference between forecast and actual load is measured as a stochastic process. This model uses the historical load data for extrapolation of future loads [8]. It is a non-weather sensitive approach. The main difficulty of this type model is large quantity of data needed and difficulty is high. Regression model derive lined models [9] [10] for the scheme load. This type of modelling method is habitually divided into smaller section and this type of model built in each subdivision of such as season day or week. This fuzzy logic approach is applied for the short term load predicting using weather data, such as illness, humidity, wind speed etc. The practiced system approach is a rule-based method for load predicting, using the logic of a power system operator to develop calculated equations for forecasting. The main disadvantage of these approaches is knowledge achievement [11][12].

III DATA COLLECTION AND NORMALIZATION

In Bharath Heavy Electricals Limited (BHEL) collected data for short term solar energy prediction from January to March. The data sheet for solar irradiance of month September has been used. So, it can forecast short term solar energy for 1hr gaining as shown inTable-1.1.Collected Data for 1hrs gaining here, it take the following input variables (solar irradiance in W/m2) i.e. month, day, hour, days of the week, holiday, power and temperature for 4 days and output i.e. based on 4 days of power and temperature, 5th day energy is predicted. Again normalized the above statistics both input and output standards in between the range 0.1 to 0.9 to avoid any conjunction problem which may occur during rule development.

TABLE 1.1 SAMPLE DATA FOR LOAD FORECASTING IN SOLAR PV CELLS

Month	Day	Hour	Days of week	Holiday	Power	Temperature
1	1	1	7	0	54.5448	19.0000
1	1	2	7	0	52.3898	18.8500
1	1	3	7	0	51.6344	17.8650
1	1	4	7	0	51.5597	17.2800
1	1	5	7	0	51.7148	15.9182
1	1	6	7	0	52.6898	16.2400

1	1	7	7	0	55.3410	17.5250
1	1	8	7	0	57.9512	17.2350
1	1	9	7	0	62.3844	18.1500
1	1	10	7	0	66.2962	19.3000
1	1	11	7	0	67.9479	21.0316
1	1	12	7	0	68.4049	22.0650
1	1	13	7	0	67.4961	23.0000
1	1	14	7	0	66.2013	24.1000
1	1	15	7	0	64.9540	24.2350
1	1	16	7	0	65.8897	25.0000
1	1	17	7	0	74.9203	24.9700
1	1	18	7	0	76.4434	24.8300
1	1	19	7	0	74.2872	24.8650
1	1	20	7	0	71.5383	24.2350

Totally it contains 8017 data. Normalization of data is done conferring to the below expression:-

$$Ls = \frac{Y\max}{L\max} - \frac{Y\min}{L\min}(L - L\min) + Y\min$$

Here, L represents the definite measure data, L refers to mounted data which is used as input to the net, Lmax represents the specific data set of supreme value, Lmin represents the specific data set of smallest value, Ymax and Ymin higher limit (0.9) and lower limit (0.1) correspondingly of standardization range.

IV FUZZY LOGIC AND KNN APPROACH FOR LOAD FORECASTING

4.1 Basic Fuzzy Logic

The main objective is to develop the model that could help to read out the accepted language process. Generally it replace the multi-valued logic to the dualistic 0/1 logic. Due to the nature of Fuzzy method .i.e., It is quite different from traditional approaches. The fuzzy logic model used the condition where, the probabilistic or deterministic data model do not suitable for singularity of the realistic report in the study. In Fuzzy logic in its place of subjects and verbs, fuzzy operatives and fuzzy sets are used to make the expressive sentences to be described as condition statements i.e., IF-THEN declarations and it contains certain rules. Also, fuzzy logic has been used as an average method in various applications such as demonstrating solar radiation at the earth superficial. Fuzzy logic comprises several steps for basic conformation like Fuzzification, Regulation base, Decision manufacture logic and Defuzzification.

Fuzzification- It helps to amount the input variable values. Fuzzification plays a major role as it incomes function of fuzzification that helps to translates input into crisp values that means transmute scale mapping the variables input range of values into individual universe of dissertation.

Rule Base- It is also known as information base or the combination of data base and philological control rule base. The rule base provides compulsory definition that could be used as to describe fuzzy data, FLC, linguistic control rules and scheming.

Rule Decision Making Logic- Decision manufacture logic also refer as the Kernel of a fuzzy logic supervisor and it can also be able to read of pretending human decision to concepts of fuzzy. It has concluding fuzzy control actions involving fuzzy insinuation and the rules of implication in fuzzy logic.

Defuzzification- Defuzzification of fuzzy value means a scale plotting which converts the range of standards of input variables to crisp output. Let us take K be widespread set. Consider the characteristic occupation of a subset of universal set Z. Then take its values in the two part set {0, 1}. So, (k) =1, if k is Z and zero then the range of fuzzy set Z values as interval {0, 1}. Here, is known as involvement function and (k) is called as grade relationship function of k in Z. The adaptation between association and non-membership is gentle rather than unexpected. The connection and union of two fuzzy subsections Y and Z, K having association function respectively then it can be articulated as Connection: (k) = min [, (k)] (1) Union: (k) = max [(k), (k)] (2) Fuzzy logic methods, the input variables value can effortlessly mapped to an output space by follows the vague perceptions like as fast runner, hot withstand, solar radioactivity, wind speed, relative clamminess etc.

4.2 kNN FORECAST

All the variables labelled in the previous sub-sections were calculated for every data point in the 3 datasets. The features are collected row-wise into matrices, in which each row resembles to a different time imprint. There are 18 matrices in complete, 6 from the irradiance statistics, and 12 from the sky imageries. The kNN forecast is computed using the features accumulated in the matrices in a two-step procedure. In the first step we compute the detachment between the variables for the new dataset (the optimization or the challenging sets) and the features in the historic dataset.

4.2.1 KNN Optimization

To acquire the kNN forecast from the algorithm labelled above several strictures need to be specified:

1. The number of adjacent nationals, K2 {1, 2, /, 150}.
2. The set of features S, i.e., which topographies are used in the search for the adjacent neighbours. The set of selected features can encompass the same feature twice but with dissimilar lengths. In this context the GHI backward regular from 5 min to 30 min, for instance, is considered a different mutable than the GHI backward average from 5 min to 60 min. The dissimilar lengths are considered through the Ni. It is significant to leave this parameter free as it is likely that some distances will be more appropriate than others for dissimilar forecast horizons.

4.2.2 Prediction Intervals

The algorithm described above revenues a single value (or point forecast), but it provides enough material to also compute Prediction Intervals (PI). Popular approaches to quantify PIs often rely on the supposition of ordinariness, but in this case such supposition is not always true. For example, whenever the irradiance methods its natural limits, the circulation of possible outcomes will tend to unequal distributions such as the gamma, or the exponential distributions. The previous subsection showed that cumulative the number of candidates for the kNN algorithm resulted in higher prediction skills. This fact shows that the length and data circulation in the poll of contenders affects the outcome of the kNN forecast model. In order to study this consequence we have computed the kNN using successively larger fractions of all the available data (ancient data plus the challenging data).

To test the heftiness of the forecast procedure the training data was selected arbitrarily. This process was repeated 10 times for each portion of the total training data. The dots show the standards for all the runs and the colour bands show the individual ranges. In all cases there is very little excessive length higher than 60%. This fact explains why in the preceding section the inclusion of testing data in the pool of adjoining neighbour's candidates resulted in small enhancement. The values change very little with exercise length, varying at most 2% from the smallest exercise length to the largest. Additionally the narrow width of the colour bands shows that the kNN results are not very affected by the randomness in the exercise data, which demonstrates the heftiness of the procedure.

4.3 Proposed Work Block Diagram:

As shown in Fig 1 the initial forecasting of irradiance is performed using the fuzzy and kNN algorithm and the output of both models are compared for forecasting the short term irradiance.

Due to ambiguous climatic conditions prediction of solar radiation and complex regression model predicting solar is very difficult. But using fuzzy techniques such type of regression problems are sorted out. The results obtained from fuzzy logic shows percentage error within 5% of permissible limit.

Furthermore, solar energy prediction would be helpful in smart grid applications too.

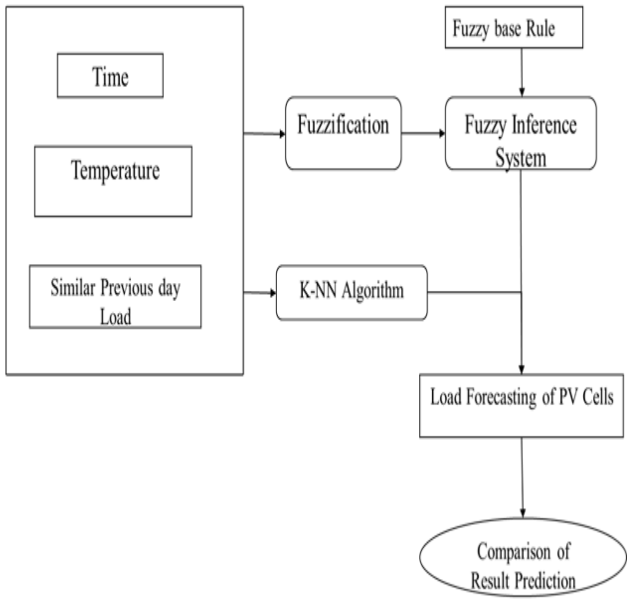

Fig. 1.Block Diagram of Proposed Work

V RESULT AND DISCUSSION

The performance of a load predicting system based on this fuzzy logic and kNN methodology is established using data from Trichy-BHEL for dissimilar day types is used for exercise and load predicting. Real time data that includes ancient hourly load demand over a week, and climate data in terms of infection, humidity, wind speed, is collected from Trichy district. Based upon the above-mentioned algorithms, both of them are associated with same data as input. From that assessment Fuzzy logic provides better solution for foreseeing load in PV cells. The investigational results are shadowed and shown from Fig. 2 to Fig. 5.

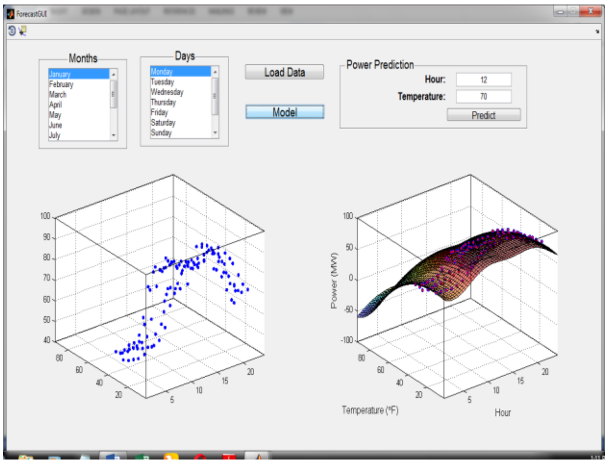

Fig. 2.Process of Loading input Data for prediction

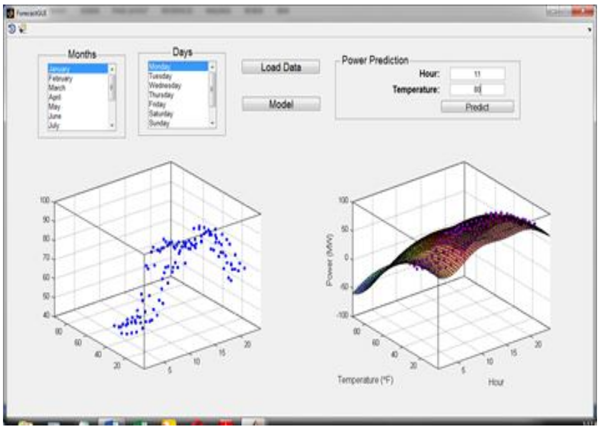

Fig. 3.Predict Load forecasting for the given Hour and Temperature

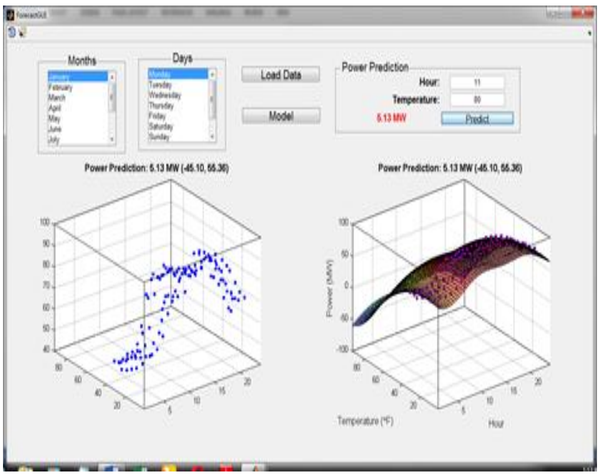

Fig. 4.Predicted result for load forecasting for given input

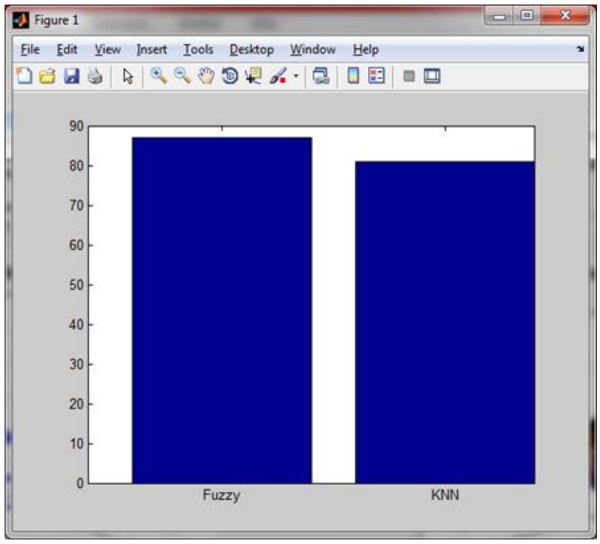

Fig. 5.Result Comparison for Load forecasting

VI CONCLUSION

In solar power submissions, solar energy predicting plays a vital issue because solar power is changeable in nature and it depends on several climatological limitations. So, considering the above fact and ppossession in view the aforesaid, general Fuzzy based model and kNearest Neighbour model presentations are compared for short term solar energy estimate. From the proposed system Fuzzy Logic has effectively predicted the global solar radiation and then becomes exploit preferably for any design of adaptation solar energy application. The Fuzzy logic model shows better results in assessment with its kNN comparison of forecasting. The evaluation results of solar radiation shows an important improvement in statistical limitations and depicts better accuracy than other models. Therefore, the precise forecasting of the load is an indispensable element in power system. Economy of processes and control of power systems may be quite delicate to predicting errors.

In future work the mean absolute proportion error in the forecasting the load can even be dropped if a large and accurate exercise data is used to train fuzzy logic model. The Absolute Percentage Error (APE) can be concentrated by increasing the number of involvement function and by using the trapezoidal, Gaussian bell involvement function. Further by using other artificial astuteness technique like Artificial Neural Network, Genetic Procedure, can be concentrated.

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