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Implementing Machine Learning – Artificial Intelligence for Optimizing Solar PV with Conventional Grid

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Abstract: ***The present conventional sources of energy have been rapidly decreasing. There is an ever-increasing demand of energy which can be fulfilled only by taking into consideration, alternative sources of energy that are also environment friendly. For integrating the renewable energy source such as Solar PV with the grid, several factors must be kept in mind for ensuring the health of the grid. In the past, this task was effectively handled with different computational algorithms such as Ant Colony, Particle Swarm Optimization. But with the advent of Big Data technologies and Machine learning techniques, this task is handled even more effectively. This paper will review different studies in which Artificial Intelligence will be used to make effective decisions regarding the load demand, optimal sizing and positioning of Solar PV energy generating stations.***

Keywords: Renewable energy sources (RES), Distributed Generation, Hybrid Energy Systems, Optimal placement techniques, System performance*.*

I. INTRODUCTION

India's population has been increasing rapidly since the advent of industrial and green revolution. [1] China has been the largest since 1750, the number of people living there are 225 million, which constitutes to 28% of the total people living in the world. In 2016, China will have population strength of more than 1.4 billion. But this will not be the case in future as India will cross Chinas population metrics soon enough. As per the projections of the UN's Population Division, India will cross over China to become the world's most populous country by 2024. There is always room for uncertainty in any projection, but this cross over could be a few years earlier or later. The country, thus, has emerged as one of the most dynamic economic powers in the world.

The same problem has been a major concern for the Energy sector of India, where they must expand the current grid capacity to satisfy the ever-increasing demand. [2] According to the current Statistics, India are the third largest producer and consumer of Electricity. As of August 31, 2019, the national grid in India has a total installed capacity of 360.788 GW. Much of this was supplied by conventional and non-renewable sources of energy like Coal, Nuclear, Gas and Diesel.

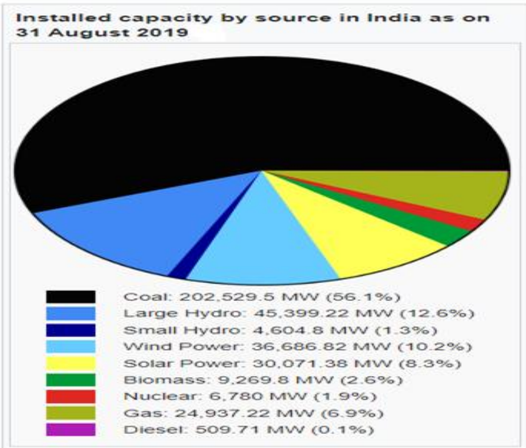

Figure 1. Different sources of Energy contributing to the installed capacity of India as of August 31, 2019

This ever-increasing demand has been fulfilled by different sectors in a variable manner due to different levels of advancements attained in different sectors. A gradual but steady increase can be seen in the coal and Hydro sector due to the increase in energy extraction efficiencies of turbine technology. The table given below gives an over-view of how the installed capacity was supplied by different power sectors.

Growth of Installed Capacity in India[5]

Installed Capacity as on	Thermal (MW)				Nuclear (MW)	Renewable (MW)			Total (MW)	% Growth (on yearly basis)
	Coal	Gas	Diesel	Sub-Total Thermal		Hydro	Other Renewable	Sub-Total Renewable		
31-Dec-1947	756	-	98	854	-	508	-	508	1,362	-
31-Dec-1950	1,004	-	149	1,153	-	560	-	560	1,713	8.59%
31-Mar-1956	1,597	-	228	1,825	-	1,061	-	1,061	2,886	13.04%
31-Mar-1961	2,436	-	300	2,736	-	1,917	-	1,917	4,653	12.25%
31-Mar-1966	4,417	137	352	4,903	-	4,124	-	4,124	9,027	18.80%
31-Mar-1974	8,652	165	241	9,058	640	6,966	-	6,966	16,664	10.58%
31-Mar-1979	14,875	168	164	15,207	640	10,833	-	10,833	26,680	12.02%
31-Mar-1985	26,311	542	177	27,030	1,095	14,460	-	14,460	42,585	9.94%
31-Mar-1990	41,236	2,343	165	43,764	1,565	18,307	-	18,307	63,636	9.89%
31-Mar-1997	54,154	6,562	294	61,010	2,225	21,658	902	22,560	85,795	4.94%
31-Mar-2002	62,131	11,163	1,135	74,429	2,720	26,269	1,628	27,897	105,046	4.49%
31-Mar-2007	71,121	13,692	1,202	86,015	3,900	34,654	7,760	42,414	132,329	5.19%
31-Mar-2012	112,022	18,381	1,200	131,603	4,780	38,990	24,503	63,493	199,877	9.00%
31-Mar-2017	192,163	25,329	838	218,330	6,780	44,478	57,260	101,138	326,841	10.31%
31-Mar-2018	197,171	24,897	838	222,906	6,780	45,293	69,022	114,315	344,002	5.25%
31-Mar-2019[3]	200,704	24,937	637	226,279	6,780	45,399	77,641	123,040	356,100	3.52%

Table 1. Showing the growth in installed capacity for India from 1947 to 2019.

[3] There is a very big difference in the demand and supply in India's Electric Power Sector. As the country's population and needs continue to grow rapidly, it will also need major reforms in infrastructure and efficiency because of the following reasons:

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1. Heavy dependency over conventional sources of energy.
We are still heavily dependent on Coal as a fossil fuel, which is fast depleting.
2. Relying on foreign trade cripples the country's economy.
India's hydrocarbon reserves are relatively small, which are diminishing at a significant rate resulting in increasing dependence on imports and concerns over energy security. This makes India more dependent on the foreign trade for quenching their energy needs.
Demand is exceeding the supply in this era of country's development. This gap has resulted into many losses for Electrical Power Trading companies.
3. Energy Deficits are continuously increasing
There is an unfair distribution of energy in India. More developed states are continuously increasing their share of the electric power. This has resulted into less power being supplied to the less developed states. Many of the rural households still have to rely on firewood and kerosene stoves to meet their energy
A general solution to this problem is to reduce our dependencies over the conventional sources of energy and focus more on the non-conventional renewable sources of energy. For getting an optimal solution and also to reduce the negative effects on environment, we need to find a mid-way as to how these non-conventional resources can slowly be integrated into the current grid system and at a later date completely replace the current sources.
But there are various challenges to integrate these renewable sources of energy to the current grid system. Some of them are discussed below:
1. **Demand v/s Supply Balance**: In central grid network, energy production depends on its users. Balance of energy demand and supply is the key factor in maintaining the stability of the grid. There can be two ways in which this stability is disrupted:
With the demand exceeding the supply, the grid destabilizes and results in poor health of the grid. When the supply exceeds the requirement: energy is lost resulting into huge losses. Hence it becomes inevitable to maintain a clear understanding of both the required demand and the source of energy which can supply to this demand. This would also be beneficial in the long run to calculate the spinning reserves and storage requirements in times of unavailability. Here we can leverage the speed of machine learning models to make accurate forecast models of demand and supply analysis [4,5]. To maintain this balance, accurate forecasts of the supply as well as the demand are necessary.
2. **Consistency in the output power**: These renewable sources of energy are mainly dependent on environmental factors like amount of solar radiation, geothermal temperature at different depths of the ocean. Their intensity is always not the same, so they are bound to produce different amount of output/power during different times of the day. Variations in voltage and frequency are the primary concerns in causing inconsistency in power output which in turn majorly affects the health of the grid.
3. **Optimal Size and positioning of the distributed/localized generation station**: It is of primary importance to calculate the optimal size and position of distributed generation in order to fully exploit the renewable sources of energy available. As renewable power plants continue to expand, it will also be necessary to determine their optimal sizes, locations to concentrate at those points in the grid is suffering from maximum reactive power losses. Machine Learning models can be used for integrating conventional energy systems with alternative and renewable energy systems [6,7]
All these decisions can be accurately made if we have enough historical data. This data should be at least of past 4-5 years to capture the latest trends in the environment conditions. In this era of Internet of things, the increase use of data collectors and sensors in grid has led to increase in collections of Big data. This data can be used to make informed decisions [8,9]. Different machine learning models can be used to make use of the big data technologies [10,11]. Basically speaking, the machine learning algorithms must have a data set on which it can learn the trends through different statistical measures. Once the algorithm is trained it can be validated through another data set which is called as the test data set. If the model works fine, then the predicted value will be significantly close to the actual value in case of supervised machine learning algorithms. In case of unsupervised machine learning algorithms, we can have an unlabeled data set and we can make use of different clustering algorithms to study the similarities in data points. This paper will focus on different Machine learning models including deep learning, ensembles, and hybrids can be used to extrapolate different environmental conditions that can serve as best possible measures to increase the efficiency of energy systems. Section 2 provides a brief introduction to machine learning concepts. Section 3 discusses the techniques in accurately predicting the power generation capacity of Solar PV. Section 4 describes methods to find the optimal location and size of Solar PV. Section 5 determines the different techniques for forecasting the load demand. Section 6 discusses the computational model for the power generation capacity of Solar PV. Section 7 describes about the Optimization Algorithm for the work done. Section 8 concludes the paper.

II. MACHINE LEARNING - NEURAL NETWORKS

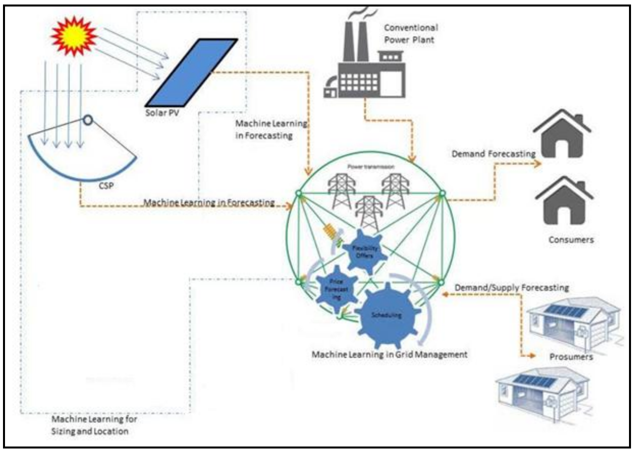


Figure 2: Flow Chart for machine learning algorithm of integrating renewable sources

Machine learning is a computational method of analyzing the data through statistical measures. It is a branch of artificial intelligence in which the computer systems learn from data, identify patterns and make decisions with minimal or no human intervention. There are two main categories in machine learning: Supervised and Unsupervised learning. The main difference between the two types is that supervised learning is done when we have some knowledge about the kind of output which will be obtained. The aim of supervised learning is to make a relation approximates the relationship between input and output. Unsupervised learning, on the other hand, does not have labeled outputs; its aim is to infer a common pattern amongst the set of data points.

Neural networks are a set of algorithms, modeled loosely after the human brain cells or neurons. They are built to recognize common relationships amongst data points. They are built for clustering and classifying data points into groups having a common characteristic. The recognizable patterns can be of various forms like numerical, vectors, images, sound and text. For our analysis, the data which we will use, will consists of variables that are useful in mapping the weather conditions like solar radiation, temperature, wind speed, height above the sea level.

After getting an overview of what is meant by machine learning methods and what are the different categories of machine learning techniques which can be leveraged? We now focus on the different stages where these methods can be employed to accurately integrate the renewable energy-based resources into the conventional grid. The complete process of delivering electrical energy to the consumers can be divided into three stages namely generation, transmission and distribution. The generation of electrical power is totally dependent on the amount of power, which is currently required by the distribution load, which also considers the future needs. Also there are a number of factors that influence the transmission of electrical power to these load centers, like a variable and bidirectional energy generation source, the voltage profile of the transmitting feeder, the amount of reactive power losses incurred in the transmission lines. Hence there are different stages in which these techniques can be used. This usually varies from predicting the amount of power that needs to be generated in future i.e. sizing calculation of power generating stations, predicting the actual positions where placement of such distributed generating stations would benefit the voltage profile of the complete grid, predicting the positions of the distribution centers that would prevent unnecessary monetary investments. Below are some of these issues addressed in detail. Firstly, we have calculated the amount of solar power that can be generated using artificial and recurrent neural networks like GNN machine learning models. Secondly, we have used Generic algorithms to accurately determine the capacity and location of distributed generating stations. Thirdly, we have made use of support vector machine methodology to predict the future load demand for accurately designing the integrated grid. Lastly we have made use of auto-regressive moving average and fuzzy techniques to accurately calculate the solar PV generation capacity.

III. FORECASTING SOLAR PV GENERATION CAPACITY

Forecasting the accurate Solar PV output will help in maintaining grid stability. Also, it will help in predicting the remaining amount of energy deficit which has to be extracted through grid so that energy wastage can be reduced. Several predictive methods make use of support vector machines.

A Support Vector Machine is a type of supervised learning method which is predominantly used in classification and regression problems. Maximum margin hyper planes and use of kernel functions is done to build non-linear models using support vector machines.

Depending on the size of the load, which can either be concentrated to a specific house or may be scattered on any given feeder, the installed capacity of the solar PV plant varies. To accurately determine the size, we can make use of Artificial Neural Networks (ANN). ANN can be used for both forecasting as well as curve fitting purposes. We can leverage the low complexity of ANN to solve multivariate problems. The noise immunity and fault tolerance of ANN results it to be the best suitor for the noise containing system such as that of the energy grid.

Boukelia et al. [12] studied in his research the ANN-based approach to accurately predict the peak nature of solar power generation capacity. He made use of an ANN model to forecast the balanced cost of electric power generated by comparing the peak of the graphs obtained for two solar power plants having secondary power storage.

Chatziagorakis et al. [13] made use of Recurrent Neural Networks (RNN) to forecast weather conditions specifically focusing on solar radiation. A forecasting model for predicting solar radiation for different hours of the day was built. The results showed that a RNN were successful in calculating the future estimation to evaluate the solar plant capacity.

Loutfi et al.

[16] in his study examined different designs of Solar PV plants. He subjected different inputs to different systems which were multilayer perceptron and neural autoregressive.

Machine learning models were very effective to account for relative humidity and temperature to accurately predict the solar radiation for different hours of the day.

Li et al. [17] in his study predicted PV generation. He made use of different seasonality and complexity analysis through data mining approaches. Also made use of multi-clustered echo state network model. He realized that utilizing this approach made him successful in predicting the solar PV output sixty minutes in advance.

A grid integrated model which was able to predict the solar radiation six hours ahead was explained in [14]. It comprises of different ensemble method like radial basis function (RBF),

Support vector machine, pace regression (PR), simple linear regression (SLR), least median square (LMS), additive regression (AR), locally weighted learning (LWL). Most of the accurate predictions were given by LMS and Support Vector Machine algorithms.

Diagne et al. [15] studied a number of deep learning techniques to accurately predict the Solar PV energy output. Comparatively we see that both ANN and RNN machine learning techniques were successful in accurately forecasting the energy which would be delivered through a Solar PV plant. Generally gradient boosting methods are avoided here, because these make use of decision trees. Multilayer perceptron can also be used in place of ANN which makes use of a feed forward neural network that makes use of supervised and back propagation methods for training the machine learning model.

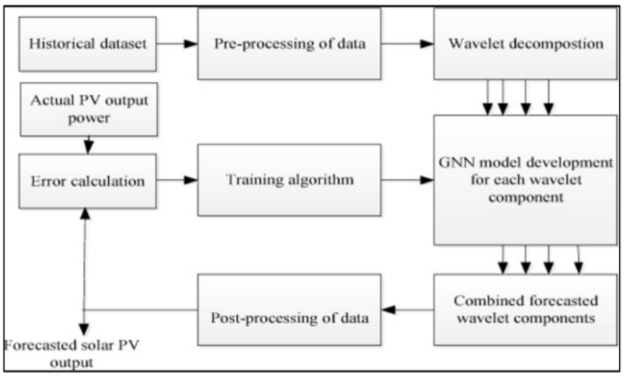


Figure 3: Flow Chart showing machine learning model GNN to propose the solar PV data

For accurately predicting the solar PV output on any given day of the month, a proper data set comprising of the weather conditions like temperature, humidity, and also the solar PV output recorded for that geographical location is required. After performing the exploratory data analysis, using visualization techniques it can be made clear what is the optimum temperature and weather conditions when the solar irradiation received is maximum for the past recorded data. After the preprocessing is completed the wavelet decomposition technique is used to split the data into test and training samples. Training data set is used to fit the model, incorporating all the necessary variables which show no correlation amongst themselves. Also, to remove biasness of the seasonality, different datasets are used for training and testing purposes using the K-Fold Cross validation techniques. Once the datasets are ready, GNN model is fitted using the machine learning models. The accuracy of the model can be inspected using the sum of squared residual score. After inspecting the R-squared scores, different variables were added and subtracted from the models after looking at the significance of the hypothesis test conducted on each variable. To gain the best accuracy, different GNN models are trained where the participating independent variables are modified to get the best fit for the model.

IV. OBJECTIVES OF DISTRIBUTED GENERATION INTEGRATION

Establishing a solar PV plant requires an apt location which gets a minimum solar radiation of 1000 W/sq. meters. The size of the plant is directly proportional to the amount of wattage you want the plant to produce. The configuration of the plant like desired position which faces the solar radiation is equally important to maintain the best possible energy conversion efficiency. All these make it inevitable to accurately determine the plants location, size and configuration. Several machine learning algorithms can be useful in this scenario. Conventional methods have been used till date to accurately determine the plant size, but those methods fail at locations where the data is not present. For such location machine learning algorithms can accurately predict the plant size depending on the estimates provided.
Senjyua et al. [18] also made use of GA based approach to build the best possible settings for Solar PV generation. This grid integrated system consisted of wind turbines, PV system and batteries for storage. In this study he proposes to accurately measure the count of solar panel arrays to precisely balance the demand between conventional source and Solar PV, and battery configurations.
Yokoyama et al. [19] in her study clarifies the use of multiple number of optimal unit sizing of hybrid power generation systems using solar photovoltaic arrays. Hernadeza et al. [20] based his research on finding out the appropriate sixe and position of solar photovoltaic arrays on the basis of Generic Algorithms to maintain balance between the two power sources for maintaining a good feeder health. He supported his solutions using a multi-objective optimization approach.
Seeling-Hochmuth [21] in his study of a Generic Algorithms to find the best configuration of the system showed that the control of the system is governed by the vector components. They can be mathematically solved using five decision variables, each of which specifies a specific time in a year.

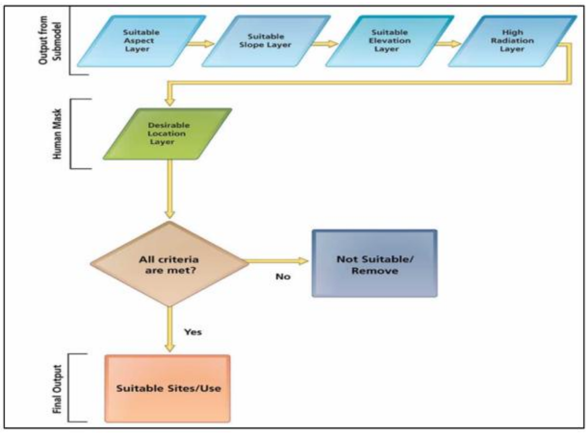


Figure 4: Flow chart on which machine learning model is used for locating Solar PV plant

All the parameters are loaded into the Generic algorithm-based learning models like the location's sea level position, the amount of humidity that different location experiences on average, the amount of solar irradiation experienced, the number of clear sunny days experienced. The algorithm is made to iterate over a given number of times changing the input variables to get the best possible fit for accurately determining the size and location of the solar power plant. We found out that the solar irradiation, the number of sunny days, the humidity factor were some of the most significant variables that were apt at determining the location of the solar power generating station.

V. PREPARE FORECASTING LOAD DEMAND

When we talk about a hybrid system supplying power to its consumers, it becomes even more important to accurately determine the amount of power that needs to be generated and the load that needs to be consumed. Variable behavior of solar causes the grid to destabilize. This can be avoided if timely disconnection of the solar PV takes place. Different deep learning and artificial intelligence techniques were used to pinpoint the factors leading to instability of the grid.

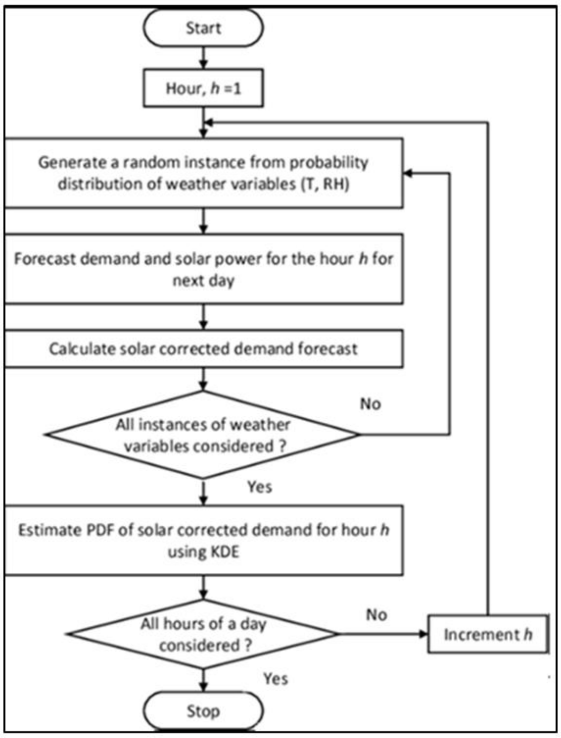
Pengetal et al. [22] in his study to accurately predict the load, made use of methods to accommodate decomposition methods making use of differential empirical characteristics and also SVM based techniques like quantum particle swarm optimization algorithm. To differentiate between different bands of frequencies of the loads, the differential empirical decomposition method was used. To optimize the parameters of support vector regression, the quantum particle swarm optimization algorithm was used. Comparing the two models with different data samples showed that machine learning methods can be used for a better forecast and interpretability.

Dou et al. [23] in his study for forecasting the load employed different energy management strategies. A system was segregated into two-levels. The first level made use of probabilistic forecasting and used Particle Swarm Optimization techniques. For the second level, a Bayesians learning model was used, which comprised of ensemble empirical mode decomposition system. After the study was conducted, the simulation results were compared to quantify the validity of the proposed method.

Burger and Moura [24] use ensemble learning method to perform model validation for demand forecasting. By learning from data for historic demand, this method needed less information on the energy end use, which made it perfect for real time evaluation.

Deng et al. [25] switched from delayed particle swarm optimization to present a grid connected short-term optimized load-predicting model. Here machine learning techniques were supplied with different kernels. Also different empirical mode decomposition methods were used to gain a clear picture. The data was then broken down into smaller batches depending on independent intrinsic mode functions. And later the entropy values were calculated. These functions were segregated in three groups depending on load severity. This study showed that the presented perdition model was accurate.

Figure 5: Flow chart followed to implement support vector machine algorithm



Different input variables are considered for fitting the machine learning models. Probability distributions of the weather variables are considered. Once the hourly generation is forecasted, it can be tested against the test sample and can be compared for calculating the accuracy of the model.

VI. OVERVIEW OF THE COMPUTATIONAL MODEL

Vitality framework planning forms are frequently led as a reproduction based advancement issue. The reaction of the vitality framework to the shifting sustainable power source potential, request and lattice conditions ought to be surveyed when mapping choice space factors into the goal space.

Typically, a period arrangement reenactment of 8760 time steps (24x365) or a lot of delegate time steps are considered during the reproduction which can be considered as a Markov Decision Process (MDP). The target work esteems rely upon both framework setup and activity methodology. Henceforth, enhancing both framework arrangement and dispatch system while experiencing the time arrangement reproduction normally takes increasingly computational time (in specific cases as long as a few days).

Energy flow model

The energy pattern of the framework is mimicked on an hourly premise. Time arrangement information for sun radiation and encompassing temperature are taken from a meteorological database. Jhalawar, a region in Rajasthan with high sunlight based vitality potential is considered for the contextual analysis.

Mapping of finalized space constraints in the proposed model

A vitality center point comprising of sustainable power sources, vitality stockpiling and ICG associated with the matrix is considered in this examination when building up the Actual Engineering Model. Techno-financial perspectives identified with the vitality framework are considered in the computational model utilizing life cycle reenactment. The computational model assesses the existence cycle cost, framework independence, unwavering quality, use of sustainable power source, and so on through an actual existence cycle reproduction. The Actual Engineering Model shows the recreation on computational model focused on to outline space factors speaking to both framework plan and activity system into the goal space.

Solar power generation

Energy generation from the sun based PV panels relies upon a few factors, for example, global sun oriented radiation, effectiveness and the quantity of PV panels introduced. Hourly worldwide sun powered illumination information on an even surface is acquired from the meteorological data. Climed and Klucher models were utilized to register tilted worldwide sun oriented light dependent on the worldwide even sun powered illumination. The Duricsh model is utilized for registering the effectiveness of the panels. The Duricsh model considers the cell temperature (Tq), air mass (am), global solar irradiation (G_t^b) and the type of solar PV panel while simulating the efficiency of the solar PV panels (Eq. 1).

$$\eta_t^{SPV} = p^{SPV}\left[q^{SPV}\left(\frac{G_t^{\beta}}{G_0^{\beta}}\right)+\left(\frac{G_t^{\beta}}{G_0^{\beta}}\right)^{m^{SPV}}\right]\left[1+r^{SPV}\left(\frac{\theta_t^{SPV}}{\theta_0^{SPV}}\right)+s^{SPV}\left(\frac{AM}{AM_0}\right)+\left(\frac{AM}{AM_0}\right)^{u^{SPV}}\right], \quad \forall t \in T$$

Standard values for G_0^{b}, q_0^{SPV}, AM_0 are taken as G_0^b = 1050 Wm^{-2}, q_0SPV = 27°C and AM_0 = 1.7.

Parameter values of p^{SPV}, q^{SPV}, r^{SPV}, s^{SPV}, m^{SPV}, u^{SPV} for various SPV advancements, for example, mono-crystalline, polycrystalline and nebulous silicon cells, are taken. The quantity of solar panels used (x^{SPV} (x^{SPV} ÎN)) formulates the sum total of energy produced which is used as a decision variable (to the Proposed structure). The hourly supply from the panels Pt SPV is determined according to Eq. 2. ASPV speaks to the region of a solitary of Solar panels.

$$Pt\ SPV = G_t^b\ ht^{SPV}\ A^{SPV}\ x^{SPV} \quad (2).$$

VII. RESULT OPTIMIZATION ALGORITHM

Optimizing calculation has been utilized in two distinct pieces of this investigation. An Optimizing calculation is utilized at first to begin the proposed model. A short time later, it is utilized to enhance the vitality framework.

Both AEM and Proposed model guide the choice space factors into the goal space. AEM utilizes a period arrangement reproduction where both framework setup and approach work identified with the dispatch methodology are considered as the choice space factors

Correlation of the Pareto results achieved using AEM and Proposed model

Pareto results acquired considering both AEM and proposed models are displayed in Fig. 7. The Pareto results cover when the network joining levels are higher (Region Q in Fig. 7). Be that as it may, they begin to occupy from one another when lattice incorporation levels are beneath 10% (Region P Fig. 7). NPV starts to increment at an a lot higher rate for the Pareto front acquired utilizing the proposed model when the framework mix levels are beneath 10%. Thus, a huge distinction in NPV can be seen when the lattice combination levels are inside the scope of 1-5%. The distinction in NPV among AEM and the proposed model marginally diminishes when arriving at the completely self-sufficient state (because of the abrupt increment in NPV saw in AEM Pareto front when arriving at the completely self-sufficient state). The Pareto front just shows the impression of the choice space factors on the goal space. The most significant factor to be investigated is the likeness between the choice space factors relating to Pareto arrangements which are acquired utilizing two models that are near one another.

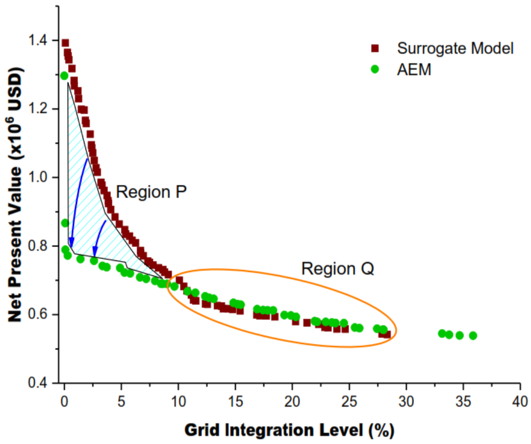


Fig. 7: Elaborates the two Pareto results obtained using Proposed model and AEM.

Region Q shows the common space where both Pareto results collide on each other. Area P denotes the region which is the deviation between the 2 Pareto results.

Semi managed strategies, for example, Active learning can be used to improve the effectiveness of our proposed model by using examples from Area P and later modifying the AEM.

RESULTS:

Table 4: Correlation of Pareto results of AEM and Proposed model achieved for grid

		NPV (x10₆USD)	GI (%)	SPV capacity
E	E-AEM	0.6680	10.81	67.6
	E-S	0.7000	10.09	70.2
F	F-AEM	0.7204	5.77	68.9
	F-S	0.8167	5.95	71.5
G	G-AEM	0.7420	3.35	75.4
	G-S	0.9772	3.32	58.5
H	H-AEM	0.7573	2.60	75.4
	H-S	1.1578	1.93	55.9
I	I-AEM	0.7623	1.42	68.9
	I-S	1.1986	1.49	81.9

VIII. CONCLUSION

The changing environmental factors and continuous depletion of fossil fuels have forced the human race to switch to alternative sources of energy. Solar Photo Voltaic has been the most promising source because of the abundant solar energy. Since solar energy is not fully controllable, hence proper forecasting techniques are required for smooth integration with the grid. Such a hybrid energy system needs to be administered continuously to ensure that balance is maintained between demand and supply.

The papers reviewed in this article makes uses of the different machine learning algorithms to tackle this problem and the results generated are optimum. While making use of these machine learning and deep learning techniques different efficiencies can be attained by passing different hyper parameters and defining what type of kernels will increase grid's overall efficiency. This shows that there is immense potential of machine learning in strategic planning of making best possible use of renewable energy sources.

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