An Efficient Predictor of Renewable Energy Based on Deep Learning Technique (DGBM) and Multi-Objectives Optimization Function

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Abstract— **This paper produces a predictor called Zero to Max Energy Predictor Model based on Deep Embedded Intelligence Techniques (ZME-DEI) to predict Dc-power which is the maximum energy generation from renewable resources that does not cause environmental pollution. ZME-DEI model consists of many stages which flow sequentially in stepwise style; the first stage presents collecting data from sensors of weather and solar plant (i.e., the sensors give a stream of data that contain multi-features). The second stage is preprocessing which contains multi-steps such as (a) Merging between two datasets. (b) Using correlation to the new dataset. (c) Splitting readings into intervals, and deleting duplication intervals. In the third stage, the ZME-DEI model is constructed based on adopting gradient boosting techniques through replacing its kernel (i.e., Decision Tree function) with multi parameters optimization functions. The stage begins with dividing the dataset into two sets using five cross-validation methods, the training dataset is used to construct the ZME-DEI model, while the testing dataset is for evaluating in the final stage. Finally, the fourth ZME-DEI stage is used for evaluation results of the testing dataset based on three measures such as coefficient of determination (R2), Root Mean Square Error (RMSE), and Accuracy(A). the results explain the robust of ZME-DEI and reduce the computation complexity while the best results get from the optimization objective function that based on three parameters Irritation, AC-Power and Temperature.**

Keywords: Embedded Intelligent, DGBM, Multi-objective functions, Renewable Energy, Solar Energy.

I. INTRODUCTION

Many researchers mention about the use of Renewable Energy could reduce premature mortality rate, waste job days, and minimize the total costs for healthcare [1][10][11]. Thus, the changing to RE, economic, reduce air pollution with harmful gases in addition to that could assist to employ a large number of workers.

The energy that is come from Renewable Energy Resources (RER) is changeable (non-dispersible, interrupted, and unreliable) [2][12][32] also the lack of sufficient spaces and extensive experience in this field, in addition to the lack of an extensive feasibility study for the implementation of this technology for electric power generation in Iraq, are the obstacles facing this technology[3][4][13].

Embedded Intelligent System (EI) is a nascent project domain, combining machine learning algorithms such as ("machine learning and neural networks, deep learning, expert systems, fuzzy intelligence, swarm intelligence, self-organizing map and extreme learning") and smart resolution-produce abilities into movable and implanted devices or systems [5][31][32]. IoT is the contraction of appliances, software, sensors, operators, and physical objects are embedded in the wireless sensor network(WSN), vehicles, house devices, and other outputs that aid these objects to transmissions and data sharing[23][24] 25][26]. IoT is rapidly growing with the recent evolutions in wireless technology and embedded devices, with lower energy Microcontrollers that have been evaluated that are typical for IoT's remotely located in separated areas to bind and operate for the large period that need not repairing [5][6][14]. Many implementations that could take advantage of EI are in independent systems and edge computing.[27] The challenges of edge computing for independent driving systems to have the ability to carry out great computational power to satisfy the energy-efficient field that is responsible for ensuring the safeness systems on independent cars[17][18]. The edge computing systems for independent driving want to own the ability to handle vast data from multi-sensing and safeness systems in existent time[7][11][15].

We mention various challenges that should handle to satisfy efficient EI application in hardware like, the requirements for high Computational processing (it is significant since algorithms for EI become so complicated; cost efficiency(to satisfying the need to cost-effective embedded devices against its low batteries power[28][30]); and scalability to adjust various nets, dimensions and topologies(to solutions detection at EI [19][20][22]. appliances that make the algorithms and techniques able to be achieved inside architectures whose malleable and able to be scale to conform the computational demands and hardware resources whose ready for applicable)[8][11]. Many countries in the world suffer from a clear lack of electricity production, which has led most countries to turn towards producing energy from natural sources or environmentally friendly sources that don’t cause the emission of carbon dioxide gas while not causing pollution to the environment[9][33][34]. The problem of producing electrical energy from environmentally friendly sources with high efficiency and low cost is one of the most important challenges in this field”[16][21][22][29]. Therefore; this paper will design an integration model based on the concept of deep embedded intelligent techniques. To determine the Main Rules (Constraints) for each unit that are effective in generating the maximum electrical energy based on the nature of each dataset. Added to that, Zero to Max Energy Predictor Model Based on Deep Embedded Intelligence Techniques (ZME- DEI).

The reminded of this paper is organized as follow: section number one shows the introduction, the second section explains the main tools, the thrid section explain the main stages related to ZME-DEI, fourth section implementation of (ZME-DEI), section fifth show how ZME-DEI suitable for the increase in the production of electrical power compared to other comparable techniques? The final section presents the main conclusion of that work.

II. BUILD MAX ENERGY PREDICTOR MODEL BASED ON DEEP EMBEDDED INTELLIGENCE TECHNIQUES (ZME- DEI)

This section shows the main stages of ZME-DEI also In Figure 1 there is illustrated the sequential stages of the ZME-DEI model's block diagram, and algorithm (1) for building it.

The summarization of this research can observe below:

- Collecting the sensor's reading from weather and solar plant.

- Merging between those datasets, after that split the result dataset into training and testing based on five cross-validation concepts.
- ZME-DEI predictor building takes the advantage of multi-objective optimization functions by considering the kernel of gradient boosting techniques.
- Evaluation results of ZME-DEI based on five measures.

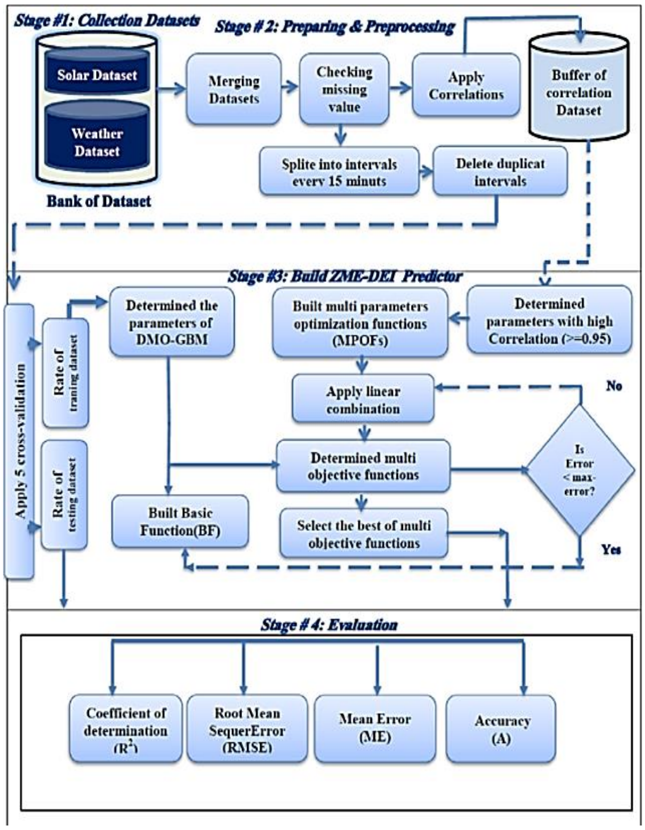


Fig.1 Block diagram of ZME-DEI construction

Algorithm#1: *ZME-DEI*

Input: *Plant dataset capture from 7 sensors; Weather dataset capture from 6 sensors*

Output: *Predict the DC_POWER generation*

// Collection data

1: ***For*** *each dataset$_i$* *// i=1,2*

2: ***Call*** *merge dataset* *//Merge based on Date-Time and Plant-Id*

3: ***Check*** *missing values*

4: ***End for***

// Pre-processing and preparing stage

5: ***For*** *i=1 to Nr* *// nr is number of rows in dataset*

6: ***For*** *j=1 to Nc* *// nc number of column in dataset*

7: ***Call*** *correlation*

8: ***Call Split*** *into intervals*

9: ***End for***

10: ***End for***

// Build ZME_DEI predictor

11: ***For*** *each id_ interval*

12: ***For*** *i in range(1: total number of records [id_ interval])*

13: *Split the dataset into Training and Testing through 10-Cross-Validation*

14: ***End for***

15: ***For*** *each Training part not used*

16: ***Call DMO-GBM*** *//predictive value of DC-power*

17: ***End for***

18: ***For*** *each Testing part not used*

19: *Test stopping conditions* *//max number of epoch and max error generation*

20: ***If*** *max error generation< Emax*

21: ***GO to step 27***

22: ***Else***

23: ***GO to step 15***

24: ***End If***

25: ***End for***

26: ***End for***

// Evaluation stage

27: ***Call Evaluation ZME-DEI***

A. The ZME-DEI main stages

This section presents four main stages for building an efficient multi objectives optimization model containing the first pre-processing stage which includes multi-steps: collection data, merging between two datasets, checking missing values, and applying the correlation step. Furthermore; we splitting the dataset into multi intervals every 30 minutes based on source key then remove the duplication intervals and take only different intervals to work on it in the next stage. The third stage building ZME-DEI through applying linear combinations to the important features result from the correlation step that affects much on an optimal prediction value of the DC-power.

1) Data Pre-processing

This section shows the pre-processing steps as explained in algorithm (2):

- Merging the two datasets by seeking the common features between the solar and weather plants and saving them in one file.
- Checking missing values is applied to drop it with its line.
- Execute the Pearson correlation function to find which parameters or features in the dataset affect much on the DC-power, the coefficient of correlation is used to find out the relationship between target and other features that affect the prediction.
- Finally, splitting data rows into intervals every fifteen minutes, applying compression between similar intervals, and keeping the difference only.

2) Building ZME-DEI predictor

This stage takes care of the kernel of the ZME-DEI by taking the advantage of multi parameters optimization functions to determine the number of parameters that optimize the quality of the GBM algorithm.

3) Determine the multi parameters optimization functions (MPOFs)

The procedure MPOFs are built to determine the best of multi-objective functions that generate maximum DC-power. Then calling that procedure to be the kernel of DMO-GBM instead of the traditional one. The steps below explain the MPOFs working:

Algorithm#2: Preprocessing

Input: Two datasets: solar plant contained features captures from seven sensors; weather dataset contained features captures from six sensors

Output: dataset after preprocessing

// Merging both datasets based on primary key(PLANT_ID, DATE_TIME)

1: Apply features comparison between the datasets

2: Merge both datasets

// Checking missing values

3: ***For*** each sample j // j=1..m

4: ***For*** each column k // k=1..n

5: **If** k has a missing value

6: Dropping j at all

7: ***End for***

8: ***End for***

// Apply correlation

9: ***For*** each sample in the dataset

10: ***For*** each column in the dataset

11: Compute Correlation // $R_{C,S} = \frac{covr(c,s)}{\sigma_c \sigma_s} = \frac{Exp(c-\bar{c})(s-\bar{s})}{\sigma_c \sigma_s}$

12: ***End for***

13: ***End for***

// Split dataset into multi intervals

14: Build empty set called Q

15: ***For*** i=1 to the total number of intervals // time of intervals equal 15 minutes

16: W[i]=read samples

17: ***End for***

18: ***For*** i=1 to the total number of intervals

19: ***If*** *w[i]= w[i+1]*

20: *Delete w[i+1]* // delete duplications

21: *Else*

22: *Q[i]= w[i]*

23: ***End if***

24: ***End for***

25: ***End preprocessing***

Where $covr(c, s)$ is the covariance between the two variables C and S, σ_C the standard deviation of C, σ_S the standard deviation of S,

$\bar{c}$ the average of C, $\bar{s}$ the average of S, and Exp the expectation values.

a) Find the parameters that have a correlation value with the target much or equal to 0.95 in the dataset.
b) Apply linear combination for those parameters from the parameters with high correlation to the parameters with the least correlation such as the equation below.

$$\sum_{i=1}^{n} \text{Fheigh Cor}_1 \ldots \text{FleastCor}_n \quad \ldots(1)$$

c) Determine the significant parameters such as (Ac, Irradiation, and Temperature) that affect the prediction.
d) Apply the multi-objective functions (maximum value) to the first two parameters, then to the second two parameters, and so on until combine the three parameters are in one function.
e) Find the best multi-objective functions from the four functions.
f) Set these functions as kernel of the DMO-GBM algorithm.

The steps below building a procedure of multi parameters optimization functions (MPOFs).

```
Procedure Multi Parameters Optimization Functions(MPOFs)
For i=1 to Nr                                   // nr is number of rows in dataset
  For j=1 to Nc                                 // nc number of column in dataset
    If correlation-value-target with j >= 0.95 then
        X= a[i,j]
        Zk= Linear combination X    // Zk is MPOFs become as new kernel of DGBM
      // Multi-objective functions of two parameters (Ac & Irr)
      For i=1 to Nr
        MoF1= max(Ac[i] + Irr[i])
      End for
      Return MoF1
      // Multi- objective functions of two parameters (Ac & Tem)
      For i=1 to Nr
        MoF2= max(Ac[i] + Tem[i])
      End for
      Return MoF2
      // Multi-objective functions of two parameters (Tem & Irr)
      For i=1 to Nr
        MoF3= max(Irr[i] + Tem[i])
      End for
      Return MoF3
      // Multi-objective functions of three parameters (Tem, AC & Irr)
      For i=1 to Nr
        MoF4= max(AC[i] + Irr[i]+ Tem[i])
      End for
      Return MoF4
    End if
  End for
End for
End MPOFs
```

Where X is a variable that contains an array a[i,j] of the dataset, Zk is a linear combination of a multi parameters objective functions (MPOFs).

B. *Develop GBM (DMO-GBM)*

In this section; using the training intervals to build models after replace the kernel of GBM by DMO. The algorithm (3) shows the steps of DMO-GBM.

```
Algorithm #3: DMO-GBM
Input:            D: dataset after preprocessing
Output:           Optimal of DC-power
Initialization:   Tr: training data, Fx: array for predicted values of Tr, rc: rows counter,
                  C_DMO-GBM: counter of develop GBM, DMO-GBM_MAX: max number of
                  DGBM, Org_target: array for original target of Tr,  y: index of
                  target, N: # data records in D.
For i=1 to total # sample in Tr
  // Find the initial prediction for all data records in Tr by:
    Calculate mean of target values Mean (Dc-power)
    While rc < N
      Fx[0,rc] = Mean(Dc-power)
      Org_target[rc] = Tr[y,rc]
      Increase row counter: rc = rc + 1
    End while
    Call MPOFs
    While C_DMO-GBM < = DMO-GBM_MAX, build optimization model by:
      rc = 0
      While rc < N, Update target values of Tr by:
        Residual [rc] = Org_target [rc] – Fx[C_DMO-GBM -1, MPOFs, rc]
        Tr[y,rc] = Residual [rc]
        Increase rows counter: rc = rc + 1
      End while
      For each multi parameters optimization function in DMO-GBM:
        While rc_ DMO-GBM < # rows in DMO-GBM, update  prediction values by:
          Fx[C_DMO-GBM -1, MPOFs, rc]=
                Fx[C_DMO-GBM -1, MPOFs, rc]+ (Sk * DMO-GBM.predictaed_valus)
          Increase counter of data rows in final DMO-GBM:
                rc_ DMO-GBM = rc_ DMO-GBM + 1
        End while
      End for
    End while
  End for
  Return DMO-GBM model with array of prediction values Fx.
// Build the testing stages of DMO-GBM model.
End DMO-GBM
```

Where DMO-GBM_MAX is a maximum development of multi-objective gradient boosting machine.

III. IMPLEMENTATION OF ZME-DEI

This section will present the main result extracted from each stage of ZME-DEI to predict DC-power which is the maximum energy generation from renewable resources that does not cause environmental degradation.

ZME-DEI model shows many activities which flow sequentially in stepwise style; stage one shows real-time collecting data from two datasets weather and solar plant each having basic features then checking if the dataset contains missing values for dropping.

Stage two pre-processing contains: (a) Merging between two datasets. (b) Using correlation to the final dataset. (c) Splitting readings into intervals every fifteen minutes. (e) Delete duplication intervals. In the third stage, ZME-DEI model is constructed based on gradient boosting techniques.

The final stage includes evaluation results based on three measures such as coefficient of determination (R2), Root Mean Square Error (RMSE), Mean Error (ME), and Accuracy(A).

A. *Collecting datasets*

In this stage, the datasets collected through 5 months are used to build and test the proposed model. These data or sensors readings were taken from two plants for generating electric power. We must point to the limitations related to the collection readings like energy consumption of sensors battery which is the main cause of unreasonable readings. Tables I and II show the sample of weather and solar plant consequently.

TABLE I. SAMPLE OF WEATHER DATASET

IRR	MODULE _TEM	AMBIENT _TEM	SOU_K	P_ID	D_T
0.00086 2721	23.096691 93	24.2892111 3	HmiyD2TTL FNqkNe	4135 001	15/05/2020 05:45
0.00588 6957	22.206756 6	24.0884460 7	HmiyD2TTL FNqkNe	4135 001	15/05/2020 06:00

0.022281607	22.35345867	24.01163527	HmiyD2TTLFNqkNe	4135001	15/05/2020 06:15
0.049409724	22.893282	23.97673127	HmiyD2TTLFNqkNe	4135001	15/05/2020 06:30
0.095394454	24.44244393	24.21899	HmiyD2TTLFNqkNe	4135001	15/05/2020 06:45
0.141940443	27.18565287	24.5373984	HmiyD2TTLFNqkNe	4135001	15/05/2020 07:00
0.154712676	28.88847786	24.8159595	HmiyD2TTLFNqkNe	4135001	15/05/2020 07:15
0.148799153	29.6056438	24.98878987	HmiyD2TTLFNqkNe	4135001	15/05/2020 07:30
0.000862721	23.09669193	24.28921113	HmiyD2TTLFNqkNe	4135001	15/05/2020 05:45
0.005886957	22.2067566	24.08844607	HmiyD2TTLFNqkNe	4135001	15/05/2020 06:00

TABLE II. SAMPLE OF SOLAR DATASET

T_YIELD	D_YIELD	AC_P	DC_P	SOU_K	P_ID	D_T
6987759	0	0	0	3PZuoBAID5Wc2HD	4135001	15/05/2020 00:15
7602960	0	0	0	7JYdWkrLSPkdwr4	4135001	15/05/2020 00:15
7158964	0	0	0	McdE0feGgRqW7Ca	4135001	15/05/2020 00:15
7206408	0	0	0	VHMLBKoKgIrUVDU	4135001	15/05/2020 00:15
7028673	0	0	0	WRmjgnKYAwPKWDb	4135001	15/05/2020 00:15
6522172	0	0	0	ZnxXZZZa8U1GXgE	4135001	15/05/2020 00:15
7098099	0	0	0	ZoEaEvLYb1n2sOq	4135001	15/05/2020 00:15
6271355	0	0	0	adLQvlD726eNBSB	4135001	15/05/2020 00:15
6987759	0	0	0	3PZuoBAID5Wc2HD	4135001	15/05/2020 00:15
7602960	0	0	0	7JYdWkrLSPkdwr4	4135001	15/05/2020 00:15

B. *Pre-Processing*

This stage involved many steps to handle problems related to the dataset to extract useful information and get thesis' target quickly as to show this later.

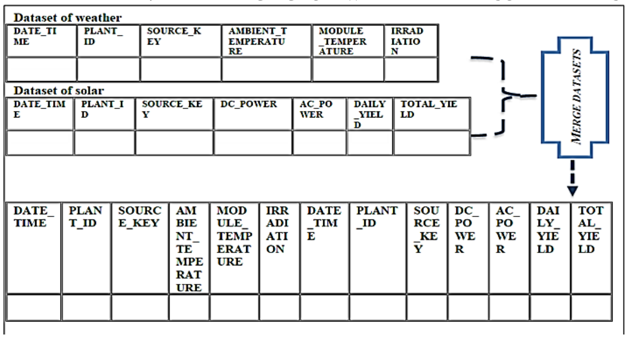
- **Step #1: Merging**

To apply merging between two datasets based on D_T and P_ID features we need firstly adjust the D_T format to each dataset from the (day, month, year, hour, and minutes) formatting (i.e, %d-%m-%Y %H:%M) to the (year, month, day, hour, minutes, second) formatting (i.e, %Y-%m-%d %H:%M:%S) to make standard formatting in the python programming language. Drop unnecessary features and apply merging through the D_T feature.

Table III shows the results of the step merging that are used to join the original datasets within one dataset along the column and rows.

The main purpose of the merging step is to fill gaps in data, increase the samples size, and improve the robustness of results.

TABLE III. THE MERGING OF WEATHER AND SOLAR DATASETS



- **Step #2 checking missing values in the dataset**

Search for the missing value is applied to drop it with its row because the dataset that dealing with contains a stream of data therefore deleting one or more rows does not affect the prediction over a long time. In general, we found that dataset don't contain missing values. The main purpose of this step is to avoid training failing and make the prediction more accurate.

- **Step #3 The Correlations between Parameters in the Dataset**

The correlation coefficient is a statistical measure of how closely two or more variables are related to one another. As a results when applying the correlation found high correlation among (DC-power, AC, IRR, and MODULE_TEM) reach to high of 0.95. Table IV show that the correlation between the target and AC is equal to 1.0 meaning there is a perfect correlation between them, while the correlation with MODULE_TEM is equal to 0.947 and with IRR is equal to 0.98 that satisfy the condition in the MPOFs procedure. The main purpose of correlation is to reduce the training computations and as a result, reduce the time and space complexity .

TABLE IV. THE CORRELATION COEFFICIENT AMONG THE 7 PARAMETERS (SENSORS READINGS)

	DC_P	AC_P	D_YIELD	T_YIELD	AMBIENT_TEM	MODULE_TEM	IRR
DC_P	1.000	1.000	0.096	0.008	0.710	0.947	0.984
AC_P	1.000	1.000	0.096	0.008	0.710	0.947	0.984
D_YIELD	0.096	0.096	1.000	0.020	0.463	0.200	0.085
T_YIELD	0.008	0.008	0.020	1.000	-0.033	-0.013	-0.003
AMBIENT_TEM	0.710	0.710	0.463	-0.033	1.000	0.852	0.719
MODULE_TEM	0.947	0.947	0.200	-0.013	0.852	1.000	0.960
IRR	0.984	0.984	0.085	-0.003	0.719	0.960	1.000

- **Step #4 Split Dataset into multi intervals**

Splitting data rows into fifty intervals every fifteen minutes, applying compression between similar intervals, and keeping the difference only.

Table V. Split Dataset into Intervals

Pre.	# Points related to Pre.	Pre.	# Points related to Pre.
Per #1	3202	Per #26	415
Per #2	3067	Per #27	414
Per #3	3010	Per #28	401
Per #4	3007	Per #29	350
Per #5	2996	Per #30	326
Per #6	2996	Per #31	324
Per #7	2978	Per #32	321
Per #8	2961	Per #33	320
Per #9	2950	Per #34	318
Per #10	2939	Per #35	307

Per #11	2913	Per #36	297
Per #12	2895	Per #37	285
Per #13	2825	Per #38	279
Per #14	2806	Per #39	262
Per #15	2771	Per #40	252
Per #16	2754	Per #41	249
Per #17	2751	Per #42	246
Per #18	2699	Per #43	239
Per #19	2643	Per #44	235
Per #20	2637	Per #45	233
Per #21	2598	Per #46	232
Per #22	2523	Per #47	193
Per #23	648	Per #48	190
Per #24	476	Per #49	188
Per #25	417	Per #50	150

C. *Where Per is an interval or period related to fifteen minutes.*

Table VI. the Result of Training dataset in DGBM

Training	Testing	MOF1=AC+IRR	MOF2=AC+TEM	MOF3=TEM+IRR	MOF4=AC+IRR+TEM
80%	20%	**232.600**	**259.883**	**28.683**	**309.332**
60%	40%	220.120	250.910	23.710	254.322
50%	50%	202.150	200.783	20.503	172.232
40%	60%	195.436	220.232	15.323	189.214
20%	80%	231.200	233.853	19.236	211.203

Table VII. the Result of Testing dataset in DGBM

Training	Testing	MOF1=AC+IRR	MOF2=AC+TEM	MOF3=TEM+IRR	MOF4=AC+IRR+TEM
80%	20%	229.467	254.403	22.661	254.452
60%	40%	118.419	138.912	15.852	109.123
50%	50%	110.987	130.952	14.202	100.325
40%	60%	192.257	220.694	12.235	251.773
20%	80%	232.600	123.213	11.235	233.452

Table XI: Results of Evaluation Measures for Training and Testing Datasets

Rate of Training Dataset	Rate of Testing Dataset	Results of the Training dataset			Results of the testing dataset		
		R2	RMSE	Accuracy	R2	RMSE	Accuracy
80%=40 intervals	20%=10 intervals	0.423	0.497	0.945	0.167	0.328	0.883
60%=30 intervals	40%=20 intervals	0.0.562	0.526	0.853	0.433	0.334	0.741
50%=25 intervals	50%=25 intervals	0.301	0.792	0.870	0.010	0.421	0.800
40%=20 intervals	60%=30 intervals	0.296	0.787	0.891	0.020	0.203	0.825
20%=10 intervals	80%=40 intervals	0.097	0.0167	0.765	0.136	0.190	0.631

IV. Disuession

This paper produces a predictor named Zero to Max Energy Predictor Model based on Deep Embedded Intelligence Techniques (ZME- DEI) to predict DC-power which is the maximum energy generation from renewable resources that does not cause environmental degradation. ZME- DEI model shows many stages: Collecting the sensor's reading from weather and solar plant, merging between those datasets, after that split the result dataset into training and testing based on five cross-validation concepts, ZME-DEI predictor building take the advantage of multi-objective optimization functions by considering the kernel of gradient boosting techniques to obtain thises goal. Evaluation results of ZME-DEI based on five measures.

A. *How is the proposed optimization model suitable for the increase in the production of electrical power compared to other such comparable techniques?*

The proposed model relied on the substitution of the core for one of the best prediction techniques represented by the gradient boosting machine by a multi-objective function in which the transactions that affect the generation of electric power (DC-power) were relied upon by merging between the best prediction technique and the multi-objective optimization function and then obtaining prediction results with high accuracy depending on different accuracy scales were taken into account.

B. *Can the polynomial optimization function improve the performance of the prediction network represented by the gradient boosting algorithm?*

Yes, the polynomial optimization function was able to improve the performance of the gradient boosting algorithm because it took into account only the most influential factors in power generation. In addition, it was able to avoid the problems in the algorithm, which is to determine the number of decision trees, the depth of each tree, and the longtime of training it.

C. *What are the factors affecting the generation of DC-power?*

by calculating the correlation between the values obtained from the sensors, it was found that irradiation, alternating current(ac), and temperature are the most influential factors in generating dc-power.

D. *Do natural factors affect the generation of DC-power?*

Yes, by defining the knowledge constraints, it was found that dust harms the efficiency of the solar cell in generating the largest possible energy, as well as the appropriate place or area to install these panels in terms of a large and open area to absorb the largest amount of solar energy.

V. Conclusions

This section explains the main conclusions found through implementing the suggested system (ZME-DEI). Where we focus on the point of how the proposed model handles the challenges shown in the previous sections (i.e., programming and application challenges. Also will suggest a set of recommendations that can work on it by other researchers in the future.

In general; we can summarize the main conclusions found from implementing this study:

Although Renewable Energy is considered one of the main resources for generating energy and it is characterized by multi-features that make it a prismatic resource to cover the need of humans for energy but on the other side, it required more effort from humans to get it.

The main challenges of IoT are collecting the data from multi-sensors that performance of it based on the life cycle of the battery. When the battery lost energy then this leads to a loss of some value or gives uncertainty values, therefore the (ZME-DEI) solves this problem by dropping any missing values.

Sometimes the data collected from multi-sensors suffer from duplications of their records, therefore, this leads to an increase in the computations. In general; the (ZME-DEI) handles this problem through split the dataset into multi-intervals, each interval represents a stream of data taken through 30 minutes. Then create a buffer to save only the different intervals to work on it in the next step.

Integration data always leads to an increase in the accuracy of results and make it more understood by users. Therefore, this work activates this feature through integrated weather and solar datasets to get more accurate results.

The GBM is one of the primitive tools for prediction based on Decision Tree results, but on the other side, it is required to determine multi-parameters such as root, number of nodes, and depth of the tree. This work handles the limitations of GBM by replacing the kernel (DT) with a mathematical function based on linear combinations. This leads to getting high accuracy results in a short implementation time. In general, the best results get through using multi-objective functions that have parameters.

The (ZME-DEI) gives the best results when splitting the different intervals through a rate of 80% of the interval to training while 20% of intervals to testing and using MOF4 as kernel of GBM this make the accuracy of the model equal to 95%.

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