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METHODOLOGIES AND APPLICATION

An Innovative synthesis of deep learning techniques (DCapsNet & DCOM) for generation electrical renewable energy from wind energy

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Abstract

Renewable energy becomes one of the main resources that help the world to safety the environment from pollution and provide the people of new type of energy; therefore, this paper presents model called multi-objectives renewable energy-generation (MORE-G) for generating electrical energy from the wind. In general, this model consists of five basic phases: in a first phase collecting and preparing the data, so to make it in format suitable for the decision-making stage, this phase split into multi-steps (i.e., handle missing values and normalization dataset), and the second phase focuses on building constraints for each dataset and develops one of the optimization algorithms called cuckoo based on horizontal combination and multi-objective optimization used in third phase to generate the energy. Another model is developed as multi-layer neural network called (***DCapsNet***) based on linear combination and multi-objective functions used in the fourth phase to generate the energy. Final phase is related to evaluation of both models (***DCOM and DCapsNet***) to determine the best. The MORE-G is characterized by addressing one of the real problems, saving on material costs (i.e., reducing the need for manpower and reducing dependence on other countries in importing electric power) and upgrading the scope of the ministry of electricity.

Keywords ***DCapsNet*** · ***DCOM*** · Search method · Optimization · Multi-objective optimization · Green energy

1 Introduction

With rapid developments in integrating renewable energy power generation with the existing power system networks, the complexities also equally amplify. Due to sustainability requirements renewable energy power generation is inevitable and becoming so vital in modern smart power generation. Perhaps modern techniques ensure effective renewable energy harvesting, and still uncertainties and complexities insist more suitable procedures to integrate the conventional power system with renewable energy sources. By integrating renewable energy resources electric industry can regularize according to The Clean Air Act Amendments, thus reducing the emission level dispersed in atmosphere. Renewable energy is a kind of inexhaustible energy that is not depleted and is called renewable energy because it comes from natural resources (i.e., wind, water, sun), the most important characteristic of a clean and environmentally friendly energy that does not lose harmful gases such as carbon dioxide, which does not adversely affect the surrounding environment. It does not play a role that affects the temperature level. Renewable sources of energy are completely incompatible with their non-renewable sources, such as natural gas and nuclear fuel. These sources lead to global warming and the release of carbon dioxide when used, and there are several types of renewable energy: solar energy, bioenergy, wind power, hydroelectric power, sustainable biofuel energy, geothermal or geothermal energy, tidal energy. For example, Iceland is one of the leading countries in renewable energy, and it provides 100% of its electricity needs by generating renewable sources, particularly geothermal energy for heating homes, lighting and electricity generation for industrial use and the like,

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the importance of renewable energy comes from the multiplicity of its use in the various areas of human life and its role in meeting the human needs and daily requirements as they enter the military, domestic, industrial and agricultural fields (Xavier et al. 2013), and the main advantage of renewable energy is available in most countries of the world, does not pollute the environment and maintains the general health of living organisms, economic in many uses, ensures their continued availability and availability and uses uncomplicated techniques (Ahat et al. 2013). Renewable energy technologies are effective and efficient solutions for clean and sustainable energy development in most countries, taking into account the geographical location of those countries where intensive use of most renewable energy resources is most important (Chehouri et al. 2015). Data are one of the most valuable treasures on the world and are the basis of computer science in different branches. Data referred to any object have set of features recognition or specific feature characteristic that object or collection of objects with their features. It takes different types and can get by observation, search or recording (Al Janabi 2018; Al Janabi et al. 2019). In general, the researchers deal with concept called data science that combines among three domain data domain, intelligence domain and statistics domain (Wu et al. 2016). There are many types of data science (i.e., small, normal and big\hug data); small data organized in uniform structure such as table or list also that size of that data does not exceed 30 samples; therefore, it does not surrender the normal distribution and cannot be used to take any decision; on the other side, normal data: it also structures data surrender to the normal distribution and useful to take different decisions such as clustering, classification, prediction, optimization (Ali 2012a, b). Finally, big data are on the other hand and take different structures such as structure, semistructure, or unstructured, and the size of these data lies in the range 1 TB to 1ZB extraction useful knowledge or pattern it by combination between two main concepts, machine learning techniques with cloud computing (García et al. 2018). Intelligent data analysis (IDA) is new field of computer science searching the ability to build new or pragmatic approach to discovery or recovery pattern. This term refers to find real problem that needs to solve that problem has specific definition and design model to handle it, that model may be for clustering, classification, prediction, optimization or generated rules or recommendation, after that analyzing the result to make it understandable by the users such as preparing reports, histogram or mathematical model or network of their result (Lamedica et al. 2018). Optimization (Deng et al. 2016; Al-Janabi et al. 2020) is a general term used in multi-field such as computer science and mathematics, and the aim of optimization is to get values of the variables that minimize or maximize the objective function while satisfying the constraints.

We can address the problem of this paper as follows; most of the countries in the world suffer from a clear lack of electricity production, which has led most countries to turn toward producing energy from natural sources or environmentally friendly sources that do not cause the emission of carbon dioxide gas while not causing pollution to the environment (Al-Janabi and Alkaim 2020; Wu et al. 2016). 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. The main objectives of this paper are to

- Determine the main rules (constraints) for each dataset that is effective in generation the maximum electrical energy based on the natural of each dataset.
- Design multi-objectives optimization models for database related to generated energy, based on developing cuckoo optimization algorithm and CapsNet algorithm (Fig. 1).

2 Related works

There are multi-researchers attempt to addressing the problem of generated electrical energy from different resources, and we will explain in that section:

Xavier et al. (2013) present important opportunities to contribute to global climate change mitigation while fostering a low-carbon energy sector and a green economy in the state. By investing the renewable energy sources, energy efficiency, technological improvements and the targets analyzed, Minas Gerais state could reduce political and financial risks originating from the reliance on fossil fuels while generating more income in the energy sector and the state economy as a whole and reducing medium- and longer-term costs, but we will use wind energy to generate renewable energy.

Ahat et al. (2013) propose a complex system based on the smart grid modeling, accentuating on the optimization by combining game theoretical and classical methods in different levels. The optimization is achieved with flexibility and scalability, while keeping its generality.

Chehouri et al. (2015) present review of the optimization techniques and strategies applied to wind turbine performance optimization. The topic is addressed by identifying the most significant objectives, targets and issues, as well as the optimization formulations, schemes and models available in the published literature, and offers the performance optimization of horizontal wind turbines by highlighting the main aspects when tackling the wind turbine optimization, and our work is similar to it by using the same design constraints while differing it by applying the different types of tools and algorithms.

Wu et al. (2016) show a multi-objective optimization method is promoted for the design of an energy system integrating biomass combined heat and power (CHP), photo-

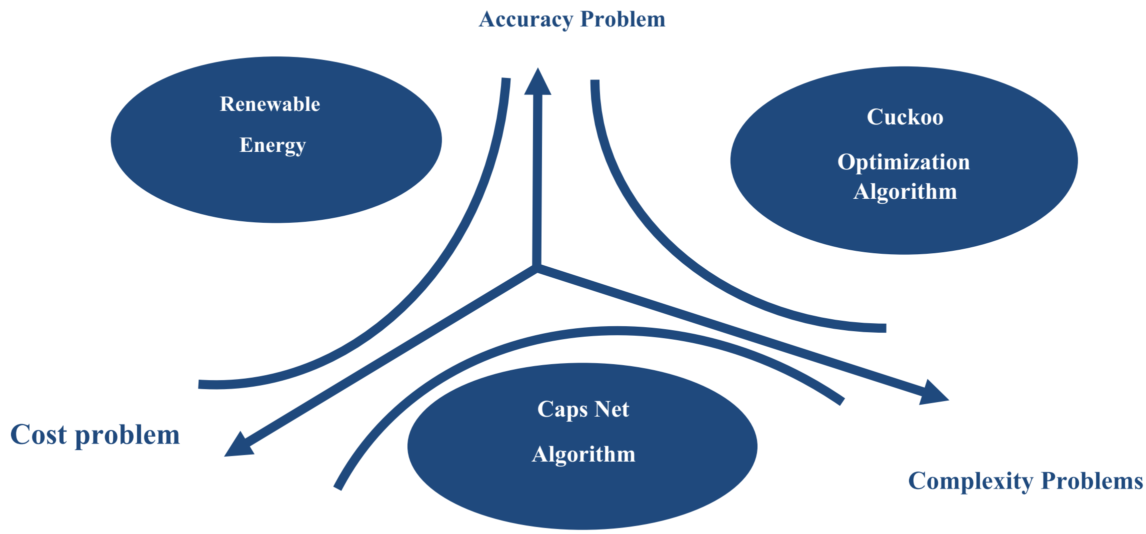

Fig. 1 Relationship among the main techniques used in this work

voltaics (PV) and heat storage. The results give a trade-off between economic and environmental performance while providing feasible generation settlements that take into account CHP, PV, together utility grid, and our work is similar to it by using the same multi-objective optimization method while differing it by using different algorithms.

García et al. (2018) apply a binary cuckoo search algorithm to different instances of crew scheduling problem and also used an unsupervised learning method based on the K-means technique to perform binarization. It was found that quality, convergence and scalability are affected by the number of solutions; however, these depend additionally on the problem that is being solved. In particular, it is observed that for medium-sized problems, the effects are not very relevant as opposed to the large problems such as G and H, where the effect of the number of solutions is much more significant, and we will use the same algorithm to different instances of wind power to generate renewable energy.

Lamedica et al. (2018) propose methodology that is based on mixed-integer linear programming (MILP) to calculate the optimal sizing of a hybrid wind photovoltaic power plant in an industrial area. The proposed methodology considers the: (1) load requirements; (2) determined the physical and geometric constraints for the renewable plants installation; (3) operating and maintenance costs of both wind and photo-voltaic (PV) power plants and the (4) electric energy absorbed by the public network. This paper is similar to our work by applying the same concept related to multi-objectives optimization, but this thesis differ in goal constraints and evaluation measures.

Eriksson and Gray (2018) provide an outline of a new method for simulation and optimization of hybrid renewable energy systems using a normalized weighted constrained multi-objective meta-heuristic search technique which takes into account technical, economic, environmental and socio-political objectives concurrently in a weighted fashion with a constraint capability, and our work is similar to it by calculating the power output of a wind turbine, while we differ from it using other measurements.

After we survey the main article related to the problem statement attempting to solve it in this thesis, we found our work is near from the article discussed in Eriksson and Gray (2018) from the step to handle the same problem, but it differs in determining the constraints and developing the search algorithm through using multi-objectives optimization.

Also, apart from machining processes, various intelligent techniques have been used for clustering based on particle swarm, genetic algorithm and, in addition, information retrieval and feature selection (Abualigah et al. 2017; Abualigah and Hanandeh 2015).

Table 1 compares among the previous works from the six points including the name of the authors (s), name of database/dataset used in that article, methodology suggested by author(s) to solve that problem, main measures used to evaluate results and the main advantages of that methodology.

3 The MORE-G design stages

In this section, we will explain the main stages required to build the multi-objectives optimization model through useful from the natural source represented by wind and will be discussed in detail below (Fig. 2):

Table 1 Comparison among the previous works

Name of authors	Name of data base/dataset	Methodology	Evaluation measures	Advantage
Qiong et al. 2016 (Xavier et al. 2013)	Primary energy Solar Bio-Energy	Multi-objective optimization using two objective functions: Economic objective Environmental objective	Precision using: (PV), (CHP) and Grid	Minimized annual energy cost and environmental Impact
Marcos, et al. 2013 (Ahat et al. 2013)	A green economy: pathways to sustainable development and poverty eradication. http://www.unep.org/greeneconomy/Portals/88/documents/ger/GER_synthesis_en.pdf	Optimization using: (BAU) and (RIC)	Accuracy using BAY & RICs	Can appreciate the magnitude of the challenge that the state will need to address over the coming years : To mitigate GHG Emissions and provide energy security in the state
Adam, et al. 2015 (Chehouri et al. 2015)	Cost energy	Optimization by using Meta-heuristic algorithms	Accuracy by using The cost of energy(CoF)	Have Advantages of 3Dcomposite (Woven, Braided, Stitched, Knitted) textiles .
Murat Ahat 2013 (Wu et al. 2016)	Smart Grid	Optimization using Smart Grid	Expression by Knapsack algorithm	(1) Minimize the risks associated with either method. (2) Algorithms work together in different sub-components to achieve the global optimization.
Jose Garcia, et al. 2018 (García et al. 2018)	Beasley's OR-Library	Optimization by: Cuckoo algorithm K-means	Accuracy by using K-means: (1) The evaluation of the average value through the variation of the solutions number. (2) The evaluation of iteration number through the solution number used to solve problems. (3) The evaluation of algorithm scalability through executor Number	
Regina et al. 2018 (Lamedica et al. 2018)	Http://Capasso R Lamedica, Podest_aL, Ruvio A, Sangiovanni S, Lazaroiu GC, Maranzano GA. A measurement campaign in a metro-train deposit/maintenance and repair site for PV production optimal sizing	Optimization by using mixed-integer linear programming (MILP) methodology	Precision by using Values of amortization (A), and V_r and Values of revenues, amortization, $C_{i;tot,}$ $C_{O\&M}$; cash flows, and NPV	Generates industrial energy and identifies the problem and sets its limits in an understandable way It is useful for correctly defining the investments according to the different Company's objectives
Eriksson and Gray 2019 (Eriksson and Gray 2018)	http://M. Sharafi,T. Elmekkawy, Multi-objective optimal design of hybrid renewable energy systems using PSO-simulation	Optimization by using Normalized Weighted Constrained Multi- Objective (NWCMO) meta-heuristic function	Accuracy by using Capital recovery factor, Levelized cost of energy, Loss of power supply probability, Total present value	Calculates the power generated by each turbine

```
Algorthim#1 MORE-G
Input: Database called friendly environment database (FED) have wind, cost, area, material and
        team,
Output: Generated max electrical energy from FED
Initialization: w_wind=0.5, w_cost=0.3, w_area=0.1,material=0.1, w_team=0.1
// Preprocessing Stage
    For each dataset_i    // i=1,2.....5
    |  FED_i= Call Handle Missing value   //sometime dataset contains missing value
    |  NFE_i= Call Normalization (FED_i)
    End for
    For each dataset_i    // i=1,2.....5
    |  Call Build constraints
    End for
    // Building Optimal Models
    // DCuckoo Model ((DCOM))
    For each dataset_i
       D_i=Call DCOM
    End for
    For each dataset_i in D
    |  w_i     // constant refer to weight of dataset
    |  D_i     // best values for each dataset result by DCOM
    |  sum=sum+(w_i*D_i)
    End for
    // DCapsNet Model
    For each dataset_j
    |  D_j=Call DCapsNet
    End for
    Computer E_DCOM
    Computer E_DCapsNet
    // Evaluation Stage
    // Compare between both Models (DCOM, DCapsNet)
    IF E_cuckoo > E_capsnet
    |     the model of DCOA is the best
    |  Else
    |     the model of DCapsNet is the best
    End if
    End MORE-G
```

In general, we can summarize the main modifications of this paper as explained below: It deals with database having five parts of dataset (i.e., wind, cost, area, team and material), and each dataset has constraints that differ from other. The pre-processing stage involves building of constraints for each dataset and developing cuckoo optimization model (COM) through using horizontal combination to find the best evaluation results. Develop the CapsNet network model, which consists of six layers, so that each layer represents the optimization of each dataset with its constraints.

3.1 Pre-processing stage

After collected environment-friendly database ("FED") through this step, we found that the database suffers from multi-problems that need to handle; first missing value, second the values of the features of that database not computed with the same unit; therefore, these databases need to normalize and finally need to determine the constraints for each dataset.

A. Handling missing value

Some features have missing values that affected on the taking decision such as clustering, classification, prediction and optimization. Therefore, we need to handle these values by dropping it or replacing it by other real values (Khare et al. 2013). In this work, we will replace that missing values by means of that features:

$$\text{Mean} = 1/n * \sum xi, \quad \text{where } i = 0\ldots n-1 \tag{1}$$

B. Normalization

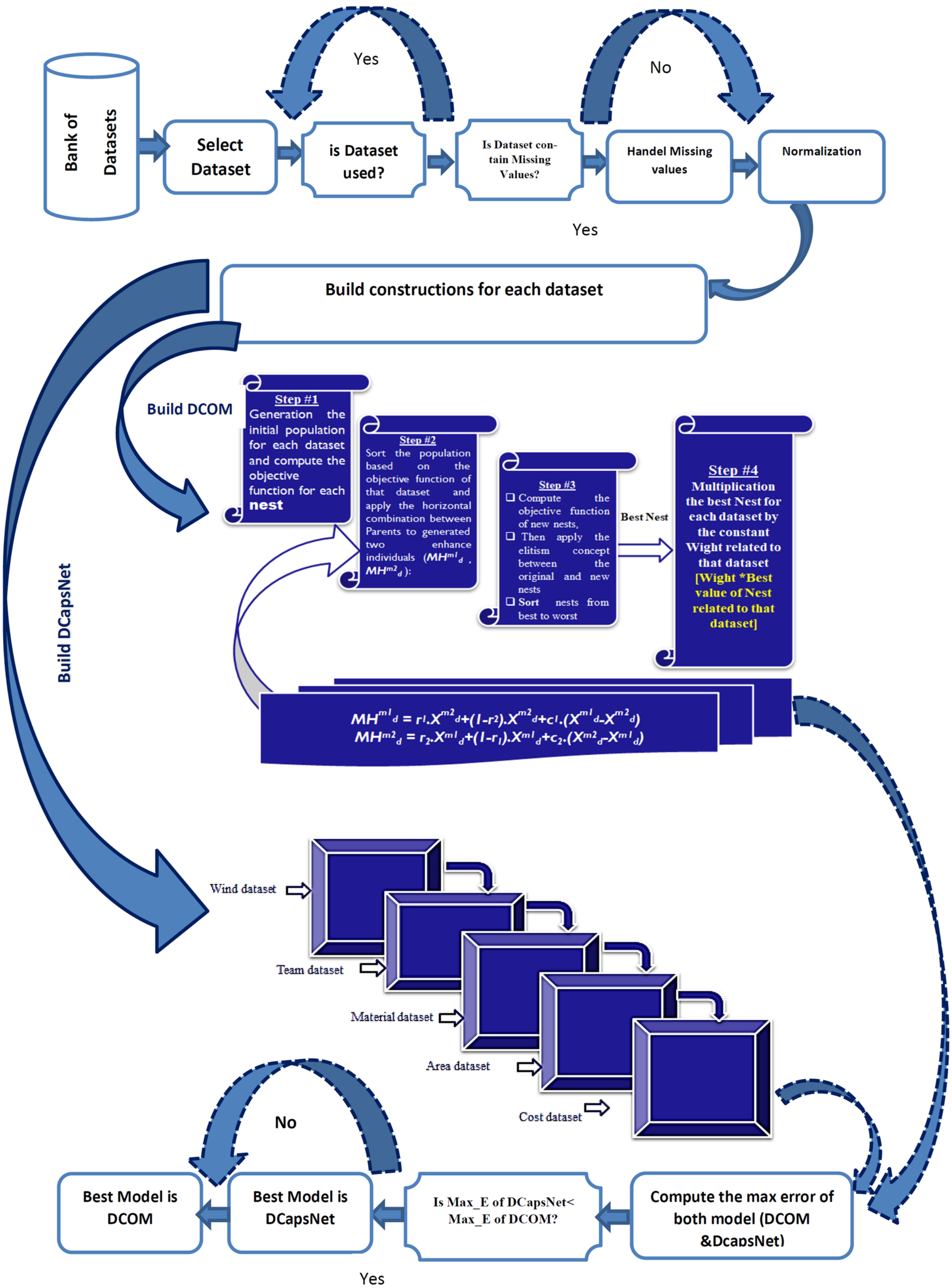

Fig. 2 An innovative synthesis of deep learning techniques (DCapsNet & DCOM)

This stage converts all the features of the different dataset related to that database in the same range [0,1], to avoid the problem of using different unit in computing each feature of dataset. The normalized value, ei, is the value of feature i that needs to convert it in range (0,1) and can be computed as (Al-Janabi et al. 2015; Al Janabi et al. 2018):

$$\text{Normalized}(ei) = (ei - E\min)/(E\max - E\min) \tag{2}$$

where $E\min$ presents the minimum value for variable E, while $E\max$ represents the maximum value for variable E.

C. Build constraints

Each dataset related to FED has constraints different from other datasets as follows (Lamedica et al. 2018; Eriksson and Gray 2018):

- Wind dataset

After collected the wind dataset in step number one of this model, we found that dataset contains multi-features (i.e., fields(date/time), wind direction (DEG), wind speed (MPH)). In general, we descripted that constraints as follows: If the value of wind speed in range (min_value of speed-min_value of speed) and the value of wind direction in range (min_value of direction-max_value of direction) can compute the objective function as below, where these ranges determined based on the natural of each dataset :

$$F = \sum(\Delta wt), \quad t = 1\ldots T \tag{3}$$

where Δwt is wind power curtailment at time t, and T is total dispatch period.

- Cost dataset

It contains the three features (i.e., area, team, material) and, to find the minimum cost, should apply the flowing: If the value of cost area in range(min_value of cost_area − max_value of cost_area) and the value of cost _team in range(min_value of cost_team − max_value of cost_team) and the value of cost_material in range(min_value of cost_material − max_value of cost_material) in this way can achieve the objective function as follows :

$$Min\_\cos t = mi\left(\sum ki\right) \tag{4}$$

where i = 1…N, N is the number of features

- Area dataset

These constraints are with respect to the wind energy production, a constraint arises owing the limited available ground area for the installation of the wind turbines, in order to resolve these obstacles, and consideration should be given to the following constraints:

First constraint should be the total number of turbines in the area taken by each turbine and should be less or equal than the total area available:

$$X1 * Ab < = A\max \tag{5}$$

where X is the number of turbines, Ab is the area of turbine, $A\max$ is the max area.

For example, let number of turbines = 5, the area that takes each turbine = 4 m and the max area = 400 m:

X1 * Ab <= Amax
5 * 4 = 20
20 < 400 The area is acceptable

Second constraint, it is achieved if the first constraint is processed:

$$X_2 < = \left([(S_1 - 3)(S_1 - 3)]/\left[L^2 * \cos\beta(1 + \tan\beta/\tan\gamma)\right]\right) \tag{6}$$

$$D = L * \cos\beta(1 + \tan\beta/\tan\gamma) \tag{7}$$

Third constraint, it is achieved if both the first and second constraints are processed:

$$\text{Max turbine} = (S1 - 3)/D \tag{8}$$

$$X3 < = ([(S1 - 3)/L] * \text{ Max turbine}) \tag{9}$$

where Xi >=0, i = 1,2…N, Xi is the energy generated in each turbine, $X2$ is the type of turbine, $S1$ is the large side of the available area for installation of turbine, L is the feather length related of turbine plus 50 Cm, β is wind speed, γ is the wind direction, X3 is total values of turbine types. In this way we can compute the objective function:

If (first constraint is true) and (second constraint is true) and (third constraint is true) then

The area is accepted, otherwise not accepted

- Material dataset

After collected it, this dataset contains some features (i.e., wire, type, stats, years, batteries) and to find the best tools used in the power generation process from:

If the values of wire, type, stats, years and batteries in ranges (min_value of wire − max_value of wire),(min_-value of type − max_value of type),(min_value of stats − max_value of stats),(min_value of years − max_value of years),(min_value of batteries − max_value of batteries), respectively, can compute the objective function as below, we first find the sum of all features for each t-th according to the flowing equation as follows:

$$\text{Bestmaterial} = \max\left(\sum Mt\right) \tag{10}$$

where $t = 1 \ldots N$, N is the number of features

- Team dataset

After collected it, we found that dataset contains some features (i.e., certificate, number of work clock, number of experience certificate, number of cycles, age), and to find the best team used in generation process, we should apply: If the features certificate, number of work clock, number of experience certificate, number of cycles and age have values in ranges(min_value of certificate − max_value of certificate),(min_value of number of work clock − max_-value of number of work clock),(min_value of number of experience certificate − max_value of number of experience certificate),(min_value of number of cycles − max_value of number of cycles),(min_value of age − max_value of age), respectively, in this way we can compute the objective function as below, and we first find the sum of all features for each r-th according to the flowing equation as follows:

$$best\_team = \max\left(\sum Tr\right) \tag{11}$$

where $r = 1 \ldots N$, N is the number of features.

3.1.1 Building optimization models for MORE-G

This stage considers the core of proposed model including two steps. The first step develops cuckoo optimization algorithm through adding new types of combination among candidates, and these combinations are called horizontal combination to achieve the goal of this thesis (i.e., generated max renewable energy with lowest cost and highest efficiency). The second step develops CapsNet that contains multi-layer to achieve the goal of this thesis, where each layer of that network satisfies the optimization for one of the datasets related to FED and the output of that layer becomes as input to the next layer with another dataset. At the same time this layer will satisfy the constraints of that dataset and the output of it represents the optimal value of datasets #1 and #2, continues with entering dataset for each new layer and satisfies the constraints of it. The result of final layer represents the linear combination to optimization solution (i.e., max renewable energy generated based on wind).

A. Develop Cuckoo optimization model (DCOA)

After complete handling the database and determining the constraints of each dataset, we need to determine the objective function for each dataset that represents the optimization objective function of it that satisfies the set of constraints related to it. While the cuckoo starts its work by generation, the initial population consists of n host nests. If the stop criteria of cuckoo do not satisfy (i.e., number of generations not arrived to max number of generations determined by user). Then cuckoo chooses randomly one of individuals of that population and put it in the suitable location of first table that represents the possible solution and continues that for all individuals in that population, after that is replaced among the individual (possible solution) by performing Levy flights and computing the fitness for each one. To choose the optimal solution, we develop cuckoo through achieving one of the combination methods called horizontal combination, which is the candidates that gain knowledge from various dimensions of other candidates to generate moderation solutions as given below: Assume that the parent individuals *Xm1* and *Xm2* (*m1*, *m2*) execute horizontal combination at d dimension, and the moderation solution is generated as follows:

$$MH_d^{m1} = r_1 \cdot X_d^{m2} + (1 - r_2) \cdot X_d^{m2} + c_1 \cdot \left(X_d^{m1} - X_d^{m2}\right)$$
$$MH_d^{m2} = r_1 \cdot X_d^{m1} + (1 - r_1) \cdot X_d^{m1} + c_2 \cdot \left(X_d^{m2} - X_d^{m1}\right)$$

Here *MHm1*, *MHm2* are two new generated moderation solutions. *r1*, *r2* are uniformly distributed random values between [0,1], *c1*, *c2* are expansion coefficients which are uniformly distributed random values between [− 1,1]. After the moderation solutions obtained by horizontal combination, it needs to perform the competitive operation between *MHm* and *Xm* (m = 1,2,…M). Only the individual with higher fitness can survive. Thus, X retains a set of personal best solutions called as dominant horizontal solutions (DHSm).

```
Algorthim#2 :Pre-processing
Input:  Database called friendly environment database (FED) have wind, cost, area, material and  team
Output: Dataset after preprocessing
For each dataset_i  //i=1..5
    For each sample j  //j=1..M
        IF j have missing value
            For each features k  //k=1..N
                // Handle Missing Value
                IF a[i,j,k]=" "
                        a[i,j,k]=mean(1/n*∑x_k)
                Else
                        return a[i,j,k]
                End if
            End for
        Else
        // Normalization
            a[i,j,k]= (a[i,j,k]-min[i])/(max[i]-min[i])
        End if
    End for
End for
// Build Constraints
// Constraints of Wind Dataset
For each sample_j  // j is number of sample in wind dataset & j in range 1 to number sample -1
    For each features k // k is number of features
        IF ((speed in range (min_value of speed- max_value of speed)) and (direction
            in range(min_value of direction- max_value of direction) ))  then
        // Objective Function
            delt-wind=0
            delt-wind = delt-wind+(a[j+1]-a[j])
        End if
    End for
End for
/ Constraints of Cost Dataset
For each sample_j // j is number sample of cost dataset
    For each features_k // k is number features in cost dataset
        IF [(cost_area in range(min_value of cost_area - max_value of cost_area))
            and  (cost_team in range(min_value of cost_team - max_value of
            cost_team))and (cost_material in range(min_value of cost_material-
            max_value of cost_material))] then
        // Objective Function
            sum[j,k]=0
            sum[j,k]=sum[j,k]+a[j,k]

            w[j]=sum[j,k]
        End if
    End for
    min-cost=min(w[j])
End for
```

where X is the number of turbine, Ab is the area of turbine, Amax is the max area, $X\ i >=0$, $i = 1,2\ldots N$, Xi is the energy generated in each turbine, $S1$ is the large side of the available area for installation of turbine, L is the feather length related of turbine plus 50 Cm, β is wind speed, γ is the wind direction.

```
//Constraints of Area Dataset
For each sample j // j is number sample in area dataset
    For each features k // k is number features of area dataset
        IF (X1*Ab<=Amax) &( X2<= ( [(S1-3)(S1-3)]/[L^2*cos β (1+tan β/tan γ)] )&
            ( Max turbine =(S1-3)/ D)&( D=L*cos β (1+tan β/tan γ))&(X3<= ([(S1-
            3)/L]* Max turbine)) then
            //Objective Function
            the area is accepted otherwise not accepted
        End if
    End for
End for
// Constraints of Material Dataset
For each sample j // j is number sample of material dataset
    For each features k // k is number features in material dataset
        IF [wire in range(min_value of wire - max_value of wire)and type in
            range (min_value of stats - max_value of stats)and state in range
            (min_value of years - max_value of years)and years in range(min_value
            of batteries - max_value of batteries) then
            // Objective Function
            sum[j,k]=0
            sum[j,k]=sum[j,k]+a[j,k]
            m[j]=sum[j,k]
        End if
    End for
    best-material=max(m[j])
End for
// Constraints of Team Dataset
For each sample j // j is number sample of team dataset
    For each features k // k is number features in team dataset
        IF [certificate in range(min_value of certificate - max_value of certificate)
            and number of work clock in range(min_value of number of work clock
            - max_value of number of work clock) and number of experience
            certificate in range(min_value of number of experience certificate –
            max_value of number of experience certificate) and number of cycles in
            range(min_value of number of cycles - max_value of number of cycles)
            and age in range (min_value of age - max_value of age)] then
            // Objective Function
            sum[j,k]=0

            sum[j,k]=sum[j,k]+a[j,k]
            t[j]=sum[j,k]
        End if
    End for
    best-team=max(t[j])
End for
End Pre-processing
```

B. Develop capsule network model (DCapsNet)

The CapsNet consists of multi-layers. Each layer implements a specific equation for that layer so that the first layer implements the soft-max equation, second layer processes the weight mean predicted equation, while the third layer implements the weighted sum, and the final layer performs the squash equation. All of these equations are explained in detail by the DCapsNet model in algorithm (4).

4 Experiment

4.1 Description of database

Database has five datasets (wind, area, material, team and cost). Each dataset has different features. Each dataset consists of over 631286 samples. First dataset for the wind contains 2 features (wind direction (DEG), wind speed). Second dataset for cost includes 3 features (area, turbine, material), and we used three types of turbine and these types encode as follow (1: small turbine, 2: normal turbine, 3: large turbine). Third dataset for area contains 4 features (size of turbine, the area of each turbine, type of area, number of turbine) where the type of area encodes as follows: high, flat, low. The fourth dataset for team includes 5 features (certificate, number of work clock, number of experience certificate, number of training courses, age), and these features encode as follows: certificate (1: bachelor, 2: diploma, 3: master, 4: PhD, 5: expert), number of work (6–12), number of experience certificate (5–15), number of training courses (5–15),age (25–70). The fifth datasets for materials contain 5 features (wire, type, stats, years, batteries) (Fig. 3).

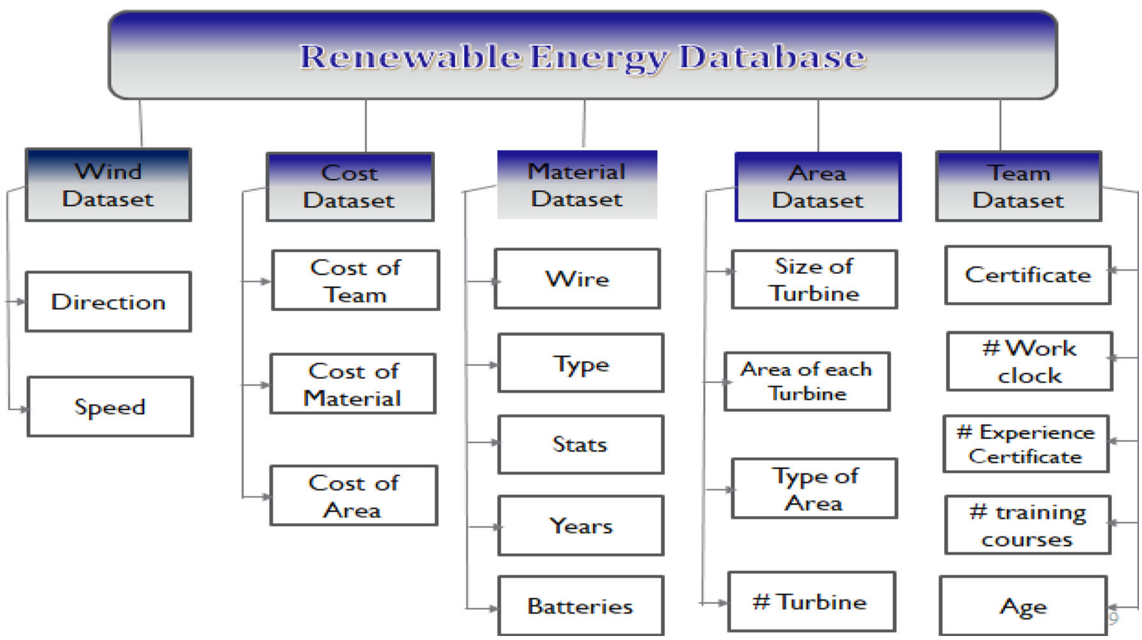

Fig. 3 Description of database

Algorithm #3: DCOM

```
Input: a // the database after pre-processing
Output: Max Energy Generated FED
Initialization: t: number of iteration, n: number of nests host, Fi: objective function, Max Generation
For each dataset_i // i =1,2..5
    For each sample in dataset_j
        For each column in sample_k
            // Generated population
            pop[i,j,k]=random a[i,j,k]
            compute objective function
        End for
    End for
    While (t< Max Generation) or (stop criteria)
        For each sample in dataset_j
            For each column in sample_k
                select randomly(pop1[i,j,k],pop2[i,j,k])
                child1=r1.pop2[i,j,k]+(1-r1). pop2[i,j,k]+c1.( pop1[i,j,k]-
                 pop2[i,j,k])
                child2=r1.pop1[i,j,k]+(1-r1). Pop1[i,j,k]+c2.( pop2[i,j,k]-
                 pop1[i,j,k])
                compute objective function for each child
            End for
        End for
        choice the Elite among population and children, whichever is
         better
        IF Fi < Fj then
            Replace j by the new solution
        End if
        a fraction pa of the worse nests are abandoned and new ones
         are built
        Keep the best nests
        Rank the nests and find the current best
        Pass the current best solutions to the next generation
    End While
End for
End DCOM
```

4.2 Implementation of MORE-G model

This section will show the results for each stage in MORE-G. Also, it will be given justification for all results and it will be compared it with the previous works.

Algorithm #4 : DCapsNet

```
Input: a  // the database after pre-processing
Output: Max Energy Generated FED
For each dataset_i  // i =1,2..5
    For all capsule i in layer ℓ and capsule j in layer (ℓ+ 1):
        b_ij = 0
    End for
    For iteration t do
        For all capsule i in layer ℓ
            c_ij = exp(b_ij) / ∑_i exp(b_ik)
        End for
        For all capsule j in layer (ℓ + 1)
            s_j =∑_i c_ij μ_j|i
            sj = sj / ||sj||
        End for
        For all capsule i in layer ℓ and j in layer(ℓ +1)
            b_ij = b_ij +w_j< μ_j|i,sj>i,     where    w_j = ||sj||^2 / 1+|| sj||^2
        End for
    End for
    Return w_j s_j
    Pass w_j s_j from layer_i to layer_i+1
End for
End DCapsNet
```

4.2.1 Collection of database

At this stage, the database is collected which contains five dataset, redundant and not readily available, and they are collected from several different locations. These datasets are different in features but must be equal in number of record because we want to find multi-objective optimization.

4.2.2 Pre-processing of database

This is the first stage to implement the MORE-G model, which consists of three phases, ***handle missing value;*** In this paper, our feasibility study relies on the existence of real data. If one of the data is lost, the missing value is treated using the mean equation in two stages, first each value of nan is replaced by zero, and then the value zero is replaced by the mean value. ***Normalization:*** It is a problem that can be handled after the missing value is processed so that the data range between zero and one: ***and*** *Build* ***constraints,*** it is the final phase of pre-processing stage, explained with details in algorithm 2.

4.2.3 Implementation DCOM

In this model, we deal with five datasets and each dataset contains 631286 samples. In each iteration, we will choose 200 individuals to the pool recombination (crossover) to find the value satisfying the objective function and constraints of that dataset. The following section shows the main implemental steps.

Table 2 Main parameters of DCO

Parameters	Initial value
# individual in each population	200
t (number of iteration)	1000
Max Generation	50
w_wind(weight of wind)	0.5
w_cost(weight of cost)	0.2
w_area(weight of area)	0.1
w_material(weight of material)	0.1
w_team(weight of team)	0.1

A. Set of parameters

Table 2 describes all parameters and their initial values except the variable n, where n is the number of features in each dataset.

B. Generate initial population

The algorithm generated initial population based on the features of these dataset and location. In general, because each dataset is different on others from side number of features, Table 3 shows the initial population.

C. Compute objective function for initial population

The table shows the values result from computing the objective function for each dataset (Table 4).

D. Sort the values of objective function for initial population

In Table 5, the objective function values are sorted in ascending order for all dataset.

E. Apply horizontal combination to generate new population

Since we have five datasets of different features as mentioned earlier, to illustrate the process of horizontal combination in it we will display the results of the cost dataset and for ten iterations only to facilitate the viewing of results as below (Fig. 4, 5).

In Table 6 the horizontal combination process is applied to several stages where each column represents one of these phases, the first column represents the number of iterations where we will review 10 iterations to illustrate the process, the second column represents the randomly selected parents where in each iteration different parents are selected so that the first parents should be different from the second parents, in the third column the objective function is calculated for all the selected parents, the fourth column represents the children born after the applying the horizontal combination process described above, and the fifth column represents the objective function that is calculated for the children, the sixth column represents a comparison between children and parents as the objective function to choose a new generation called elitism, and finally the seventh column represents the value of the objective function of the new generation (Elitism) (Fig. 6).

F. Compute the best value to each dataset

In this step the constraints are applied to find the best values for each dataset:

Table 3 Initial population for all datasets

Wind dataset	Cost dataset	Team dataset	Material dataset	Area dataset
[1, 0]	[1, 2, 0]	[1, 0, 2, 3, 4]	[3, 4, 2, 0, 1]	[1, 2, 0]
[0, 1]	[2, 0, 1]	[2, 3, 4, 1, 0]	[1, 0, 2, 3, 4]	[2, 0, 1]
[1, 0]	[1, 0, 2]	[1, 2, 0, 3, 4]	[4, 0, 1, 3, 2]	[0, 1, 2]
[0, 1]	[0, 1, 2]	[2, 3, 4, 1, 0]	[0, 1, 4, 2, 3]	[2, 1, 0]
[1, 0]	[1, 2, 0]	[0, 4, 1, 2, 3]	[0, 1, 2, 4, 3]	[2, 1, 0]
[0, 1]	[2, 0, 1]	[2, 1, 3, 4, 0]	[1, 2, 0, 3, 4]	[1, 0, 2]
[1, 0]	[1, 2, 0]	[2, 3, 1, 4, 0]	[4, 0, 1, 2, 3]	[1, 2, 0]
[0, 1]	[0, 1, 2]	[0, 1, 2, 3, 4]	[3, 4, 0, 1, 2]	[2, 0, 1]
[1, 0]	[1, 2, 0]	[4, 3, 0, 1, 2]	[3, 4, 0, 2, 1]	[0, 1, 2]
[0, 1]	[2, 0, 1]	[3, 4, 2, 0, 1]	[0, 4, 1, 2, 3]	[2, 1, 0]

Table 4 The values of objective function for initial population to each dataset

Wind dataset	Cost dataset	Team dataset	Material dataset	Area dataset
1.025	1.076	0.839	1.538	1.395
1.025	1.076	0.839	1.788	1.395
1.025	1.649	1.322	2.08	1.395
1.025	1.076	0.839	2.223	1.540
1.025	1.076	1.478	2.33	1.540
1.025	1.076	1.506	2.788	1.395
1.025	1.076	1.939	2.913	1.395
1.025	1.076	2.172	2.913	1.395
1.025	1.649	2.211	2.996	1.540
1.025	1.076	2.867	3.352	1.540

Table 5 Sort the values of objective function for initial population

Wind dataset	Cost dataset	Team dataset	Material dataset	Area dataset
1.025	1.649	2.867	3.352	1.540
1.025	1.649	2.211	2.996	1.540
1.025	1.076	2.172	2.913	1.540
1.025	1.076	1.939	2.913	1.540
1.025	1.076	1.506	2.788	1.395
1.025	1.076	1.478	2.33	1.395
1.025	1.076	1.322	2.223	1.395
1.025	1.076	0.839	2.08	1.395
1.025	1.076	0.839	1.788	1.395
1.025	1.076	0.839	1.538	1.395

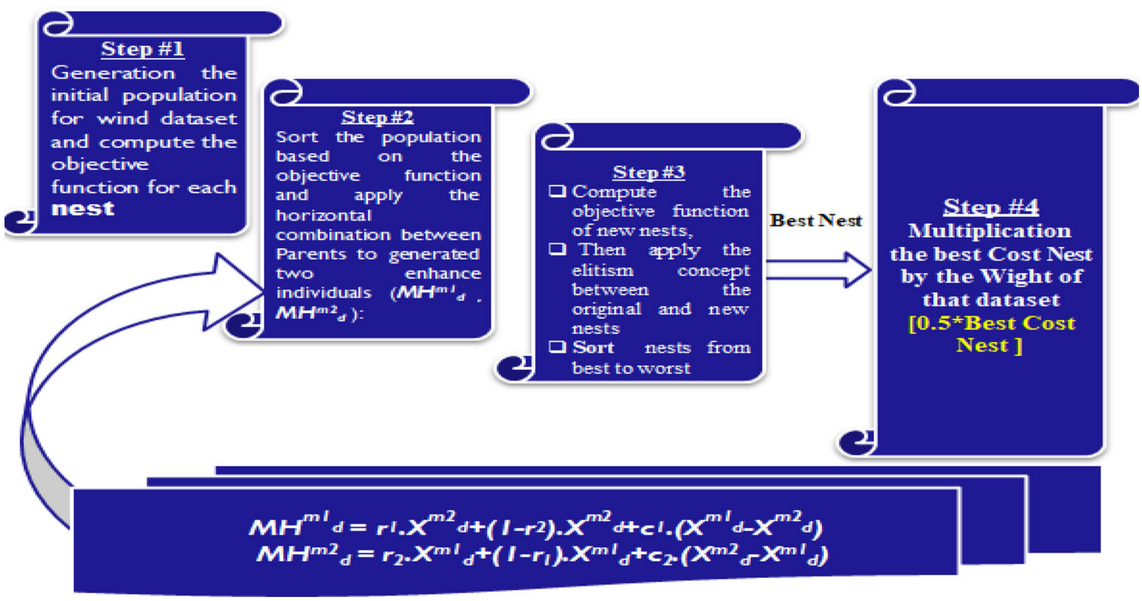

Fig. 4 Implementation of DCOA to cost dataset

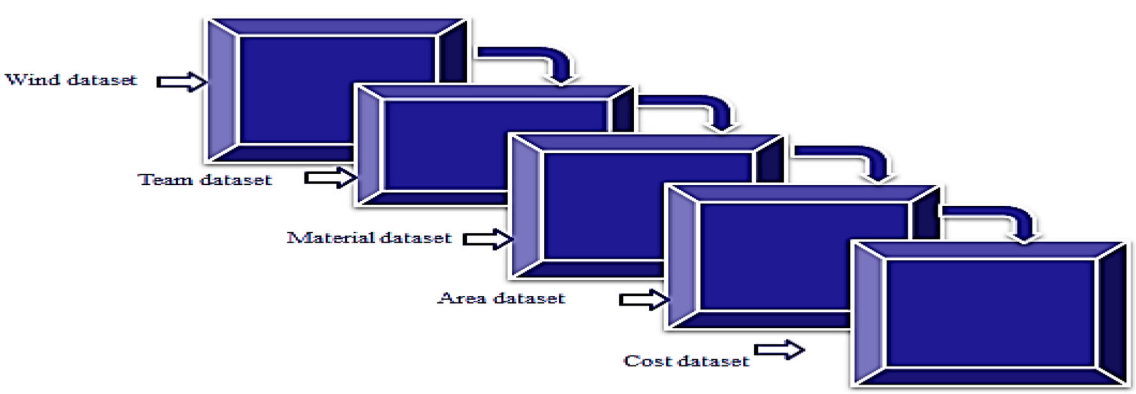

Fig. 5 Implementation of DCapsNet model

- Result the constraints of cost dataset

min_ wind = 1.025, This value comes from the best values of Wind_direction = 94.906, wind_speed = 7.337

- Result the constraints of cost dataset

min_cost = 1.075, This value comes from the best values of Cost_area = 25, cost_team = 269, cost_material = 10.

Table 6 New population after applying horizontal combination to cost dataset

#Iteration	Parents from initial population	Objective function of parents	Children after hor. combination	Objective function of children	Elitism	Objective function of elitism
1	[1, 0, 2]	1.649	[1, 0, 2]	1.649	[1, 0, 2]	1.649
	[2, 1, 0]	1.649	[2, 1, 0]	1.649	[2, 1, 0]	1.649
2	[1, 2, 0]	1.0757	[1, 2, 0]	1.0757	[1, 2, 0]	1.0757
	[2, 0, 1]	1.0757	[1, 2, 0]	1.0757	[2, 0, 1]	1.0757
3	[1, 2, 0]	1.0757	[1, 2]	1.761	[1, 2]	1.761
	[2, 0, 1]	1.0757	[1, 1, 0]	1.555	[1, 1, 0]	1.555
4	[2, 1, 0]	1.649	[0, 1, 2]	1.0757	[1]	2.134
	[0, 1, 2]	1.0757	[1]	2.134	[2, 1, 0]	1.649
5	[1, 2, 0]	1.0757	[2, 0, 1]	1.0757	[1, 2]	1.761
	[2, 0, 1]	1.0757	[1, 2]	1.761	[1, 2, 0]	1.0757
6	[1, 2, 0]	1.0757	[1, 2, 0]	1.0757	[1, 2, 0]	1.0757
	[1, 2, 0]	1.0757	[1, 2, 0]	1.0757	[1, 2, 0]	1.0757
7	[1, 0, 2]	1.649	[1]	2.134	[1, 1, 1]	2.134
	[1, 2, 0]	1.0757	[1, 0, 2]	1.649	[1, 0, 2]	1.649
8	[1, 2, 0]	1.0757	[1, 2, 0]	1.0757	[1, 2, 0]	1.0757
	[1, 2, 0]	1.0757	[1, 2, 0]	1.0757	[1, 2, 0]	1.0757
9	[1, 2, 0]	1.0757	[1, 2, 0]	1.0757	[1, 2, 0]	1.0757
	[1, 2, 0]	1.0757	[1, 2, 0]	1.0757	[1, 2, 0]	1.0757
10	[1, 0, 2]	1.649	[1, 2]	1.891	[1]	2.134
	[1, 2, 0]	1.0757	[1]	2.134	[1, 2]	1.891
…	…	…	…	…	…	…
	…	…	…	…	…	…
…	…	…	…	…	…	…
	…	…	…	…	…	…
993	[1, 0, 2]	1.649	[1]	2.134	[1]	2.134
	[1, 2, 0]	1.0757	[1, 0, 2]	1.649	[1, 0, 2]	1.649
994	[1, 2, 0]	1.0757	[1, 2, 0]	1.0757	[1, 2, 0]	1.0757
	[1, 2, 0]	1.0757	[1, 2, 0]	1.0757	[1, 2, 0]	1.0757
995	[1, 2, 0]	1.0757	[1, 2, 0]	1.0757	[1, 2, 0]	1.0757
	[1, 2, 0]	1.0757	[1, 2, 0]	1.0757	[1, 2, 0]	1.0757
996	[1, 0, 2]	1.649	[1, 2]	1.891	[1]	2.134
	[1, 2, 0]	1.0757	[1]	2.134	[1, 2]	1.891
997	[1, 2, 0]	1.0757	[1, 2, 0]	1.0757	[1, 2, 0]	1.0757
	[2, 0, 1]	1.0757	[1, 2, 0]	1.0757	[2, 0, 1]	1.0757
998	[1, 2, 0]	1.0757	[1, 2]	1.761	[1, 2]	1.761
	[2, 0, 1]	1.0757	[1, 1, 0]	1.555	[1, 1, 0]	1.555
999	[2, 1, 0]	1.649	[0, 1, 2]	1.0757	[1]	2.134
	[0, 1, 2]	1.0757	[1]	2.134	[2, 1, 0]	1.649
1000	[1, 2, 0]	1.0757	[2, 0, 1]	1.0757	[1, 2]	1.761
	[2, 0, 1]	1.0757	[1, 2]	1.761	[1, 2, 0]	1.0757

- Result the constraints of material dataset

best_ material = 4.347. This value comes from the best values of wire = 8, type = 2, state = 2, years = 1, batteries = 4000

- Result the constraints of area dataset

min_area = 1.116. This value comes from the best values of the area for each turbine = 50, type = 0.78452086, # turbine = 32

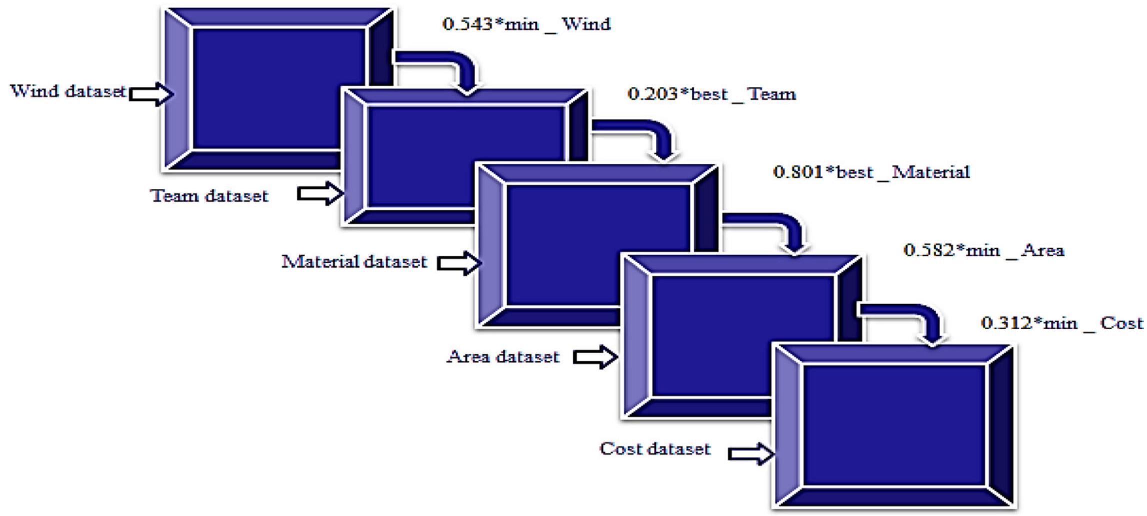

Fig. 6 Implementation of DCapsNet model with best weight

- Result the constraints of team dataset

best_ team = 3.416. This value comes from the best values of certificate = 5, # clock = 11, #expert = 12, # cycle = 12, # age = 68

G. Compute maximum energy

We will apply the principle of linear combination to obtain the maximum energy generated based on pre-imposed weights :Weight_wind = 0.5, Weight_cost = 0.2, Weight_material = 0.1, Weight_team = 0.1, Weight_area = 0.1,

Max_Energy = weight_wind * min_wind + weight_cost * min_cost + weight_material * best_material + weight_team * best_team + weight_area * min_area

Max_Energy = 1.744

H. Compute error for DCOM

Error = 0.2, Best error = 0.17 in iteration 750

4.2.4 Implementation developed DCapsNet model

Each layer has different structures based on number of number of features of that dataset (input nodes). The activation function represents the objective function that results in optimal values and in each layer will save weights for each feature that leads to optimal values. First layer has one output, second layer has the output of that dataset with the result passes from layer one, third layer has the output of that dataset with the results passed from layer #1 & #2, fourth Layer has the output of that dataset with the results passed from layer #1, #2 & #3, fifth layer has the output of that dataset with the results passed from layer #1, #2, #3 & #4 and it is described below (Fig. 7):

A. Compute the best value for each dataset

In this step the constraints are applied to find the best values for each dataset:

min_wind = 0.487
min_cost = 0.405
best_material = 0.721
best_team = 0.701
min_area = 0.401

B. Compute maximum energy for DCapsNet

Best weight for wind = 0.543
Best weight for cost = 0.312
Best weight for material = 0.801
Best weight for team = 0.203
Best weight for area = 0.582

Max_Energy = weight_wind * min_wind + weight_cost * min_cost + weight_material * best_material + weight_team * best_team + weight_area * min_area

Max _ Energy = 1.344007

C. Compute error for DCapsNet

Error = 0.08, Best error = 0.01 in iteration 800

4.2.5 Evaluation stage

In this stage, we will compare the error to both DCOA & DCapsNet, and this is explained in Table 7 and Fig. 7.

In Table 7, the bold values represent the best value where the table compares between two models to

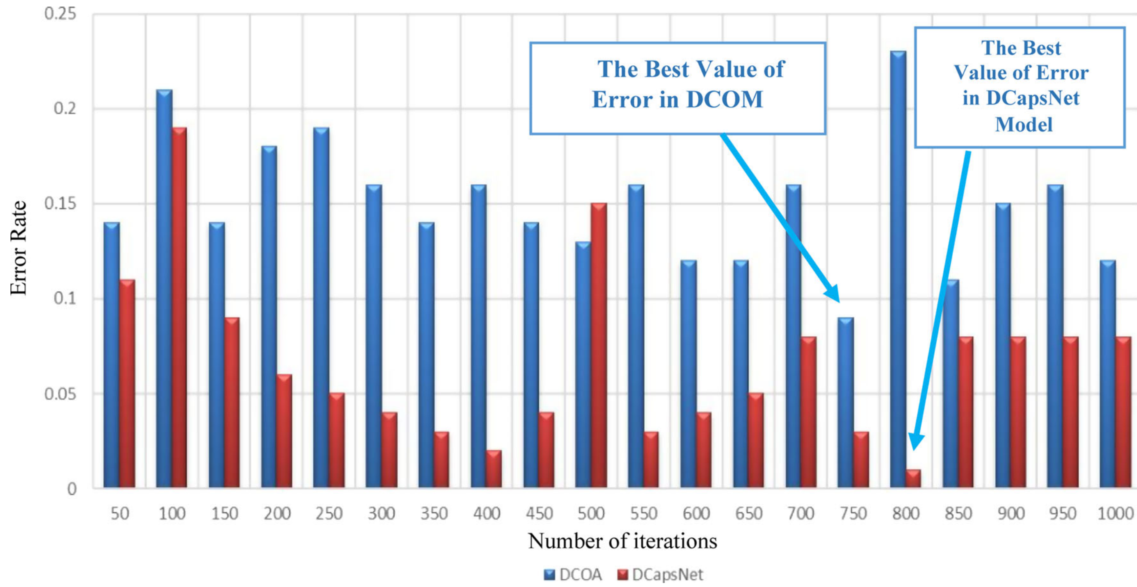

Fig. 7 Compare the error between DCOM and DCapsNet

Table 7 Comparison between the error of DCOM and DCapsNet model

# Iteration	DCOM	DCapsNet model
50	0.14	0.7
100	0.21	0.52
150	0.14	0.56
200	0.18	0.48
250	0.19	0.59
300	0.16	0.32
350	0.14	0.27
400	0.16	0.15
450	0.14	0.04
500	0.13	0.15
550	0.16	0.03
600	0.12	0.04
650	0.12	0.05
700	0.16	0.08
750	0.09	0.03
800	0.23	0.01
850	0.11	0.08
900	0.15	0.08
950	0.16	0.08
1000	0.12	0.08

determine which one is better. We used the same number of iterations in both models and compute the error each 50 iteration as shown in table, where the table consists of three columns, the first column contains the number of iterations, the second column represents the error resulting from the DCOM model in each 50 iteration, while the third column contains the error value resulting from DCapsNet model. As a result, we found DCapsNet to give best result than DCOM this is because it is based on computing through training the network rather than the weights assumed by the user in the first model.

5 Discussions and conclusions

Based on the principle that the upgrading of any nation begins by raising the level of performance of its institutions that serve the community, including the Ministry of Electricity and given the development in the field of technology and the growing need to generate electric power, we find that the world has tended in recent years to generate that energy from environmentally friendly sources that do not cause CO_2 emissions during generation such as solar, wind, water and other sources. Finding a solution to the problem of generating electricity from environmentally friendly energy is a very difficult and important issue because it is one of the basic problems in our Arab societies.

The main purpose is to preserve the environment from the pollution resulting from the process of generating electricity as well as reducing the material costs in its production. This paper deals with two main points: How to present the optimal feasibility study for the process of generating electricity from wind energy at the lowest cost and the highest efficiency.

The paper conclusions drawn from this work are summarized as follows: It solves one of main problems related to generate the renewable energy from the minimum rate of available wind. The data that have been dealt with are relatively complex and composed of more than one dataset (wind, cost, area, team, material). The pre-processing stage involves three stage; first stage involves processing of missing value, then after this stage doing normalization to make all values between one and zero because the values of the objective function should be between zero and one, and the final stage is building of constraints for each dataset. Since we have five datasets, we will have different constraints that vary according to the dataset.

There are many optimization algorithms to find the best solutions, but the cuckoo algorithm was chosen because all our dataset has a few features and this algorithm was chosen accordingly because the cuckoo algorithm gives high accuracy in the results when the number of features is few. Develop cuckoo optimization (DCO) using horizontal combination to find the best results. Develop neural network algorithm, which consists of multi-layers so that each layer represents the optimization of each dataset with its constraints, using linear combination to generate the renewable energy in lowest cost and highest efficiency. Compare between the models to determine the best model. In general, the main purposes of design MORE-G are attempting to answer the following equations:

How the proposed optimization scheme suitable for the increase in the production of electrical power compared to other such comparable techniques? All of the above techniques use the traditional optimization method, which deals with one objective function, while we used the optimization method to solve multi-objective function problems, and each objective function has different constraints from the second. One of the best optimization algorithms was developed by the combination method, which is called horizontal combination to find the optimal value based on the objective function. Finally, the optimal values for each dataset were collected after determining the importance of the linear combination so that different weights were given to each dataset according to their importance, as for why the linear combination function was used only because it preserves the behaviors of each dataset, and it maintains the importance of the dataset.

How it satisfies the main challenges of optimization (the max rate of power extraction, high precision of design stations and less cost)? In this paper, two basic optimization techniques used and developed are DCOA and CapsNet. After specifying the constraint for each dataset it will satisfy the efficiency and multi-objective optimization with constraints satisfying the precision and less cost and the development for the optimization techniques with multi-objective optimization and constraints will satisfy the max rate of power generation.

Is the proposed technique suitable enough to lead to an optimal solution to satisfy the requirements? Depending on the nature of the data that has been developed, as well as the constraints that have been built, there are two methods that were first built, dealing with a certain number of characteristics and achieving the concept of optimization is called DCOA. The second method is DCapsNet and it is capable of dealing with a huge data with a different number of properties.

In future the long short-term memory (LSTM) neural network can test to achieve the same goal with Page Rank Clustering algorithm.

Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

Ethical approval This article does not contain any studies with human participants or animals performed by any of the author

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