Artificial Intelligence Based Security Constrained Economic Dispatch of Ethiopian Renewable Energy Systems: A Comparative Study

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Abstract. In this study, a comparison of two artificial intelligence inspired solution methods employed to solve Security Constrained Economic Dispatch (SCED) of Ethiopian Renewable Energy Systems (ERES) is presented. The solution methods are Efficient & Parallel Genetic Algorithm (EPGA) and Hopfield Neural Network (HNN). This paper argues that employing intelligent SCED that considers power mismatch and intermittency of renewables can solve ERES's recursive blackouts. A simulation was conducted on MATLAB. According to the results, both solution methods provide the best solutions for their respective purposes. For providing accurate forecast & predictive control of intermittent generation, it is imperative to employ HNN. When obtaining global maxima of multi-objective function is required, it is recommended to employ EPGA. Generally, employing intelligent SCED is a key planning step in adopting smarter grids as it reduces the production cost and the number of blackouts while increasing the security level of ERES.

Keywords: Hopfield neural networks · Genetic algorithms · Security constraints · Economic dispatch · Renewable energy systems · Ethiopian power grid

1 Introduction

Access to a secure and affordable energy supply is a prominent prerequisite for economic growth of a developing country like Ethiopia. With a formidable dependency on hydropower, renewable generation is increasing from the current 0.3 GW of wind capacity to 2.4 GW by 2025, before reaching 3.6 GW by 2030. Concurrently, emerging grid-connected solar PV capacity extends to an impressive 3.3 GW by 2025 ahead of the 5.3 GW projected installed capacity [1]. The Ethiopian grid is now entirely prime-moved by renewable energy sources and the Ethiopian Growth and Transformation Plan (GTP) imply that this trend will continue [2, 3] in compliance with the country's Climate Resilient Green Economy (CRGE) strategy [1, 4, 5]. Even though the

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country's plans are promising, there are still challenges regarding demand-supply balance that lead to recursive electricity blackouts [4].

One of the main challenges of power system operation is that electrical energy is cumbersome to store in significant amounts. This aspect requires a continuous balance between generation and demand subject to operational constraints. The second challenge is related to the integration of intermittent renewable energy sources. Variability and intermittency of wind and solar are challenges that cannot be ignored. Integrating them with other sources, providing storage and probabilistic forecast are their corresponding possible solutions [6]. For example, integrating solar and wind with geothermal & hydro stabilizes a given electrical system by providing flexibility and reserve services [7].

Table 1. Unit-based partial outages and their reasons for outage (2015–2016)

Power plant	Unit	Outage (MW)	Reason
	UNIT I	29	Under frequency
	UNIT II	29	Under frequency
FINCHA	UNIT III	29	Under frequency
	UNITIV	16	Under frequency
AMERTI	UNIT I	15	Under frequency
	UNIT II	15	Under frequency
GIBE I	UNIT I	10	Under frequency
	UNIT II	10	Under frequency
	UNIT I	102	Over-voltage
	UNIT II	99.2	Over-voltage
	UNIT II	12	Under frequency
AWASH II	UNIT II	10	Under voltage
	UNIT I	35	Under frequency
	UNIT II	35	Under frequency
MELKA	UNIT I	2.5	Over-current
	UNIT II	2.5	Over-current
	UNIT I	20	Under frequency
	UNIT I	10	Phase unbalance
ADAMA	ALL	16.4	Lost voltage
ASHEGODA	ALL	0.64	Lost voltage
ADAMA	ALL	14.64	Lost voltage
Total outage		704.38	

A daily power operation task which coins these two challenges is Security constrained Economic Dispatch (SCED). SCED is a process of planning generation schedules for generating units to completely and economically supply the demand while satisfying security constraints [8]. Here the argument for the importance of SCED hinges on the link among demand-supply imbalance, intermittency of renewables, and operational security needs [9]. There is growing evidence that most blackouts and outages of the Ethiopian power system are caused by poorly dispatched generating units [9, 10]. For one, under frequency and over frequency occur due to the imbalance between generation and load as presented in Table 1.

Official blackout report of the Ethiopian electric power from 2013 to 2016, reported 15 unit and plant blackouts. Contingencies such as natural incidents, equipment failures, and power mismatch caused these blackouts. Industries and commercial centers were not functional for an average of four months a year [5].

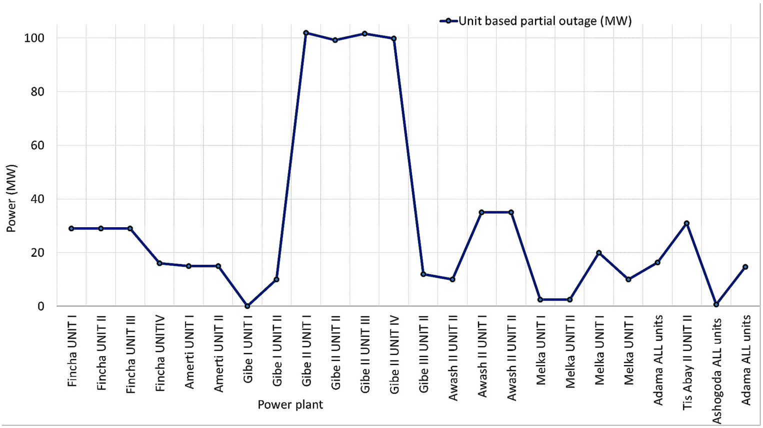

Fig. 1. Unit-based partial outages (2013–2016)

As determining an optimal solution of different functions with conflicting objectives is a moving target, a view of power system operation that ignores SCED is shortsighted [11, 12]. The recursive blackouts presented in Figs. 1 and 2 imply that the existing Ethiopian load dispatch center cannot address the challenges that the sector is facing in connection with intermittent renewables, power imbalance, and fluctuating demand.

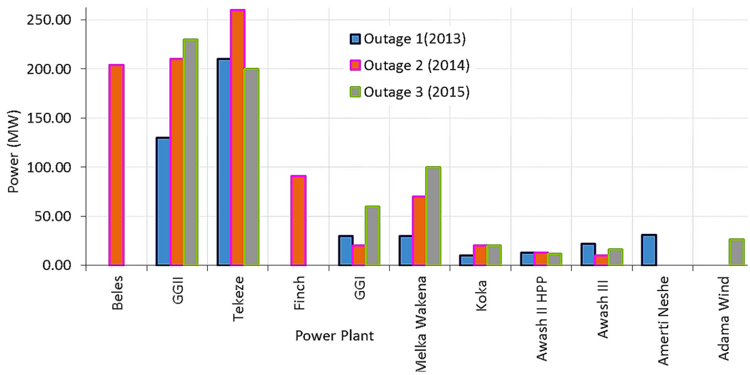

Fig. 2. Plant-based full outage samples (2013–2016)

This study utilized primary data such as forecasted load, interchange schedule, reserve requirements, transmission limits, generation cost offering, reserve limits, ramp rates and pre-scheduled generation level collected from generation-station control rooms and Ethiopian electric utility. This paper thus firmly chose to:

- Study and analyze ERES's potential, generation plan and capacity as supply side, demand profiles as demand side, of the supply-demand balance.
- Show the connection among recursive blackouts, reasons for an outage, intermittent renewables, power mismatch and SCED.
- Solve SCED of ERES using EPGA and HNN, and compare results.

2 Ethiopian Renewable Energy Systems

Integrating renewables without considering their economic and technical challenges leads to recursive blackouts and power service interruptions that subsequently affect the economic growth of the country [4]. For instance, in the Ethiopian power system, operation and planning decisions are carried out without the employment of economic dispatch. Ethiopia is gifted with various renewable energy resources. The estimated potential for hydropower is 45 GW, geothermal is 5 GW, and solar irradiation ranges from 4.5 kWh/m^2/day to 7.5 kWh/m^2/day [13, 14].

As of hydropower generation, large and small hydro potential estimates to 45 GW, of which 5% is only exploited. Wind potential is close to 1,350 GW but less than 1% of this potential is exploited [15]. The entire generation plan of ERES is depicted in Fig. 3. In a comprehensive construct, several papers presented renewable energy resource potential assessments and prospects of integrating renewable generation [15]. Hossain Mondal et al. [15] clearly articulated the prospects of improving energy efficiencies and mitigating greenhouse gasses emission of Ethiopian energy generation.

2.1 Generation Capacity

Electric power generation in Ethiopia currently depends on hydropower. At the same time, in 2012, only about 23% of the total population was connected to the national grid. The Ethiopian electricity grid is dominated by renewables, and the priority projects imply that this trend will continue. Geographic access to electricity is 56% with household connectivity of 25% and per capita electricity consumptions of 100 kwh/day [16, 17].

From a comprehensive understanding of the Ethiopian power grid, 99 power plants as renewable energy systems are identified. These include 48 operational power, 16 plants under construction, and 35 planned. Technology-wise, the planned power grid constitutes 35 hydropower plants, 18 geothermal power plants, 11 wind power plants, 9 solar power plants, and 21 renewable thermal power plants. In this study, the operational plants and plants that are under construction were used. Hence, the considered

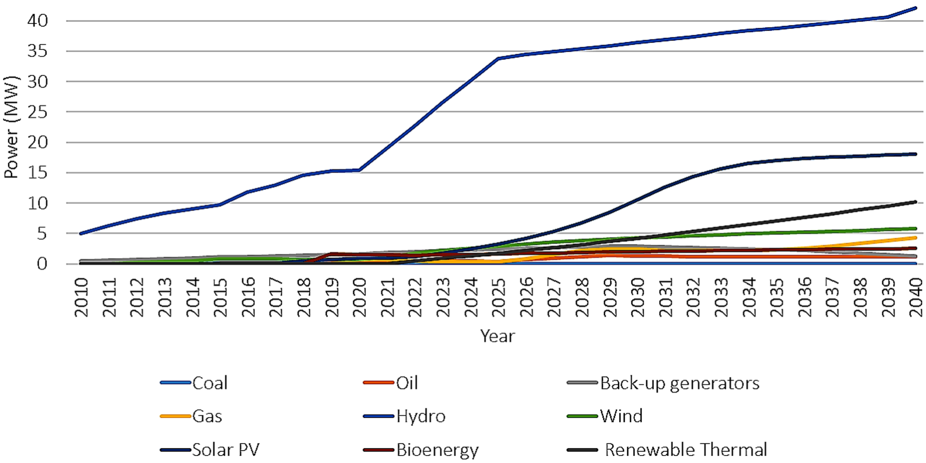

Fig. 3. Renewable generation capacity

renewable energy system constitutes 85 generating units and is dispatched for the projected year of 2025 according to the forecasted generation presented in Fig. 4.

2.2 Demand Forecast

The average annual growth in electricity demand from 2012 to 2013 was approximately 14% while electricity consumption per capita 60 Kw in the year 2012. According to [18], an estimated 23% population had access to electricity in 2012. Ethiopia faces a significant challenge while working to achieve sustainable development. Economic growth, population growth and industrialization greatly increase electricity demand [19]. To dress these challenges, the Ethiopian Electric power (EEP) is launching several projects considering demand for electricity to enhance its capacity in line with the growth of the country.

The electricity demand has doubled for the past 10 years and is expected to increase by 28%–32% per year in the next five years. GTP II aims to reach the power generation capacity of 17.3 GW and 21,728 km of transmission lines by 2020 [20]. These figures do not signify the effect of variable demand, recursive blackouts and intermittent generation. Most electric grids and utilities serve different customers of different sectors such as residential, commercial, and industrial as shown in Fig. 5. The electric usage is not the same for customers that belong to different sectors but somewhat similar for customers within the same sector [19].

To cope up with the growing demand's pace, intensive study on the demand profiles, accurate short-term planning, load forecast, and demand-supply balance should be provided. Apart from the prospects of empowering skilled workforce and advancing weak institutional capacity, providing economic and regulatory framework is a crucial power planning decision.

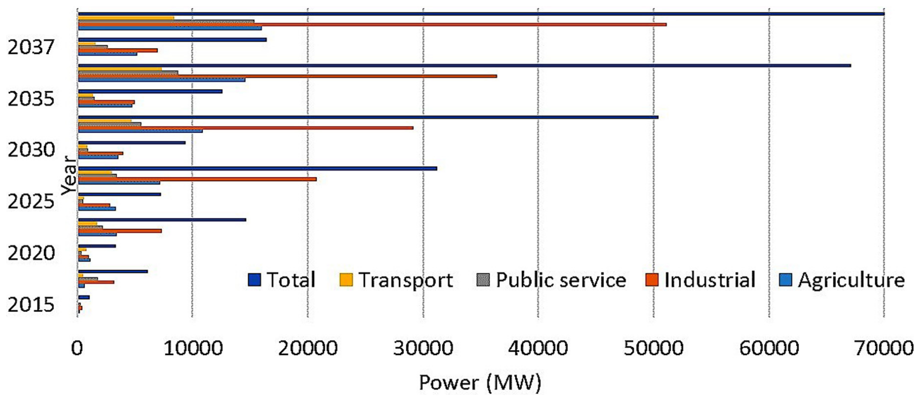

Fig. 4. Sector-wise demand forecast

2.3 Power Mismatch

To dispatch a power system, it is imperative to study supply and demand profiles. Supply refers to the existing generation capacity of the power system, while demand refers to the load of the grid. Ethiopia has a final energy consumption of around 40,000 GWh, whereof domestic appliances consume 4%, the transport sector consumes 3% and the industrial sector consumes 92%. Integrating renewables without considering their economic and technical challenges leads to recursive blackouts and power service interruptions that subsequently affect the economic growth of the country [21]. Ethiopia's current grid is inadequately maintained, and grid stability are already matters of concern, making the integration of renewables a heightened challenge.

Employing computationally efficient SCED can overcome these challenges. For example, with large reservoirs, hydropower can store energy over weeks, months, seasons or even years. Hydropower can therefore provide a full range of ancillary services such as spinning reserve, non-spinning reserve, operating reserves, responsive reserve, and contingency reserves that are required for high penetration of wind and solar [22]. To do this accurate dispatch interval, dispatch level and reserve allocation are needed. This way, the so-called 'duck curve' challenge of solar PV generation can be solved.

3 SCED Mathematical Formulation

3.1 Objective Functions

Power generating and operating cost functions, also known as objective functions rely on power flow output and forecasted values of demand determined for each dispatch interval [6, 23, 24]. The general form of SCED objective function is:

$$optimize f(x), x \in R^{n} \tag{1}$$

Subject to

$$h_k(x) = 0 \forall 1, 2 \ldots m \tag{2}$$

$$g_l(x) \leq 0 \forall 1, 2 \ldots L \tag{3}$$

Practically, the SCED objective function is non-linear and multi-objective due to operation constraints. Type of optimization method, multi objective optimization, which exhibits these characteristics is therefore selected.

General form of multi objective optimization is [6]:

$$Optimize f(x) = (f_1(x), f_2(x), f_{Nobj}(x) \tag{4}$$

Subject to

$$\begin{gathered} g_l(x) = 0 \forall i = 1, 2 \ldots m \\ h_k(x) \leq 0 \forall k = 1, 2, \ldots K \\ x_i(1) \leq x_i \leq x_i(0) \end{gathered} \tag{5}$$

This study uses the objective functions of the following renewable resources.

SCED for Hydro: $f_1(x)$ in the multi objective formulation represents objective function of hydro power generation [6, 8].

$$\min f_1(x) = C_h \sum_{i=1}^{N_{hg}} P_{hgj}(t) \tag{6}$$

Where

$$P_{hgj}(t) = \sum_{t=1}^{24} \sum_{i=1}^{N_G} 0.00981 \eta_i H_{ij} Q_{ij} \tag{7}$$

***SCED for Wind*:** The power for assumed wind speed is given by [6, 12, 25]:

$$P_{wr} = \left\{ \begin{array}{l} 0, for\, v_{wt} \leq v_i and\, v_{out} \geq 0 \\ P_{wr}(\dfrac{v_{wt} - v_i}{v_r - v_i}), for\, v_i \leq v_{wr} \leq v_{out} \\ P_{wr}, for\, v_r \leq v_{wt} \leq v_{out} \end{array} \right\} \tag{8}$$

SCED objective function of wind generation is $f_2(x)$

$$f_2(x) = C_w \sum_{i=1}^{N_{WG}} P_{wgj}(t) + \sum_{t=1}^{24} \sum_{i=1}^{N_{WG}} C_R + C_P \quad (9)$$

C_R and C_P defined by $C_{Rw} + P_w j(t) - (P_{wr} j(t) - \alpha V)$, $C_{Pw} + ((P_w j(t) - \alpha V) - P_{wr} j(t))$ represent the reserve cost function and penalty cost function of wind power generation respectively. Reserve cost function helps to calculate the debit generated from the probability distribution function of variable wind speed [25]. The probability distribution function for the wind power output in the range of ($v_i \leq v \leq v_r$) can be obtained using:

$$f_{pw} = \frac{K_{rvi}}{P_{wc}} \left[\frac{1 + \frac{h_{pw}(v_t)}{P_{wr}}}{C} \right]^{K-1} xe^{\left[\frac{h_{pw}(v_t)}{P_{wr}}\right]}{}_K \quad (10)$$

Where K and C are Weibull probability distribution function factors.

$$K = (\frac{\sigma}{v_m})^{-1.086} \quad (11)$$

$$C = \frac{V_m}{T(1 + \frac{1}{K})} \quad (12)$$

***SCED for Solar PV*:** The solar power output that can be extracted from a given solar irradiance G is [6, 10, 13]:

$$P_{sg} j(t) = P_{sg}(G) = P_{sr} j(\frac{G^2}{G_{std} + R_{ca}}) \quad (13)$$

And its corresponding objective function is represented by $f_3(x)$

$$f_3(x) = C_s \sum_{i=1}^{N_{sg}} P_{sg} j(t) + \sum_{t=1}^{24} \sum_{i=1}^{N_{sg}} C_R + C_P \quad (14)$$

Where for 0 < G < R ca:

$$P_{sg} j(t) = \sum_{t=1}^{24} \sum_{i=1}^{N_{sg}} (C_R + C_P) \quad (15)$$

C_R and C_P defined by $C_{RS} + P_S j(t) - (P_{Sr} j(t) - \alpha V)$, $C_{PS} + ((P_S j(t) - \alpha V) - P_{Sr} j(t))$ represent the reserve cost function and penalty cost function of solar PV generation respectively. Reserve cost function helps to determine the debit produced from the probability distribution function of variable solar radiation. The probability distribution function for the power output of variable solar irradiance can also be determined using Weibull probability distribution function [6, 13, 21].

***SCED of Renewable Thermal*:** Despite the difference in their constraints, renewable energy sources adapted from thermal power plants have similar objective function [21, 22]. Renewable thermal plants considered in this study include geothermal power plants, solar thermal power plants, biomass and waste to energy plants.

$$f_4(x) = C_{th} \sum_{i=1}^{N_{th}} P_{th} j(t) \left[\alpha_1 \sum_{i=1}^{N_{Gth}} F_{Gth} P_{Gth} + \alpha_2 \sum_{i=1}^{N_{Sth}} F_{Sth} P_{Sth} + \alpha_3 \sum_{i=1}^{N_{Bth}} F_{Bth} P_{Bth} \right] \tag{16}$$

Where

$$F_{th} = a_i P_{th}^2 + b_i P_{th} + c_i \tag{17}$$

$$F_{Gth} = a_i P_{Gth}^2 + b_i P_{Gth} + c_i \tag{18}$$

$$F_{Sth} = a_i P_{Sth}^2 + b_i P_{Sth} + c_i \tag{19}$$

$$F_{Bth} = a_i P_{Bth}^2 + b_i P_{Bth} + c_i \tag{20}$$

Security Index: Security index as an objective function that shows the severity of contingency during outages is considered and is introduced as an extension of SCED problem formulations in [6, 23, 26].

$$f_5(x) = f_{SL} = \sum_{i=1}^{NL} \left(\frac{P_{Gactive}}{P_{Gactive}^{\max}} \right)^{2m} \tag{21}$$

Where N_L denotes the total number of transmission lines $P_{Gactive}$ and $P_{Gactive}^{\max}$ represent active power flow and maximum active power flow at the k^{th} line respectively.

3.2 Constraint Functions

In power systems, continuously respected operation constraints and limits ensure a reliable and secure operation of the system [6].

1. Demand and generation balance

$$P_D + P_L = \sum_{i=1}^{N_{hgg}} P_{hg} + \sum_{i=1}^{N_{wg}} P_{wg} + \sum_{i=1}^{N_{sg}} P_{sg} + \sum_{i=1}^{N_{th}} P_{th} \tag{22}$$

2. Generation limits

$$P_i^{\min} \le P_i \le P_i^{\max} \tag{23}$$

$$P_{\min} \le 0.00981 \eta_i H_{ij} Q_{ij} \le P_{\max} \tag{24}$$

$$0 \leq P_w j(t) \leq P_{wr} \tag{25}$$

$$0 \leq P_s j(t) \leq P_{sr} \tag{26}$$

$$0 \leq P_h j(t) \leq P_{hr} \tag{27}$$

3. Prohibited operating zones

$$P_i^{\min} \leq P_i \leq P_i^{Lj} \forall j = 1, 2 \ldots N_{Poz} \tag{28}$$

$$P_i^{V_j - 1} \leq P_i \leq P_i^{lj} \tag{29}$$

$$P_i^{V_J - 1} \leq P_i \leq P_i^{\max} \tag{30}$$

4. Transmission constraints: For transmission constraints Kron's loss equation is considered [23].

$$P_L = \sum_{i=1}^{n} \sum_{j=1}^{m} P_{gi} B_{ij} P_{gj} = B_{oo} + \sum_{i=1}^{n} B_{io} P_{gi} + \sum_{i=1}^{n} \sum_{j=1}^{m} P_{gi} B_{ij} P_{gj} \tag{31}$$

Where

$$B_{ij} = \frac{\cos(\theta_i - \theta_j) R_{ij}}{\cos \phi_i \cos \phi_j V_i V_J} \tag{32}$$

$$B_{oo} = \sum_{i=1}^{n} \sum_{j=1}^{m} P_{Di} B_{ij} P_{Dj} \tag{33}$$

$$B_{ij} = -\sum_{j=1}^{m} \left(B_{ij} + B_{ji} \right) \tag{34}$$

5. Security limits

$$S_1 \leq S_1^{\max} \forall l = 1, 2 \ldots N_L \tag{35}$$

$$\phi_j P(t) > o \forall j = 1, 2 \ldots N_C \tag{36}$$

6. Generator ramp rate limits

$$\max(P_i^{\min}, P_i^{t-1} - DR_i) \leq P_i(t) \leq \min(P_i^{\max}, P_i^{t-1} + DR_i) \tag{37}$$

7. Spinning reserve limits

$$\sum_{i=1}^{N_G} S_{Ri} \geq S_{Sr} \tag{38}$$

8. Water discharge and reservoir limits:

$$X_i^{\min} \leq X_i \leq X_i^{\max} \tag{39}$$

$$V_i^{\min} \leq V_i \leq V_i^{\max} \tag{40}$$

$$Q_i^{\min} \leq Q_{ij} \leq Q_j^{\max} \tag{41}$$

$$V_i^{\min} \leq V_{ij} \leq V_j^{\max} \tag{42}$$

$$V_{i,j+1} = V_{ij} - (Q_{ij} - q_i + S_{ij})\Delta t + \sum_{K \in K_j} \left(Q_{ij} + S_{kij} + I_j\right)\Delta t \tag{43}$$

9. Renewable generation penetration rate

$$P_w j(t) + P_s j(t) + P_h j(t) + P_{th} j(t) \leq \Psi P_D \tag{44}$$

Constraint (9) considers thermal (biomass, solar-thermal, geothermal), hydro, wind, and solar PV penetration ratios, ψ and ERES's penetration ratio is 97%.

4 Artificial Intelligence Methods

4.1 Hopfield Neural Networks (HNN)

1. *General Hopfield neural networks search mechanism formulation*

Setting values of the units to the specific start pattern initializes the Hopfield neural networks. The attractor pattern in Eq. (45) updates iteratively until the network converges. Hopfield networks proved that the attractors of the nonlinear phase spaces are stable, not periodic, or chaotic as in another systems. Convergence is therefore guaranteed, [24, 26, 27].

Hopfield neural networks learn by lowering the tolerance (ΔE) of states that the network must remember. This enables the network to function as an associative memory. This implies convergence to a remembered state if it is only a part of the state. The network recovers from a distorted input to a trained state that is most similar to the input. These properties are crucial, since a learning rule, satisfying them, is more biologically acceptable [28].

2. Hopfield neural networks flowchart

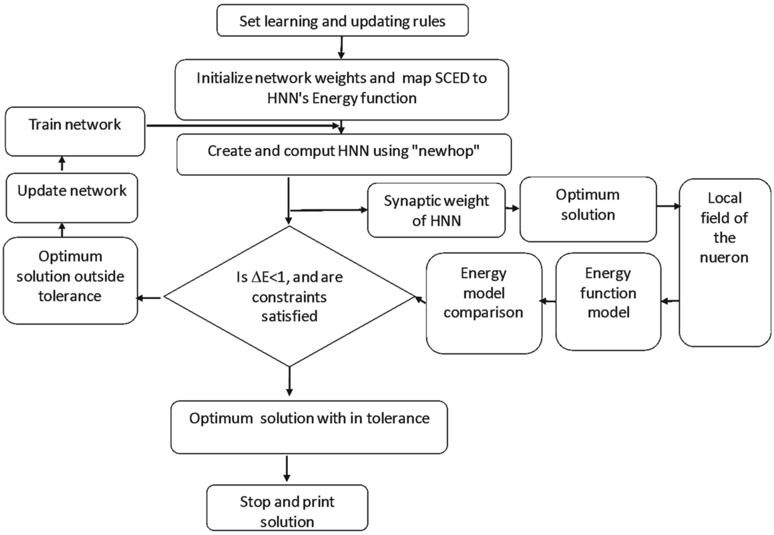

Fig. 5. Flow chart for HNN

3. Parameter Set-Up and Initialization

The attractor pattern in Hopfield Networks is a final stable state which should not change any value within its updating limit.

$$V_i^0 = P_{Gi}^{\min} + rand(P_{Gi}^{\max} - P_{Gi}^{\min})$$

The initial values of inputs for these neurons are determined by the inverse sigmoid functions respective to the initial outputs of the continuous neurons representing power outputs of generating units [24, 28].

$$u_i^0 = \frac{1}{2\sigma}\ln\left(\frac{V_i^0 - P_{Gi}^{\min}}{P_{Gi}^{\max} - V_i^0}\right) \tag{45}$$

Neuron inputs come from two sources, one from the external inputs Ii and the other from the other neurons V_j. Where: U_i is the total neuron input to i, T_{ij} is the interconnection conductance from the neuron output of j to the input of neuron i, Ii denotes external input to neuron i, and V_j stands for the output of neuron j. The continuous variables of SCED are foundations for the continuous model of HNN [26, 28].

4. Mapping Economic Dispatch to Hopfield Neural Network

The objective function of an economic dispatch problem has two parts i) the operation & generation cost minimization part ii) the generation and computation error minimization part. To solve the economic dispatch problem the energy function is defined by combining the target functions with their constraints as [24, 28]:

$$E = A\left(P_D + P_L - \sum_{i=1}^{N} P_G\right)^2 + B\sum\left(a_i + b_i P_{Gthi} + c_i P_{Gthi}^2\right) + \left(\frac{C}{2}\right)P_L^2 \tag{46}$$

Mapping the energy function to SCED determines synaptic strengths and external inputs of HNN. After replacing the output of unit i from P_{Gio} to P_{Gi}, and the transmission loss from P_{Lo} to P_L the loss can be obtained by [27]:

$$P_L = P_{Lo} + dP_L \cong P_{Lo} + \sum_{i=1}^{N} I_{Lio}(P_{Gi} - P_{Gio}) \tag{47}$$

The energy function of HNN is formed by merging the objective functions and their corresponding constraint functions, using weight coefficients, which determine the weightage of each factor. This starts with the energy function of HNN given by [28]:

$$E = -\frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N} T_{Ij} V_i V_j - \sum_{i=1}^{N} I_i V_i \tag{48}$$

The time derivative of this energy function should be negative in order to ensure convergence. HNN based SCED can be solved by the employment of the penalty function.

$$E = \frac{A}{2}\left(\sum_{i=1}^{N}\left(a_i P_{Gthi}^2 + b_i P_{Gthi} + c\right)\right) + \frac{B}{2}\left(P_L + P_D - \sum_{i=1}^{N} P_{Gthi}\right)^2 \tag{49}$$

This energy function consists of an objective function also known as a cost function and design constraints function.

$$P_L = P_{Lo} + dP_L \cong P_{Lo} + \sum_{i=1}^{N} I_{Lio}(P_{Gi} - P_{Gio}) \tag{50}$$

$$\frac{\partial P_L}{\partial P_{Gi} P_{Gio}} = 2\sum_{i=1}^{N} B_{ij} P_{Gjo}(P_{Gi} - P_{Gio}) \tag{51}$$

$$P_L = \sum_{i=1}^{N}\sum_{j=1}^{N} P_{Gio} B_{ij} P_{Gjo} + 2\sum_{i=1}^{N}\sum_{j=1}^{N} B_{ij} P_{Gjo}(P_{Gi} - P_{Gio}) \tag{52}$$

Mapping this equation into HNN, the computation should start by equating (54) and (55) to obtain the following set of equations.

$$T_{ii} = -Aa_i - B, T_{ij} = -B \tag{53}$$

$$I_i = B(P_D - P_L) - \frac{\lambda}{2} b_i \tag{54}$$

$$I_i = A(P_D + P_L) - \frac{Bb_i}{2} \tag{55}$$

A and B represent weighting factors where, A varies from 0.1 to 3, B is set to 1 and to 0.000055. A&B should be greater than or equal to zero. The relation that updates these values is called an adaptive calculation of weighting factors.

$$A = \frac{I_M + 0.5Bb_m}{P_G} \tag{56}$$

$$B = \frac{I_m - AP_D}{0.5b_m} \tag{57}$$

Where, $I_M = \left(\frac{1}{N_G}\right) \sum I_{ED_i}$, $b_m = \left(\frac{1}{N_G}\right) \sum b_i$ and $P_G = \sum P_{Gi}$, N_G is the number of committed generating units. In the selection procedure of weighting factors, A is associated with power mismatch (P_m), as it is assigned the highest priority over the other terms [9].

$$A(P_m)^2 \geq B(\Delta f_T) \tag{58}$$

$$A \geq B(\Delta f_T)/(P_m)^2 \tag{59}$$

The value of A is determined from any value of B and the value of weighting factor C is calculated by.

$$C = 2AP_m \tag{60}$$

4.2 Efficient Parallel Genetic Algorithm(EPGA)

1. *Parameter Set-Up and Initialization of the population*

Initialize the amount of generating units N and population size, NP and specify credible contingencies and. Population size and dimension randomly generate an initial vector Ptij. Ptij is the real power value of jth unit of the ith population randomly generated within the operating limits using [26, 29, 30];

$$P_{ij}^t = P_i^{\min} + rand(0, 1)(P_i^{\max} - P_i^{\min}) \tag{61}$$

Evaluate the fitness value of every vector Ptij according to the fitness function given below:

$$F_A = -(f_1(x) + f_2(x) + f_3(x) + f_4(x) + f_{Penality} + f_{\text{Reserve}} + f_{loss}) \tag{62}$$

Perform mutation operation on the target vectors to obtain new parameter vectors called mutant vectors using:

$$Z_{ij} = P_{ij}^t + F(P_{Rij}^t - P_{Rji}^t) \tag{63}$$

Perform crossover operation to create trial vectors from mutant and target vectors. If the generated random number value is less than or equal to the assumed value of the crossover constant, then the mutant vector is chosen, else the parent vector is chosen as given below. The considered crossover constant (C_R) must be within the domain of (0,1).

$$U_{ij}^{t+1} = \left\{ \begin{array}{l} Z_{ij}, if(R_{ij}) \le C_R \\ P_{ij}, if(R_{ij}) \ge C_R \end{array} \right\} \tag{64}$$

Decide members to constitute the population of subsequent generation (t + 1). The new vector $U_{ij}^{(t+1)}$ is selected based on the comparison of fitness of both target vector, P_i and trial vector, U_i. Compute generation after generation to meet the stopping criteria t_{max} [26, 31] (Fig. 6).

2. Genetic algorithm flowchart

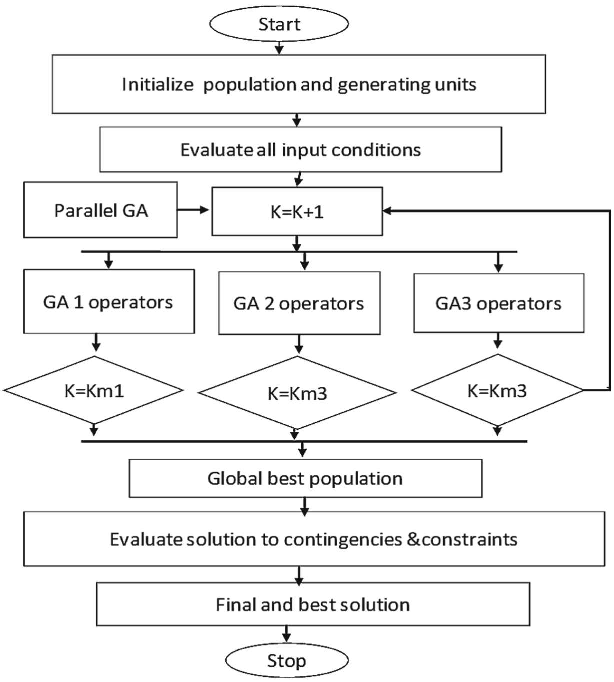

Fig. 6. Flow chart for EPGA

5 Results and Discussions

Figures 7 and 8 depict the simulation results including the behaviors of a particular Hopfield Neural Network. A dispatch comparison between different solution methods of a 3 unit fixed generation supplying a fixed demand is presented in Table 2. This comparison was done to indicate the robustness of HNN and EPGA.

Table 2. Comparison table between solution methods

Unit generation (MW)	MVMO solution	HNN solution	EPGA solution
P1	450	450	450
P2	324.66	322.85	321.91
P3	200.38	201.98	200.72
Pm (Mw)	-4.6×10^{-5}	-4.6×10^{-5}	-4.86×10^{-5}
Cost($/hr)	8236.20	8236.18	8206.18
Run time (sec)	0.125	0.105	0.115

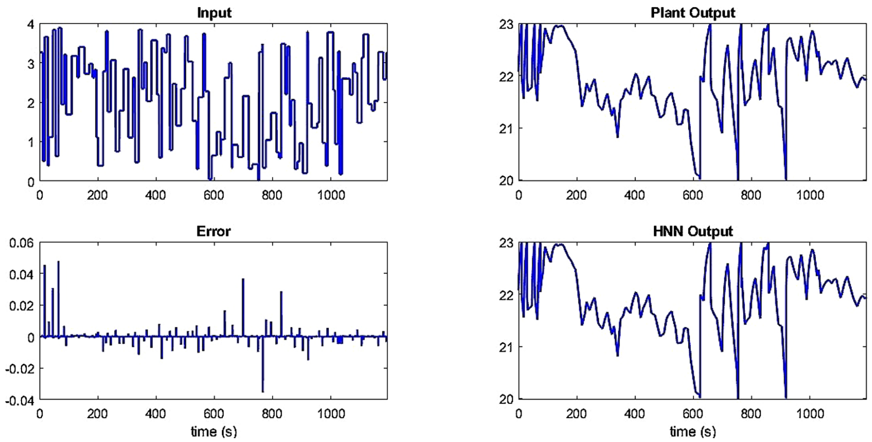

Fig. 7. Predictive control of variable renewable energy resources using neural networks for Ethiopian renewable energy systems

Predictive control enables the Hopfield net to lower the energy state that the net should remember as shown in Fig. 7. From weight positions plotted in Fig. 8, the attractor pattern on the final state, penalty function weights, and adaptive calculation of weighting factors can be obtained. HNN trains, learns and updates itself from feedback through weighting factors. In this study, errors and result fluctuations are considered as dispatch losses due to contingencies. This consideration helps in allocating contingency reserves.

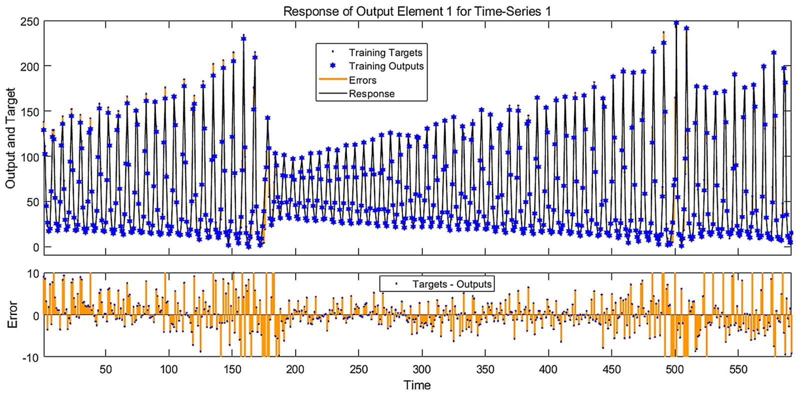

Fig. 8. Time series response of training the created GA-HNN

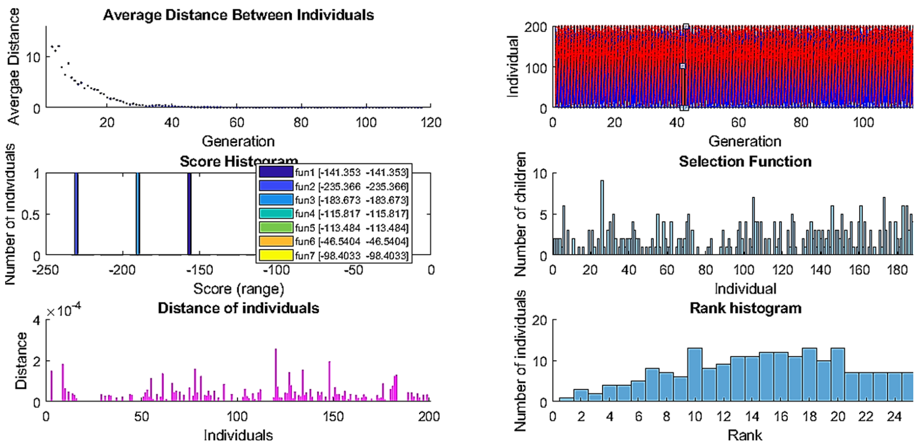

Fig. 9. Daily dispatch of Ethiopian renewable energy system using HNN enhanced EPGA

Figure 9 depicts daily dispatch of Ethiopian renewable energy systems altogether with the computational behaviors of EPGA. Unlike HNN, EPGA learns and updates itself from experiences through genealogy, natural selection and adaptation SCED is important for scheduling when/which generator to dispatch, determining how much reserve is need for spinning, standby, ramping, and contingency. As it is indicated in Table 3, the comparison of daily dispatches using both solution methods i.e. HNN and EPGA helps ERES concurrently increase its security level and reduce its generation cost.

Table 3. Comparison of HNN and EPGA.

Time	HNN Solution	EPGA Solution
1	11847.04	11847.04155
2	11547.13	11547.12606
3	23394.17	23394.16761
4	11662.13	11662.1314
5	11768.15	11768.15114
8	11866.71	11866.71086
7	12034.89	12034.88594
8	12219.79	12219.79114
9	12543.93	12543.93396
10	13130.48	13130.47914
11	13397.93	13397.92534
12	13540.31	13540.30971
13	13260.92	13260.92285
14	12859.55	12859.55294
15	12431.65	12431.65383
16	12312.82	12312.81593
17	12017.45	12017.45115
18	12041.08	12041.07891
19	11757.06	11757.05716
20	11453.42	11453.41733
21	11424.6	11424.6024
22	11654.52	11654.52416
23	12368.03	12368.02728
24	12642.14	12642.14203
Pm(MW)	3.22315E-05	3.16214E-05
P loss (MW)	36.78	36.23
Cost($/MW)	520,614.85	520,001.24
Run time (sec)	0.6875	0.2692

There is an important difference in the demand between weekdays and weekends. Furthermore, Mondays and Fridays being adjacent to weekends exhibit structurally different loads than Tuesday through Thursday. Day and night also, have a different share of load and generation effects Fig. 10. Thus helps to grasp the effect of weekend demand profiles on SCED of ERES.

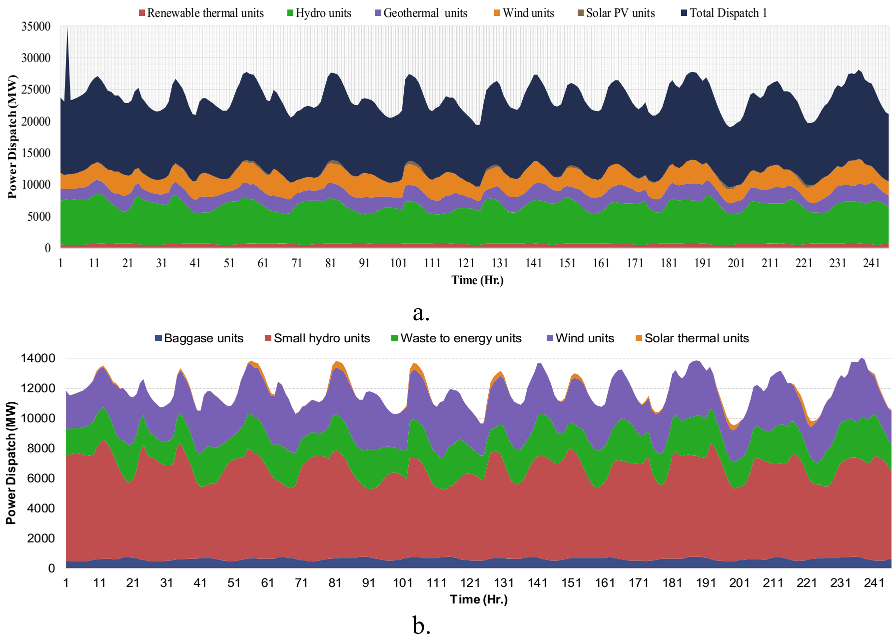

Fig. 10. Weekly dispatch Ethiopian renewable energy systems (a). Using HNN (b). Using EPGA

6 Conclusions

Recursive blackouts, frequent outages and power surges caused by intermittent renewables related contingencies, are the major obstacles of socio-economic advancement of the Ethiopian community. After the connections among these outages, reason of outages, and demand-supply imbalance are made, it is imperative to solve the challenges in connection with SCED. This paper thus argues that recursive blackouts can be reduced by employing computationally intelligent SCED of renewables that considers demand-supply imbalance, intermittency of renewables, variable demand and contingencies.

In the existing Ethiopian power grid, generation plan, load forecast, intermittency of renewable generation, storage constraints, contingencies, and ramping requirements are not considered. To date, there is no such practice in the Ethiopian power grid. For this reason, it is imperative to use AI based SCED of ERES. Renewable energy potential, generation capacity, and generation plan are analyzed for the supply side, whereas demand profiles are analyzed for the demand side of SCED of the Ethiopian power grid. Solving SCED of ERES using EPGA and HNN was carried out on MATLAB.

According to the results obtained, both solution methods provide the best solutions for their respective purposes. For providing accurate forecast and predictive control of intermittent generation, it is imperative to employ HNN. When obtaining global maxima of multi-objective function is required, it is recommended to employ EPGA.

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