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SOLVING THE COMBINED ECONOMIC AND EMISSION DISPATCH PROBLEM USING A ONE-LAYER DYNAMIC NEURAL NETWORK

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In this paper, a one-layer dynamic neural network (OL-DNN) has been proposed to find optimal solutions to combined economic and emission dispatch (CEED) problems. The goal of the CEED problem is to schedule generators to meet load demand and operational constraints while minimizing fuel costs and emissions. The fuel cost and emission objectives of the generating units are taken into account when formulating the CEED problem from a multi-objective to a bi-objective problem. This is done by applying a price penalty factor. The new algorithm is applied to and tested on three examples from the literature, and the solution is then compared with those obtained by other algorithms to demonstrate the superiority and effectiveness of the proposed algorithm.

1. INTRODUCTION

The electric energy industry is very important in people's practical lives and industrial production. Given that thermal power generation currently produces the majority of power, economic load dispatching (ELD) is a crucial task for the power system. The ELD is the process of allocating the required load between the available generation units such that the cost of operation is minimized, while meeting the operation constraints [1]. When used properly, electricity is a clean and relatively safe energy source, but its production and transmission have a negative impact on the environment, especially when thermal power plants, which burn coal, natural gas, or oil, are involved. And with the world is facing significant challenges, including the depletion of fossil fuels, rising carbon emissions, and climate change [2]. This is why we should not only focus on the cost but also consider the emission of harmful gases (such as CO_2 NO_X) to reduce pollution to the environment. Combined economic emission dispatch (CEED) aims to minimize the environmental effects produced from the burning of fuels in thermal power plants and the operating costs of these generating units simultaneously to produce the required demand, fulfilling all technical constraints [3]. Using the max/max price penalty factor h_i to convert the multi-objective problem into a single-objective optimization problem is one method for solving the CEED problem [4,5].

Several optimization techniques have been adopted to solve the ELD and CEED problem in the literature, such as lambda iteration [6,7], linear programming (LP) [8], non-linear programming (NLP) [9], quadratic programming (QP) [10], mixed integer linear programming (MILP) [11], and interior point method (IPM) [12,13]. However, these conventional methods cannot solve such problems satisfactorily because of the non-linearity and non-convexity of modern power generation systems, as well as the numerous constraints present in practical production processes. In addition to their computational complexity, these methods are sensitive to initial estimates and converge to a local optimal solution.

In recent years, a variety of optimization methods have been presented for solving this problem with different constraints, for example, those based on artificial intelligence (AI). The artificial neural network (ANN) is a typical representative of AI, which was used to solve CEED almost two decades ago [14]. Algorithms imitate the behavior of agents in nature called swarm intelligence (SI), such as bottlenose dolphin optimizer (BDO) [15], moth swarm algorithm (MSA) [16], tunicate swarm algorithm (TSA) [17], and the bat algorithm (BA) [18]. Techniques used to analyze and learn from data, identify patterns and relationships, and make predictions and decisions are called computational intelligence (CI), such as differential evolution (DE) [19], Jaya algorithm, genetic algorithm (GA) [20], and harmony search (HS) [21].

In the past two decades, neural networks for optimization have been studied and developed massively, and many good results have been obtained in the literature. Various dynamic neural network models have been developed for solving linearly constrained nonlinear optimization problems and convex optimization problems. See [22–29] and references therein. e.g. [22] proposed a neural network for solving a nonlinear program (NLP) subject to linear constraints. In [23–26], general projection and delayed projection neural networks are proposed for solving the linear, quadratic, convex programming, and linear variational inequalities (LVI) problems. [27,28] proposed a neural network for solving convex quadratic problems, and in [29], neural networks are developed for solving constrained convex optimization problems.

This paper is organized as follows. In Section 2, the Combined Economic Emission Dispatch problem CEED with standard linear constraints and its equivalent formulation are described. In Section 3. A one-layer dynamic neural network model (OL-DNN) is proposed to solve CEED with linear equality constraints. In Section 5, the OL-DNN is investigated for the solution of the CEED problem, considering the objective and constraints of this problem. Effectiveness and efficiency of the proposed OL-DNN technique were tested on well-known 3, 6 and 11-unit power systems. The results obtained by this algorithm are compared with other optimization techniques listed in the literature. Section 6 gives the conclusion of this paper. As illustrated by theoretical and simulation results, OL-DNN provides a simple and efficient tool to get the CEED problem solution, with a transparent design procedure and few parameters to be adjusted.

2. CEED PROBLEM FORMULATION

It is feasible to convert the dual-objective optimization problem, focusing on emission and fuel cost, into a single-objective optimization problem with the introduction of a price penalty factor [31]. The CEED problem requires minimizing simultaneously two competing objective functions, the fuel cost and the emissions.

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2.1 MINIMIZATION OF TOTAL FUEL COST

The ELD problem is to find the optimal combination of power generation that minimizes the total fuel cost while satisfying the total demand and power system constraints. In general, the fuel cost function is defined through the sum of a quadratic function. This function is illustrated as follows [31]:

$$F(P_i) = \sum_{i=1}^{n} \alpha_i P_i^2 + \beta_i P_i + \gamma_i, \qquad i = 1,2,\dots,n, \quad (1)$$

$$\text{subject to: } \sum_{i=1}^{n} P_i = P_L + P_D, \quad (2)$$

$$P_{imin} \le P_i \le P_{imax}, \quad (3)$$

where $F(P_i)$ is the total fuel cost (\$/h), P_i is the generation unit i power (MW), $\alpha_i, \beta_i, \gamma_i$ are the unit i fuel cost coefficients and n is the number of generating units. P_D is the total load demand (MW). $P_{imin}$and P_{imax} are the minimum and maximum generation output of the i-th generator and P_L is the power losses can be calculated using Kron's loss formula [30]:

$$E(P_i) = \sum_{i=1}^{n}\sum_{j=1}^{n} P_i B_{ij} P_j + \sum_{j=1}^{n} B_{0i} P_j + B_{00},\ j = 1,2,\dots,n \quad (4)$$

2.2. MINIMIZATION OF EMISSION

In this paper, the total emissions from burning fossil fuels in thermal power plants are defined as the sum of a quadratic function. Only $\mathbf{NO_X}$ emission is taken into account. This function is illustrated as follows,

$$E(P_i) = \sum_{i=1}^{n} \rho_i P_i^2 + \sigma_i P_i + \delta_i, \quad (5)$$

where $E(P_i)$ is the total emission (kg/h) and $\rho_i, \sigma_i, \delta_i$ are unit i emission coefficients.

2.3. MATHEMATICAL FORMULATION OF CEED

The mathematical model for the CEED problem, including its objective functions and constraints, can be mathematically formulated as

$$\begin{aligned} C_T(P_i) &= F(P_i) + h_i E(P_i) \\ \text{subject to: } &\sum_{i=1}^{n} P_i = P_L + P_D, \\ P_{imin} &\le P_i \le P_{imax}, \end{aligned} \quad (6)$$

where h_i is the price penalty factor (\$/kg), which is calculated as a ratio between maximum fuel cost and maximum emission of the corresponding generating unit and is described as follows [32]:

$$h_i = \frac{F(P_{imax})}{E(P_{imax})} = \frac{\alpha_i P_{imax}^2 + \beta_i P_{imax} + \gamma_{imax}}{\rho_i P_{imax}^2 + \sigma_i P_{imax} + \delta_{imax}}. \quad (7)$$

The CEED (6) can be formulated as a quadratic optimization problem subject to equality and equalities constraints as follows:

$$\min C_T(P) = \frac{1}{2} P^T A P + B^T P + c, \quad (8)$$

$$\text{subject to: } \quad E^T P - d = 0, \quad (9)$$

$$P_{imin} \le P_i. \le P_{imax}. \quad (10)$$

where: $a_i = \alpha_i + h_i \rho_i$, $b_i = \beta_i + h_i \sigma_i$, $c = \sum_{i=1}^{n} \gamma_i + h_i \delta_i$, $d = P_L + P_D$, $A = 2\mathrm{diag}(a_i)$, $P = [P_1 \quad P_2 \cdots \quad P_n]^\mathrm{T}$, $E = [1 \quad 1 \cdots \quad 1]^\mathrm{T}$, $P_{min} = [P_{1min} \quad P_{2min} \cdots \quad P_{nmin}]^\mathrm{T}$, $P_{max} = [P_{1max} \quad P_{2max} \cdots \quad P_{nmax}]^\mathrm{T}$, and $B = [b_1 \quad b_2 \cdots \quad b_n]^\mathrm{T}$.

Since the objective function in (8) is strictly convex (due to A>0 i.e., definite positive matrix) and the feasible region of linear constraints (9),(10) is a closed convex set, if not empty, it follows that the constrained optimal power vector P^* solution of (8)-(10) exists and is unique and satisfies the Karush-Kuhn-Tucker (KKT) optimality conditions

3. OL-DNN APPROACH TO CEED OPTIMIZATION

This section describes a primal-dual dynamical Quadratic Programming (QP) solver. It is a dynamic neural network model based on a one-layer dynamic neural network [22]. By the duality theory [37], for the primal problem (8)-(10), its dual problem can be derived with the aid of dual decision variables. To reduce the resulting neural network complexity, we only need to define the corresponding dual decision variable for the equality constraint (9) and the inequality constraint (10). The dual decision variable is often defined as the Lagrangian multiplier for each constraint.

The Lagrangian function of problem (8) is indicated as:

$$L(P, y) = C_T(P) + y^\mathrm{T}(E^\mathrm{T} P - d), \quad (11)$$

or, equivalently,

$$L(P, y) = 0.5\, P^\mathrm{T} A P + B^\mathrm{T} P + c + y^\mathrm{T}(E^\mathrm{T} P - d), \quad (12)$$

where $y \epsilon R^m$ is referred to as the Lagrange multiplier. m is the number of equality constraint.

According to the Karush-Kuhn-Tucker (KKT) condition [33], P^* is an optimal solution of problem (8) if and only if there exists $y^* \epsilon R^m$ such that (P^*, y^*) satisfies the following conditions:

$$\begin{cases} \nabla C_T(P) - A^\mathrm{T} y \ge 0, \\ P^\mathrm{T}(\nabla C_T(P) - A^\mathrm{T} y) = 0 \\ E^\mathrm{T} P - d = 0, \\ P_{imin} \le P_i. \le P_{imax}. \end{cases}, \quad (13)$$

This can be equivalently written as

$$\begin{cases} (P - P^*)(\nabla C_T(P) - A^\mathrm{T} y) \ge 0, \\ \forall\, P_{imin} \le P_i \le P_{imax}, \\ EP - d = 0. \end{cases} \quad (14)$$

Using the well-known projection theorem [33], we can obtain easily the following Lemma.

LEMMA 1: P^* is a solution to (8) if and only if there exits $y^* \epsilon R^m$ such that (P^*, y^*) satisfies

$$\begin{cases} \Omega(P - \mu\nabla C_T(P) + \mu A^\mathrm{T} y) - P = 0, \\ EP - d = 0, \end{cases} \quad (15)$$

where m is a positive constant, $\Omega(\cdot): R^m \to \Omega(\cdot)$ is a projection operator (activation functions) defined by $\Omega(P) = [\Omega(P_1) \quad \Omega(P_2) \dots \Omega(P_n)]^\mathrm{T}$ and

$$\Omega(P_i) = \begin{cases} P_{imin} & \text{if } P_i \le P_{imin,} \\ P_i & \text{if } P_{imin} \le P_i. \le P_{imax}, \\ P_{imax} & \text{if } P_i \ge P_{imax.} \end{cases} \quad (16)$$

The piecewise linear function $\Omega(P_i)$ depicted in Fig. 2 guarantee the fulfillment of constraints (10).

Based on the equivalent formulation in (15), the following dynamic neural network is proposed for solving (8)-(10), with its dynamical equation given by

$$\frac{\mathrm{d}}{\mathrm{d}t}\begin{pmatrix} P \\ y \end{pmatrix} = \lambda \begin{pmatrix} \Omega(P - \mu\nabla C_T(P) + \mu A^\mathrm{T} y) - P \\ \mu(-EP + d) \end{pmatrix}, \quad (17)$$

where λ is a scaling constant.

We will study some stability and convergence properties of the OL-DNN (17) by following the theorems.

THEOREM 1*:* Assume that $C_T(P)$ is strictly convex and twice differentiable. Then the proposed neural network of (17) with the initial point $z(0) = (P(0), y(0))$, where $z(0) \in \Phi \times R^m$ is stable in the Lyapunov sense and globally convergent to the stationary point $z^* = (P^*, y^*)$, where P^* is the optimal solution of (17) and $\Phi = \{P \in R^n, P \geq 0\}$.

THEOREM 2*:* Assume that $\nabla^2 C(P)$ is positive–definite on $\Phi = \{P \in R^n, P \geq 0\}$. The convergence time of the OL-DNN in (17) is finite.

Similar to the proof of Theorems 1 and 2 in the reference [22], we can get the following stability result of the neural network in (17).

Because of this, for any $\mathbf{P} \geq 0$, $C_T(\mathbf{P})$ is strictly convex and twice differentiable. The neural network of (17) is then globally convergent to the stationary point $\mathbf{z}^* = (P^*, y^*)$, where $\mathbf{P}^*$ is the optimal solution of (17), and stable in the Lyapunov sense.

Furthermore, with the existence of at least one optimal solution to the QP (8)-(10), starting from any initial state $(\mathbf{P}(0), \mathbf{y}(0))$ the state vector $(\mathbf{P}(t), \mathbf{y}(t))$ of the OL-DNN (17) is convergent to an equilibrium point$(\mathbf{P}^*, \mathbf{y}^*)$, of which the first $\boldsymbol{n}$ elements constitute the optimal solution to the CEED problem (8)-(10). Moreover, the convergence speed of the proposed neural network in (17) is proportional to the design parameter λ. The proof can be found in [22].

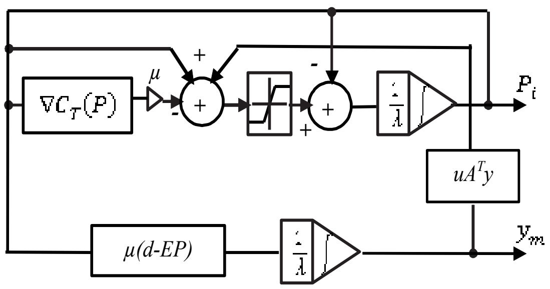


Fig. 1 – A simplified neural network diagram for model (17).

Equation (17) can be realized in a dynamic neural network with a single-layer structure as shown in Fig. 1, where $\lambda = 1$ and $\Omega(\cdot)$can be implemented by using a piecewise linear activation function as shown in Fig. 2 [34].

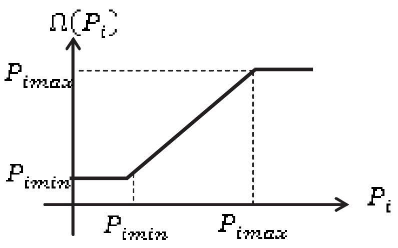


Fig. 2 – Activation function.

According to Fig. 1, the proposed neural network is composed of $n + m$ integrators, n piecewise linear activation functions, n processors for $\nabla C(P)$, n connection weights, and $2n$ summers.

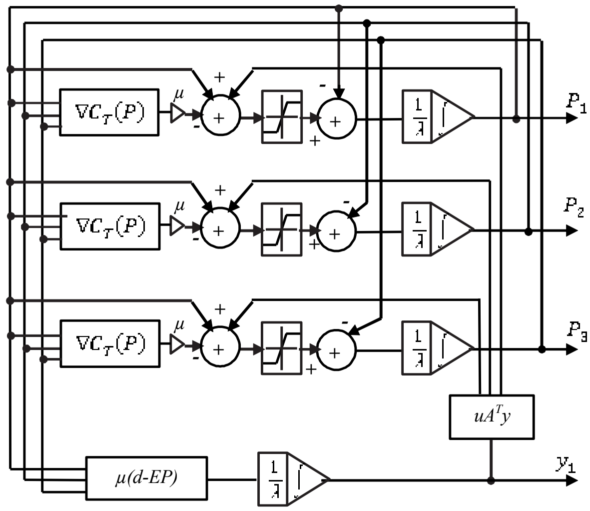


Fig. 3 – Block diagram of 3-unit CEED OL-DNN solver .

Arithmetic operations per iteration: For a system with n generation units, each iteration requires approximately $11n$ arithmetic and logical operations: $6n$ operations for the cost-emission gradient, $n + 2$ for the equality constraint, $2n$ logical operations for the inequality constraints, and $2n$ for updating the state (integration).

Total memory required: The algorithm must store approximately $14n$ units of memory: n state vector values (**P**), n dual variables (μ_i), one value of λ, $3n$ of cost and emission coefficients, $2n$ min/max bounds, and $3n$ temporary gains and buffers. The OL-DNN network therefore has a linear complexity and a linear memory consumption that increase together with the system size.

4. SIMULATION RESULTS AND DESCRIPTION OF TEST SYSTEMS

In this section, the proposed OL-DNN is applied to find the optimum solution for the studied cases of single- and bi-objective CEED problem. Three power generation systems (3-unit, 6-unit and 11-unit) with different load levels have been used to validate the proposed algorithm. These systems are a combination of small, medium and large scale power systems which prove the effectiveness of the developed algorithm.For simulation purposes, the initial generated powers were set to $\mathbf{P}_i(\mathbf{0}) = \mathbf{P}_{imin}$, $\boldsymbol{y}(\mathbf{0}) = \mathbf{1}$; $\mathbf{15}$; $\mathbf{5}$, for 3, 6 and 11-unit respectively and $\boldsymbol{\lambda} = \mathbf{10^{-5}}$.

Test system 1: This case studies a 3-unit generating thermal system considering emission impact. In this case losses are included in the equality constraint and the total demand is set as 400 MW. The transmission loss coefficients are shown in (19). The details of the characteristics of this system are given in [35].

$$B_{ij} = 10^{-4} \begin{bmatrix} 0.71 & 0.30 & 0.24 \\ 0.30 & 0.69 & 0.32 \\ 0.25 & 0.32 & 0.80 \end{bmatrix}, \tag{19}$$

Test system 2: This test system consists of six generating units having quadratic cost and emission functions. The input data for the 6-generator system are taken from [36], and the total demand is set as 1000 MW. In this test system, loss coefficients are not taken into account.

Test system 3: This system consists of eleven generating unit having quadratic cost and emission functions. The input data for the 11-unit system are taken from [36]. The total demand is set as 2500 MW. In this test system, loss coefficients are not taken into account.

Table 1

ELD, EED and CEED solution of 3 unit system.

P_i (MW)	ELD	EED	CEED
P_1	77.362	105.056	101.8298
P_2	176.842	151.170	153.9164
P_3	153.410	151.170	151.6715
$\sum P$ (MW)	407.616	407.398	407.4178
P_L (MW)	7.616	7.398	7.4178
FC ($/h)	20811.67	20843.35	20837.03
EC (kg/h)	205.176	196.714	200.254
TC $/h)	29719.61	29383.92	29369.32
CPU (sec)	0.182	0.190	0.094

Table 2

CEED comparative results for the 3-unit system.

P_i (MW)	GA [35]	PSO [35]	FPA [35]	OL-DNN
P_1	102.617	102.612	102.4468	101.8298
P_2	153.825	153.809	153.8341	153.9164
P_3	151.011	150.991	151.1321	151.6715
P_L (MW)	7.41324	7.41173	7.41260	7.4178
FC ($/h)	20840.1	20838.3	20838.1	20837.03
EC (kg/h)	200.256	200.221	200.224	200.254
TC $/h)	29563.2	29559.9	29559.81	29558.10
CPU (sec)	0.282	0.235	0.175	0.094

Table 3

ELD, EED and CEED solution of 6-unit system

P_i (MW)	ELD	EED	CEED
P_1	36.0824	124.9999	78.6174
P_2	15.9677	138.3956	83.7159
P_3	163.3064	150.0453	169.8169
P_4	158.2416	150.0455	159.5452
P_5	313.2028	218.2817	257.9435
P_6	313.1988	218.2315	250.3608
P_L (MW)	1000	1000	1000
FC ($/h)	50365.2946	53519.5586	51264.4752
EC (kg/h)	976.2409	784.6350	827.0856
TC $/h)	94962.0726	91042.5329	90933.2228
CPU (sec)	0.724	0.656	0.644

4.1. SOLUTION OF ELD AND EED SEPARATELY

In this scenario, each objective function is optimized separately. In the classical economic dispatch problem (ELD), the fuel cost is reduced, and in the emission economic dispatch (EED), the emission of gases is minimized for all of the load demands. As seen from the optimal results shown in Tables 1, 3, and 6 for 3-unit, 6-unit, and 11-unit, respectively, there is a trade-off between the fuel cost minimum and emission level minimum. The difference in generation cost between these two cases, in real power loss and in emission level, clearly shows this trade-off. To decrease the generation cost, one has to sacrifice some of the environmental constraints.

Table 4

CEED comparative results for the 6-unit system.

Methods	Cost ($/h)	Emis (kg/h)
γ -iteration [36]	51264.6	828.720
Recursive [36]	51264.5	828.715
PSO [36]	51269.6	828.863
DE [36]	51264.6	828.715
SR [36]	51264.6	828.715
OL-RNN	**51264.47**	**827.085**

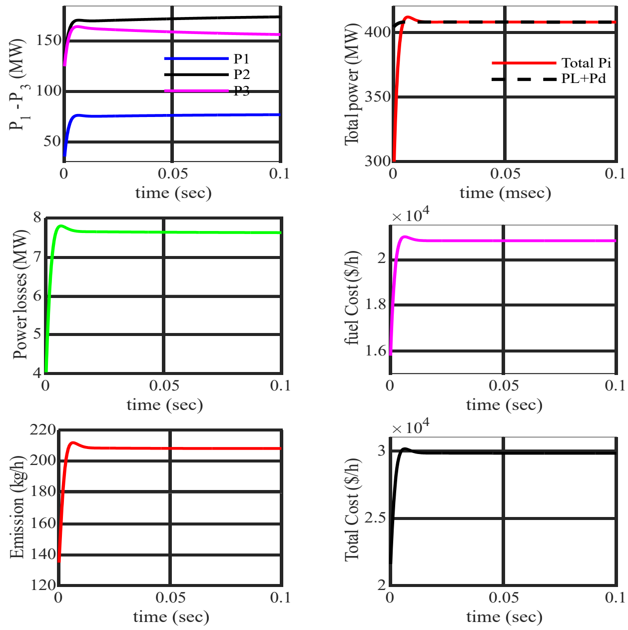


Fig. 4 – OL-DNN based 3-unit system ELD response.

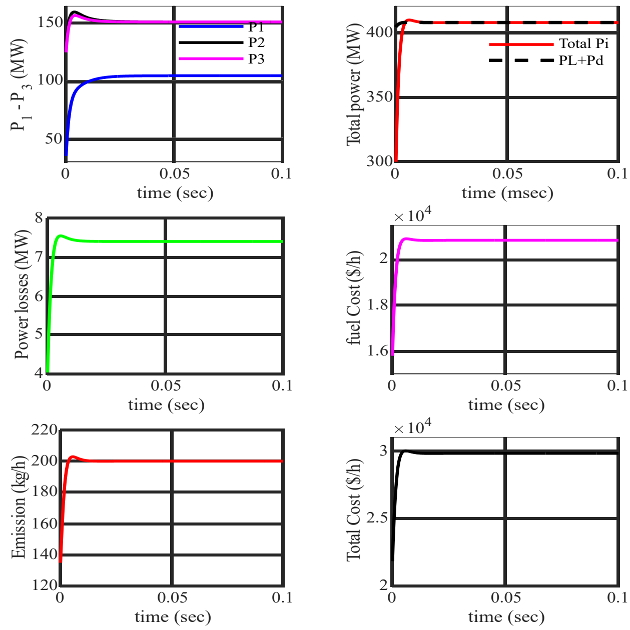
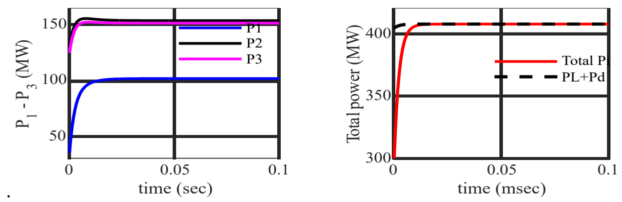


Fig. 5 – OL-DNN based 3-unit system ED response.

4.2. ALL OBJECTIVES ARE OPTIMIZED SIMULTANEOUSLY

Table 2 summarizes the results of solving CEED for the 3-unit system for 400MW demand using OL-DNN compared with GA, PSO, and FBA, all from [35]. As shown in Table 2, OL-DNN donates superior results in terms of fuel cost, total cost, and the computation time required for convergence, also less in the case of OL-DNN. Moreover, the equality and inequality constraints are accomplished.



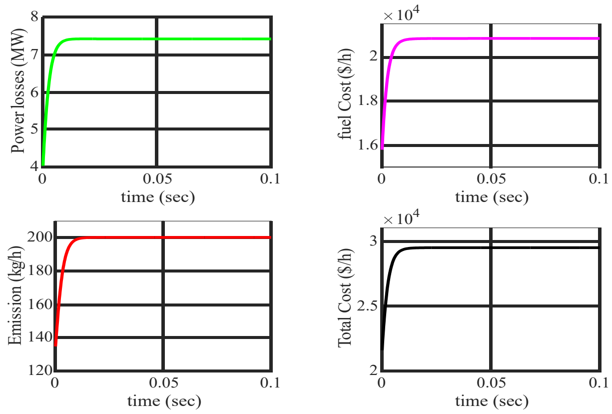


Fig. 6 – OL-DNN based 3-unit system CEED response.

Table 5

CEED comparative results for the 11-unit system.

Methods	Cost ($/h)	Emis (kg/h)
γ -iteration [36]	12424.94	2003.301
Recursive [36]	12424.94	2003.300
PSO [36]	12428.63	2003.720
DE [36]	12425.06	2003.350
SR [36]	12424.94	2003.300
OL-DNN	12424.93	2003.300

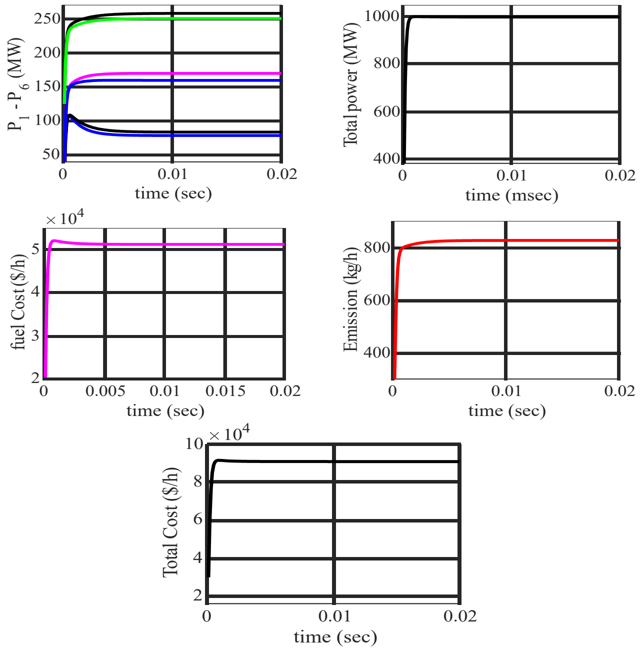


Fig. 7 – OL-DNN-based 6-unit system CEED response.

In order to demonstrate the efficiency and the robustness of the proposed OL-DNN algorithm, the best CEED results obtained from OL-DNN and other five methods, such as Lambda iteration, recursive, PSO, DE, and SR, are all from [36], and are compared in Table 4 for the test system with 6 units and in Table 5 for the test system with 11 units. It is obvious that the proposed method produced a better solution than the compared methods in terms of fuel cost and emission for these test systems. The computation time required for convergence is also less in the case of OL-DNN.

The computational times for the five algorithms are given in Tables 4 and 5. The total computational time here for the OL-DNN technique is the total time for the calculation of 1000 iterations. Clearly, the computational time by OL-DNN is much shorter than that by other methods.

The computational times for the five algorithms are given in Table 4 and 5. The total computational time here for OL-DNN technique is the total time for the calculation of 1000 iterations. Clearly, the computational time by OL-DNN is much shorter than that by other methods.

Table 6

ELD, EED and CEED solution of 11-unit

P_i (MW)	ELD	EED	CEED
P_1	58.1765	153.1830	139.6724
P_2	41.3252	121.0851	112.7808
P_3	60.5815	155.8814	145.8021
P_4	281.9570	215.8072	221.5270
P_5	200.4129	133.3532	136.7736
P_6	258.3319	214.2311	218.5777
P_7	189.9180	136.9090	140.2608
P_8	362.4250	339.7723	345.0462
P_9	338.2416	326.2366	329.4837
P_{10}	361.1947	359.9394	363.6449
P_{11}	347.4351	343.6012	346.4302
$\sum P$ (MW)	2500	2500	2500
FC ($/h)	12275.882	12466.9584	12424.9379
EC (kg/h)	2546.4429	1952.4870	2003.305
TC $/h)	20364.9873	18975.7268	18953.3759
CPU (sec)	0.813	0.694	0.578

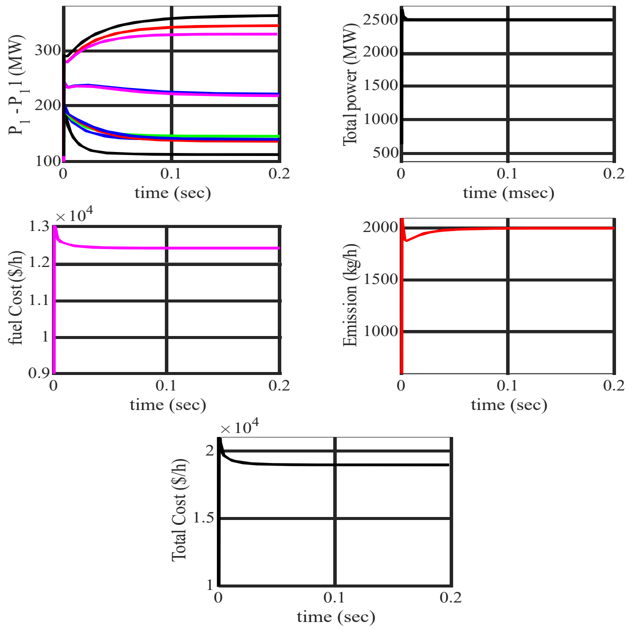


Fig. 8 — OL-DNN-based 11-unit system CEED response

The OL-DNN-based CEED optimization responses are shown in Fig. 4-6 for the 3-unit system, in Fig. 7 for the 6-unit system, and in Fig. 8 for the 11-unit system. It is clear from the given responses that OL-DNN achieves a faster convergence rate.

5. CONCLUSION

A novel strategy for the economical operation of power systems was presented in this paper. A dynamic neural network model is employed to ascertain the most efficient scheduling of the power plants. The performance of this approach was tested on three different test systems. OL-DNN was tested on three generators, six generators, and eleven generators, with a quadratic cost and emission function for combined economic emission load dispatch problems. Moreover, the results of the proposed technique have been compared to those of the techniques published in the literature. Numerical results demonstrate that the economic effect, computation efficiency, and convergence property have highly optimal solutions. Therefore, this suggested method can be used for online combined economic and emission dispatch in power systems.

CREDIT AUTHORSHIP CONTRIBUTION STATEMENT

SMAIL BOUDAB: methodology, simulation, validation, wrote the main manuscript.
GHANIA DEBACHE: investigation, writing, validation, review.
NOUREDDINE GOLEA: methodology, investigation, validation, review.

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