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A hybrid HNN-QP approach **to the** dynamic economic **shipping** problem

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A R T I C L E I N F O

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A B S T R A C T

This **article proposes** a solution **to the problem** of **Dynamic Economic Distribution** (DED) using a hybrid approach of **Hopfield Neural Network** (HNN) and **Quadratic Programming** (QP). The hybrid algorithm is based on **the use of improved** HNN; solve the static part of the **task;** QP algorithm for solving the dynamic part of DED. This **technology ensures a solution thanks to a** global **optimal forecast.** The new algorithm is **implemented** and tested **on a literary example,** and **then** the solution is compared with **a solution** obtained by **another technique** to **show** the superiority and **efficiency** of the proposed algorithm.

1. Introduction

Dynamic **Economic Delivery** (DED) is considered as one of the most important steps to obtain a **perfect** generation **timing** solution. **The purpose of** DED **is** to schedule the **outputs of grid** generators **according to** the predicted load **demand for** a certain period of **time, so that the** power system **can be operated** economically within its **safety** limits [1,2]. By solving the DED problem, the **required** total **production** is **distributed** among the available **network heat generation devices during** a certain period of time [3]. To solve the DED problem, it is assumed that **the heat** unit **duty is determined in advance.** Mathematically, **the** DED problem is considered a second-order dynamic optimization **problem, which** takes into account the **constraints** imposed on the system by the **ramp speed limits of the** generators [1]. What distinguishes DED from the traditional static **Economic Load Dispatcher** (ELD) problem is the mechanical **limitation introduced** to avoid shortening the **life** of turbines and boilers. The thermal gradients of the **devices** must be kept within safe **limits.** This mechanical **limit** is **converted** into a limit **of** the **growth** rate of **electrical energy for each emitted unit. No unit may** increase or **decrease** more than **the number** of **megawatts specified** by the **unit's manufacturer at any time.**

Since the DED must be solved over a certain period of time with a predefined load profile, thus the overall cost of producing this load profile of electricity demand must be minimized over the whole scheduling horizon, not only for each single time interval, without violating the technical constraints. This is another difference between the DED and the traditional ELD problems.

Several methods have been proposed to solve the DED problem. However, most of the previous work in this field is not able to provide an optimal solution and usually get stuck at a local minimum point [1]. Methods of solving the DED problem can be classified into classical, artificial intelligence (AI) based and hybrid methods.

Lagrangian relaxation (LR) is an example of the classical methods. This technique suffers from myopia for nonlinear search spaces leading to a less than desirable performance. To avoid this, approximations may be used to limit the problem complexity [3].

Another classical method is the dynamic programming (DP). DP has been used in many previous papers in literature to solve this problem. In Ref. [4], DP is used to solve DED simulating what so-called the valve point loading. Also it managed to have a look-ahead capability for the solution in order to predict the effect of the current generation value on the generation levels of the next time intervals. Anyway, the results are not compared with any other method to prove the superiority of the proposed method in computational time or accuracy. Price-based ramp rate model for the DED problem is introduced in Ref. [5]. The effect of ramp rate constraint is shown by examples and compared with the heuristic approaches. DP and Dantzig-Wolfe decomposition are also implemented to solve a linearized form of the problem. Constructive dynamic programming and dual optimization technique are among the classical methods used to solve this problem [6].

AI-based optimization techniques such as simulated annealing (SA), genetic algorithms (GA), evolutionary programming (EP) and particle swarm optimization (PSO) have been used to solve the DED problem. Such techniques use probabilistic rules to update their candidates' positions in the search space. Anyway, these algorithms do not always guarantee discovering the global optimal solution in a finite time but they can only find a feasible solution in short time [1,3].

The appropriate setting of the control parameters of SA is very difficult and is done by trial and error. Also the speed of convergence of the algorithm is slow when applied to a real power system. Encoding and decoding schemes that are essential in GA approach are not needed in DED. It is claimed in Ref. [1] that all heuristic techniques take long computational time in order to obtain the global optimal solution.

Hybrid methods combine two or more techniques previously mentioned in order to get the best features in each algorithm. Hybrid methods usually combine probabilistic and deterministic methods together. Probabilistic method is used as a base level search procedure to find a feasible and near optimal solution. The deterministic method is then used to fine-tune that solution reaching to the global optimum solution [1,3].

EP and sequential quadratic programming (SQP) are used in Ref. [1] to solve the DED with non-smooth fuel cost function. PSO and SQP are employed in Ref. [3] to solve the reserve constrained DED problem together with security constraints. Spinning reserve requirements are satisfied. Security constraints include maintaining the voltages of all busses between maximum and minimum values. Also the load flow on every transmission line must not exceed the maximum allowable transmission line capacity.

Hopfield neural network (HNN) is used to solve the DED problem in Ref. [2]. The ramp up and down rates constraint is included in the solution algorithm by obtaining the optimum dispatch for the first interval to determine the required generating levels of each unit. The maximum and minimum allowable output of each unit is then updated to be the generation level of the previous interval plus the maximum allowable ramp up rate for ramping up or minus the maximum allowable ramp down rate for ramping down. This algorithm may reach the optimum value for each interval but does not guarantee reaching the global optimum of the whole simulation horizon.

In this paper, the enhanced HNN explained in Ref. [7] serves as a base level search procedure to find a near optimal solution without applying the ramp rate constraints. The ramp rate constraint is then applied by the quadratic programming approach in order to consider the effect of the current load on the next time interval dispatch. This method ensures that the solution will have what the so-called look-ahead capability of the solution. An example from the literature is solved by the proposed method and the solution is compared with some other methods to prove the validity and superiority of the proposed technique.

2. Problem description

The (DED) problem is concerned with minimizing the overall generating cost of N dispatchable generating units over the whole scheduling period H subjected to some operating constraints. In this section, the symbols used are introduced then the mathematical formulation of the problem is presented.

2.1. Notation

B_{ij}	loss coefficient between the ith and jth generators (MW^{-1})
C_T	total cost of generation of all generators through the whole simulation horizon in $
$C(P_{ih})$	cost of generating P_{ih} MW from the ith generator during the hth interval in $
h	interval index
H	number of intervals in the simulation horizon
i	generator index
I_i	external input (bias) of the ith neuron
k	iteration index
L_h	load demand during the hth interval in MW
N	number of dispatchable generators
P_{ih}	output of the ith generator at the hth interval in megawatts (MW)
$P_{i\text{-max}}$	maximum allowable output of the ith generator in MW
$P_{i\text{-min}}$	minimum allowable output of the ith generator in MW
$P_{\text{Loss-}h}$	transmission losses at the hth interval in MW
RDR_i	maximum allowable ramp down rate of the ith generator in MW/h
RUR_i	maximum allowable ramp up rate of the ith generator in MW/h
T_{ij}	interconnection conductance (weight) from the output of the jth neuron to the input of the ith neuron.
U_i	input to the ith neuron
$V_{i\text{-max}}$	maximum allowable value for the output of the ith neuron
$V_{i\text{-min}}$	minimum allowable value for the output of the ith neuron
V_j	output of the jth neuron
λ	scaling factor termed as the slope

2.2. Problem formulation

The DED problem can be stated as follows [3]:

Minimize

$$C_T = \sum_{h=1}^{H}\sum_{i=1}^{N} C(P_{ih}) \tag{1}$$

where

$$C(P_{ih}) = a_i \times P_{ih}^2 + b_i \times P_{ih} + c_i \tag{2}$$

Subjected to the following constraints:

i. Real power balance

$$\sum_{i=1}^{N} P_{ih} = L_h + P_{\text{Loss-}h} \quad \forall\ h = 1:H \tag{3}$$

Transmission losses can be modeled either by running a complete load flow analysis to the system [3] or by using the loss coefficients method (also known as the B-coefficients) developed by Kron and adopted by Kirchmayer [7]. The later method is adopted in this work.

In the B-coefficients method, the transmission losses are expressed as a quadratic function of the generation level of each generator as follows:

$$P_{\text{Loss-}h} = \sum_{i=1}^{n}\sum_{j=1}^{n} P_{ih} B_{ij} P_{jh} \tag{4}$$

a_i, b_i, c_i cost coefficients of the ith generator

ii. Real power generation limits

$$P_{i-\min} \leq P_{ih} \leq P_{i-\max} \quad \forall \; i = 1:N \text{ and } h = 1:H \tag{5}$$

iii. Ramp up and down rates

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To avoid undue thermal stresses on the boiler and the combustion equipment, the rate of change of the output power of each thermal unit must not exceed certain rate during increasing or decreasing the power output of each unit [4]. This can be formed mathematically as follows:

$$RDR_i \leq |P_{ih+1} - P_{ih}| \leq RUR_i \quad \forall \ i = 1:N \text{ and } h = 1:H-1 \tag{6}$$

3. Hopfield neural network

Hopfield neural network is a single layer, recurrent, and non-hierarchal neural network. The action of this network is to minimize an energy function [8].

In HNN, all connective weights are calculated initially from the system data without training. The neurons are initiated by an initial value (guess) then the network goes through a series of iterations until it reaches a final output that represents the minimum of an energy function [9].

The dynamics of each neuron can be described by the following differential equation [10]:

$$\frac{dU_i}{dt} = \sum_{j=1}^{n} T_{ij}V_j + I_i \tag{7}$$

First-order Euler–Cauchy integration technique has been used in Ref. [10] to solve Eq. (7) as follows:

$$U_i(k) = U_i(k-1) + \sum_{j=1}^{n} T_{ij}V_j(k-1) + I_i \tag{8}$$

The input–output model of the conventional HNN adopted in this work is the sigmoid function:

$$V_i = V_{i\text{-}\min} + \frac{1}{2}(V_{i\max} - V_{i\min})(1 + \tanh(\lambda U_i)) \tag{9}$$

The energy function of HNN is given by

$$E = -\frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} T_{ij}V_iV_j - \sum_{i=1}^{n} I_iV_i \tag{10}$$

The time derivative of this energy function was proven to be negative so the network always moves in such a direction that the function gradually converges to a minimum [10].

To solve the DED using HNN, penalty function method is used to represent the ELD as a quadratic function as follows [8]:

$$E = \frac{A}{2}\sum_{i=1}^{n}\left(a_iP_{ih}^2 + b_iP_{ih} + c_i\right) + \frac{B}{2}\left(L_h + P_{Loss\text{-}h} - \sum_{i=1}^{n}P_{ih}\right)^2 \tag{11}$$

The energy function consists of the total fuel cost (the objective function) and the power mismatch (the equality constraint). A and B represent weighting coefficients that introduce the relative importance for their respective associated terms. Ramp rate constraint will be forced into the solution using the quadratic programming (QP) approach as will be explained in the following section.

To obtain the interconnection conductances and the external inputs, substitute (4) in (11) and compare the resulting equation with (10) after replacing V_i and V_j with P_{ih} and P_{jh}, respectively thus we get the following set of equations:

$$T_{ii} = -A \times a_i - B \tag{12}$$

4. Proposed algorithm

The proposed algorithm is a hybrid between the enhanced HNN [7] and the QP. The enhanced HNN is used to obtain a schedule of generation satisfying the given load profile without considering the ramp rate constraint. In other words, HNN solves the static part of the DED problem. To enforce this constraint into the solution, backward and forward evaluations are made. The proposed algorithm is introduced as follows:

1. Obtain a complete generation schedule for the given load curve using the enhanced HNN described in Ref. [7] for each time interval in the simulation horizon without the ramp rate constraint being considered. This is the unconstrained DED solution. The values of the HNN parameters A, B and λ will be 1.6, 2 and 10^{-3}, respectively as being recommended in Ref. [7].
2. Backward evaluation:
   For $i = 1:N$
   For $h = H:2$
   a. If $P_{ih} - P_{ih-1} > 0$, then it is ramp up case, else it is a ramp down case.
   b. Calculate the amount of violation to the ramp rate constraint as follows:
   i. If ramp up is detected:

$$\text{Violation} = |P_{ih} - P_{ih-1}| - RUR_i \tag{15}$$

If violation > 0

$$P_{ih(\text{updated})} = P_{ih} - \frac{\text{violation}}{2} \tag{16}$$

$$P_{ih-1(\text{updated})} = P_{ih-1} + \frac{\text{violation}}{2} \tag{17}$$

   ii. If ramp down is detected:

$$\text{Violation} = |P_{ih} - P_{ih-1}| - RDR_i \tag{18}$$

If violation > 0

$$P_{ih(\text{updated})} = P_{ih} + \frac{\text{violation}}{2} \tag{19}$$

$$P_{ih-1(\text{updated})} = P_{ih-1} - \frac{\text{violation}}{2} \tag{20}$$

3. Forward evaluation:
   For $i = 1:N$
   For $h = 1:H-1$
   a. If $P_{ih+1} - P_{ih} > 0$, then it is ramp up case, else it is a ramp down case.
   b. Calculate the amount of violation to the ramp rate constraint as follows:
   i. If ramp up is detected:

$$\text{Violation} = |P_{ih+1} - P_{ih}| - RUR_i \tag{21}$$

If violation > 0

$$P_{ih+1(\text{updated})} = P_{ih+1} - \frac{\text{violation}}{2} \tag{22}$$

$$P_{ih(\text{updated})} = P_i + \frac{\text{violation}}{2} \tag{23}$$

   ii. If ramp down is detected:

$$\text{Violation} = |P_{ih+1} - P_{ih}| - RDR_i \tag{24}$$

If violation > 0

$$T_{ij} = -B \tag{13}$$

$$I_i = B(L_h - P_{\text{Loss-}h}) - \frac{A}{2}b_i \tag{14}$$

Full details of the mapping process can be found in Ref. [7].

$$P_{ih+1(\text{updated})} = P_{ih+1} + \frac{\text{violation}}{2} \tag{25}$$

$$P_{ih(\text{updated})} = P_{ih} - \frac{\text{violation}}{2} \tag{26}$$

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Table 1
Data of the example

Unit index	a_i (\$/MW^2 H)	b_i (\$/MWH)	c_i (\$)	$P_{i\text{-min}}$ (MW)	$P_{i\text{-max}}$ (MW)	RUR_i (MW/h)	RDR_i (MW/h)
1	0.0372	26.4408	180	155	360	20	25
2	0.03256	21.0771	275	320	680	20	25
3	0.03102	18.6626	352	323	718	50	50
4	0.02871	16.8894	792	275	680	50	50
5	0.03223	17.3998	440	230	600	50	50
6	0.02064	21.6180	348	350	748	50	50
7	0.02268	15.1716	588	220	620	100	100
8	0.01776	14.5632	984	225	643	100	150
9	0.01644	14.3448	1260	350	920	100	150
10	0.01620	13.5420	1200	450	1050	100	150

4. Let the accepted tolerance between iterations be ε:
   If the difference between the updated schedule obtained after step 3 and the schedule before step 2 is less than ε, then go to step 5.
   Else update the solution as follows:

$$\text{For } h = 1:H, \quad P_{ih(\text{updated})} = P_{ih} \tag{27}$$

   Then go to step 2 for another iteration
5. The solution is now let to undergo the correction factor algorithm described in Ref. [7] as follows:
   For $h = 1{:}H$
   Calculate the power mismatch as follows:

$$\text{power mismatch} = L_h + P_{\text{loss-}h} - \sum_{i=1}^{N} P_{ih} \tag{28}$$

   The correction factor (C.F.) is then calculated by

$$\text{C.F.} = 1 + \frac{\text{power mismatch}}{L_h} \tag{29}$$

   The solution obtained after step 4 is then multiplied by C.F. The transmission losses and the power mismatch are updated using Eqs. (4) and (28), respectively. C.F. is calculated again from Eq. (29) to adapt itself to the new mismatch. The process continues till the mismatch is acceptably small.
   This correction factor guarantees that the power mismatch between the total generation for each interval and the corresponding load is within accepted limits and that no violation happens to the maximum and minimum generation level constraint.
6. Print out the schedule obtained after step 5. It is the required optimum solution.

5. Implementation examples

Software package implementing the new proposed technique is developed using Intel Centrino® Duo, 1.83 GHz processor. To illustrate the validity and effectiveness of the proposed technique, the New England test system given in Ref. [2] is studied and solved. The system consists of 10 units, their cost data, generation limits and ramp rate limits are given in Table 1. Transmission losses are

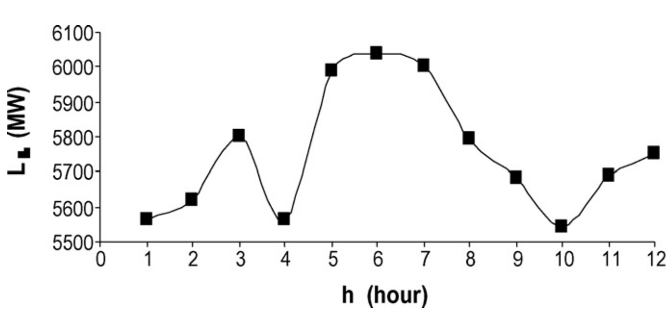

Fig. 1. Load curve for the example.

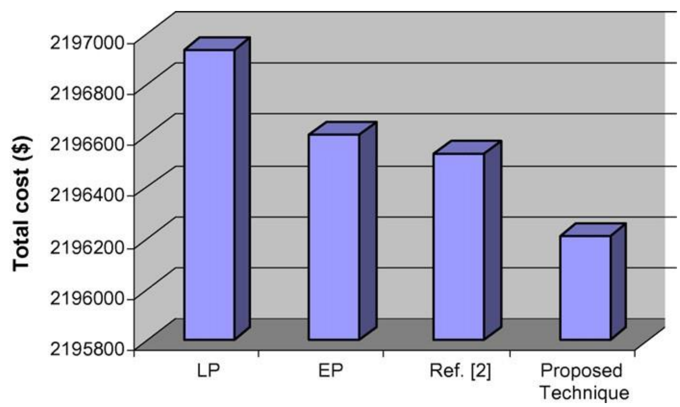

Fig. 2. Comparison of the total cost for different techniques.

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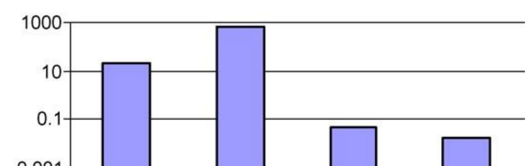
neglected. The simulation horizon of the example is 12 h. The corre-sponding load curve is given in Fig. 1. Comparison is made betweenthe solution obtained by the proposed algorithm and the solution techniques given in Ref. [2]. Figs. 2 and 3 show the superiority of the proposed technique regarding both the total cost and the com- putational time, respectively. The complete generation schedule is given in Table 2.

It can be seen from Table 1 that the first two units are the most ramp rate limited units. Their schedule using the proposed tech- nique and that of Ref. [2] is shown in Figs. 4 and 5, respectively.

By studying the results in Figs. 2 and 3, it is clear that the new proposed algorithm is efficient, faster and giving a cheaper total generating cost than the other algorithms. In other words, the new proposed algorithm is capable of giving a more optimum solution with less computational time.

Figs. 4 and 5 reveal that the new technique "smoothens" the schedules of the first two units. In other words, the more ramp-limited units are scheduled in a flat profile way thus increasing



	LP	EP	Ref. [2]	Proposed
Computational Times (seconds)	20	700	0.048	0.016

Fig. 3. Comparison of the computational times for different techniques.

Table 2
Solution of the example using the proposed technique

Unit index	Interval											
	1	2	3	4	5	6	7	8	9	10	11	12
1	209.7	212.13	219.4	209.7	226.79	228.74	227.21	218.99	214.55	208.89	214.96	217.38
2	323.9	323.21	321.73	323.9	327.01	329.79	327.61	321.79	322.62	324.15	322.53	322.06
3	524.24	530.32	548.49	524.24	566.98	571.82	568.03	547.48	536.39	522.22	537.4	543.45
4	524.24	530.32	548.49	524.24	566.98	571.82	568.02	547.48	536.39	522.22	537.4	543.45
5	504.91	510.76	528.25	504.91	546.07	550.72	547.08	527.29	516.6	502.95	517.56	523.41
6	524.24	530.32	548.49	524.24	566.98	571.82	568.03	547.48	536.39	522.22	537.4	543.45
7	548.53	554.88	573.89	548.53	593.25	598.3	594.34	572.84	561.23	546.4	562.29	568.62
8	657.35	664.97	687.75	657.35	710.94	716.99	712.25	686.49	672.57	654.8	673.84	681.43
9	813.94	823.38	851.59	813.94	880.3	887.8	881.93	850.03	832.79	810.79	834.36	843.76
10	928.95	939.71	971.92	928.95	1004.7	1013.2	1006.5	970.13	950.47	925.36	952.26	962.99
$\sum_{i=1}^{N} P_{ih}$	5560	5620	5800	5560	5990	6041	6001	5790	5680	5540	5690	5750
Interval total cost ($)	174460	177090	185110	174460	193730	196070	194240	184660	179750	173580	180190	182870

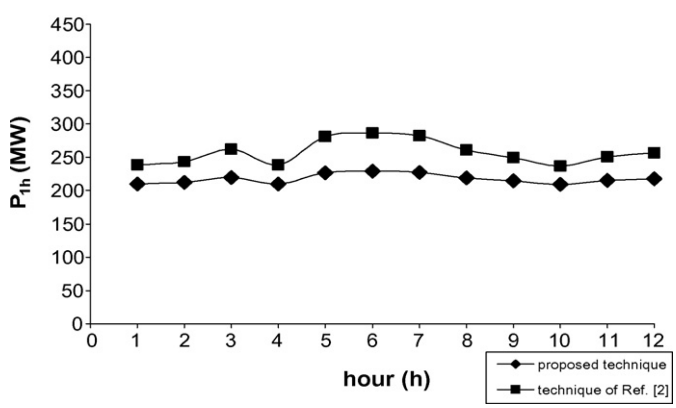


Fig. 4. Scheduling of unit no. 1.

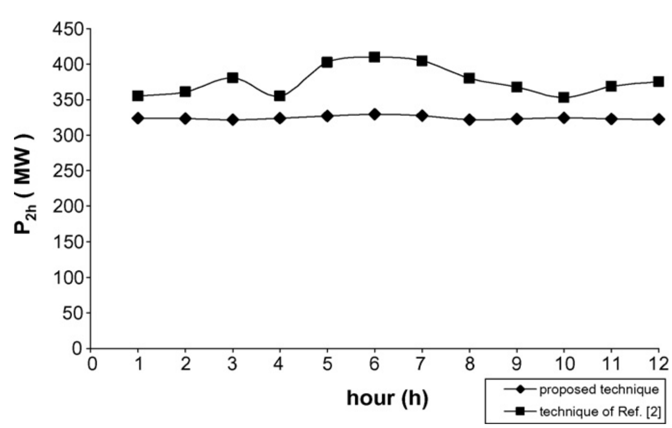


Fig. 5. Scheduling of unit no. 2.

their lifetime by preventing large ramps. This is another privilege of the new proposed technique.

6. Conclusions

This paper **presents** a **novel** hybrid method **to solve** the **slope velocity-constrained** DED **problem.** The **basic solution** is **an improved HNN, which provides an initial** solution without considering the dynamic ramp **rate limitation.** The ramp **speed limit** is enforced in the solution using quadratic programming with **successive** backward and forward **estimates.** The new technique has **predictive power, because** it **distributes** the **ramp** of **generators** over the entire simulation horizon to avoid **a** sudden **ramp** that **can** exceed the maximum allowable ramp rates. The **power** of a **given** unit **does** not **necessarily have** to be **high in** a certain **time period to achieve an optimal** solution **in** that **time period.** If this **device has a large slope** at **any subsequent interval, it is recommended that** the **power** of **this device** is **gradually increased** to **meet** the dynamic **limit.** The schedule obtained **in each** interval **may** not be the optimal schedule for that interval, **but** it is optimal over the **entire** simulation horizon. An example from the literature is solved **by** the new proposed algorithm and the results are compared with those of other **techniques.** The new **technology finds** a cheaper solution in **a** much **shorter** time than other **technologies.** The results **show** the superiority of the proposed technique both **in terms of** cheapness of total **production costs** and computational time.

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