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A load profile management integrated power dispatch using a Newton-like particle swarm optimization method☆

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ABSTRACT

Load profile management (LPM) is an effective demand side management (DSM) tool for power system operation and management. This paper introduces an LPM integrated electric power dispatch algorithm to minimize the overall production cost over a given period under study by considering both fuel cost and emission factors. A Newton-like particle swarm optimization (PSO) algorithm has been developed to implement the LPM integrated optimal power dispatch. The proposed Newton-like method is embedded into the PSO algorithm to help handle equality constraints while penalty/fitness functions are used to deal with inequality constraints. In addition to illustrative example applications of the proposed Newton-like PSO technique, the optimization method has been used to realize the LPM integrated optimal power dispatch for the IEEE RTS 96 system. Simulation studies have been carried out for different scenarios with different levels of load management. The simulation results show that the LPM can help reduce generation costs and emissions. The results also verify the effectiveness of the proposed Newton-like PSO method.

1. Introduction

IN recent years, there has been increasing attention on air-borne contaminants that contribute to climate change, terrestrial contamination, uptake of toxins in the food chain, asthma and other related health issues. Smog in China, for example, has produced great concern [1] and is considered one of the largest environmental threats to the public health of the country. The electric power industry is a major source of air pollutant emissions. In the US, about 40% of all CO_2 emissions are attributed to electricity generation [2]; in 2012, 2039 million metric ton of CO_2 were generated in the US electric power sector alone [2].

Various approaches have been proposed to reduce emissions due to electricity generation. These include air pollution control devices (e.g. scrubbers for thermal power plants), fuel switching, generation from renewable sources, etc. Emission sensitive power dispatch is an important method for reducing emissions due to electric power generation. In the last three decades, a number of environmental/economic dispatch (EED) algorithms have been developed [3–17]. Similar to an economic dispatch problem, emission dispatch algorithms were formulated by either establishing an alternative objective function of emission or incorporating the emission cost into the generation cost models [3–5]. A good summary of algorithms for EED since 1970 was given in [7], where emission modeling issues, objectives and strategies formulation, constraints formulation, fuel switching, and different application scenarios with various time scales were reviewed. EED algorithms started as a single objective problem [3–5] and then evolved to a multi-objective optimization task [6,7,10,15,17].

Load/demand management (also called demand response or demand side management) techniques have been considered as an important tool to improve voltage profile, system efficiency and stability, to match stochastic output power of renewable sources and manage electric vehicles [18–29,54,56], and to reduce

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emissions [30,31]. Load profile management (LPM), one of the load management methods, manages the load profile over a given period of study (e.g., a day) while total electricity consumption (energy) remains constant. LPM shows great potential in reducing emissions from electric power generation [30,31].

Significant research attention has been focused on the development of efficient optimization techniques for EED problems. In addition to the classic Newton–Raphson and Lagrange multiplier methods [3–7], various heuristic/evolutionary based algorithms such as genetic algorithm (GA), particle swarm optimization (PSO) and differential evolution (DE) have been proposed for solving EED problems [9,10,12,14,16]. Other optimization techniques such as abductive reasoning network (ARN) [8], simulated annealing (SA) [11], gravitational search algorithm (GSA) [15] and fuzzy satisfaction-maximizing decision approach [17] have also been developed for real-time dispatch and combined economic/emission optimization. Three evolutionary algorithms were investigated and compared for the dispatch of generation and load while only the generation cost was considered in the optimization model [53]. Recently, stochastic wind power was incorporated into EED for further reducing emissions [13,32,33]. Emission limitations have been considered for optimal generation dispatch [55]. However, little work has been done on incorporating load management for EED [30].

In this paper, a Newton-like PSO method is proposed for solving load profile management integrated environmental/economic dispatch (LPMIEED) problems to reduce emissions and cost. The remainder of the paper is organized as follows: The optimization problem formulation is discussed in Section 2. The Newton-like PSO algorithm development and illustrative examples of the algorithm are given in Section 3. Simulation studies using the IEEE RTS 96 system and the resulting power dispatch solutions are discussed in Section 4. Section 5 concludes the paper.

2. Problem formulation

Normally, EED algorithms are used to dispatch power among different generators to meet the total load demand in an economically/environmentally optimized way. Load management gives us another set of variables to carry out optimization. Though DSM methods may reduce the total electric energy consumption as a result of energy efficiency improvement, it is assumed in this paper that the load management will not change the total electricity consumption in a given period of time (e.g., a day). In other words, the LPM discussed in this paper will allow customer loads to be increased or reduced within certain time periods while the total energy consumption for the whole time period of study remains constant. In the following, the optimization problems of LPM integrated economic dispatch, emission dispatch, and EED will be considered.

2.1. LPM integrated economic dispatch

The total generation cost, including all generators and the entire duration of analysis, is:

$$F_C = \sum_{t=1}^{NT}\sum_{i=1}^{NG} F_{C,i}(t) \tag{1}$$

where NT is the total time intervals in the period of study. For example, NT can be 24 for 24 1 h intervals in a day. NG is the total number of generators in the system. $F_{C,i}$ is the generation cost ($) of generator i in a unit time (e.g., 1 h). Without considering the valve-point effect (i.e., a ripple-like effect in the heat rate curve during the value opening process of a multi-valve turbine) [11], a generator cost model can be expressed as a second order polynomial:

$$F_{C,i} = C_i(k_{i,0} + k_{i,1}P_{G,i} + k_{i,2}P_{G,i}^2) \tag{2}$$

where $P_{G,i}$ (MW) and C_i ($/MMBTU) are the output power and the fuel cost of generator i, respectively. $k_{i,j}$,(j = 1, 2, 3) is the corresponding heat rate coefficient of generator i.

The total load demand in the system at time t is:

$$L(t) = \sum_{i=1}^{NL} L_i(t) \tag{3}$$

where NL is the total number of loads in the system. It is assumed that the overall system load can be controlled to a certain extent such that the new load is $[1 - \mu(t)L(t)]$. $\mu(t)$ is the load controlling factor. If $\mu(t)$ is positive (negative), it means that the load at time interval t will be reduced (increased) to $[1 - \mu(t)]$ of its original value. As aforementioned, the total electricity consumption in the entire duration of study is assumed to be unaffected by load management, which gives the following equality constraint:

$$\sum_{t=1}^{NT} \mu(t)L(t) = 0 \tag{4}$$

There are other constraints, such as power balance, generation limits, etc., that also need to be satisfied at each time interval t.

$$H(\boldsymbol{P_G}) = \sum_{i=1}^{NG} P_{G,i}(t) - [1 - \mu(t)L(t)] + \boldsymbol{P_G^T B_2 P_G} + \boldsymbol{B_1 P_G} + \boldsymbol{B}_0 = 0 \tag{5}$$

$$P_{G,i,\min} \le P_{G,i}(t) \le P_{G,i,\max} \tag{6}$$

$$-\mu_{\max} \le \mu(t) \le \mu_{\max} \tag{7}$$

The term $\boldsymbol{P_G^T B}_2\boldsymbol{P_G} + \boldsymbol{B}_1\boldsymbol{P_G} + B_0$ in (5) is used to model the system power loss, where $\boldsymbol{P_G}$ is the generator output power vector and $\boldsymbol{P_G} = [P_{G,1} \cdots P_{G,NG}]^T$. $\boldsymbol{B}_2$, $\boldsymbol{B}_1$ and B_0 are the coefficients for calculating power loss; $\boldsymbol{B}_2$ is a $NG \times NG$ matrix, $\boldsymbol{B}_1$ is an $1 \times NG$ vector and B_0 is a scalar constant [34]. In (7), $0 \le \mu_{\max} \le 1$.

An LPM integrated economic dispatch problem can then be formulated as

$$\begin{aligned} &\underbrace{Min}_{P_{G,\mu}} F_C \\ &\textit{Subject to} \\ &\textit{the constraints in}\,(4)-(7) \end{aligned} \tag{8}$$

It should be noted that in a real power system there are other constraints (e.g., voltage regulation, security constraints) which are not included in this study. The generation unit stat-up costs and other unit commitment constraints are not considered in this paper as well.

2.2. LPM integrated emission dispatch

Modeling of generator emissions is one of the central issues for EED. The CO_2 emission is considered in this paper. The relationship between CO_2 emission and generator output power can be modeled as:

$$F_{E,i} = E_i \times (k_{i,0} + k_{i,1}P_{G,i} + k_{i,2}P_{G,i}^2) \tag{9}$$

where $F_{E,i}$ (ton) is the amount of CO_2 emission of generator i, and E_i (ton/MMBtu) is the emission factor of generator i.

The total emission (ton) during the entire period of study is:

$$F_E = \sum_{t=1}^{NT}\sum_{i=1}^{NG} F_{E,i}(t) \tag{10}$$

An LPM integrated emission dispatch problem can then be written as

$$\begin{aligned}&\underbrace{Min}_{P_{G,\mu}} F_E\\&Subject\ to\\&the\ constraints\ in\ (4)-(7)\end{aligned} \quad (11)$$

2.3. LPM integrated economic/environmental dispatch (LPMIEED)

In general, the LMPIEED is a multi-objective optimization problem. Nevertheless, it is typical to use a weight factor to combine the objective functions in (1) and (10) and to convert the problem into a single-objective optimization problem [10]. If the cost of emission can be quantified, then it also turns into a single-objective problem as:

$$\begin{aligned}&\underbrace{Min}_{P_{G,\mu}} \{F = F_C + \lambda F_E\\&Subject\ to\\&the\ constraints\ in\ (4)-(7)\end{aligned} \quad (12)$$

where λ ($/ton) is the emission cost factor.

3. Newton-like particle swarm optimization

PSO is one of many heuristic algorithms; it shares many similarities with evolutionary computation techniques such as genetic algorithms (GAs). However, in some cases it is easier and faster to implement PSO than GA due to inherent difficulties in data representation that evolutionary operators such as crossover and mutation utilize. Since it was introduced in 1995, PSO has been used in many areas including nonlinear optimization, control and artificial intelligence [35].

PSO was originally developed for solving unconstrained nonlinear optimization problems [36]. Since real optimization problems are normally constrained, several variants of PSO capable of handling constraints have been proposed [35,37–46]. The most common way of handling constraints for PSO is to convert the constrained problem into a non-constrained problem by assigning certain penalty factors into the original objective function [44]. Ranking schemes were proposed in [37] and [45] to handle constraints so that leaders with better performance were chosen to set the directions for the rest in the swarm. Xu and Eberhart presented a feasibility-checking method to handle constraints for PSO [38,39]. Luo et al. employed a method of reduced space transformation to transform the problem into one without equality constraints [46]. Liang et al. proposed a dynamic multi-swarm approach to handle constraints in each subpopulation [43]. Nevertheless, the complexity of constraints that exist in real world problems remains one of the most difficult challenges in using PSO. It is particularly challenging in those situations with highly constrained search spaces. The optimums might be achieved with active constraints, or the equality constraints must be satisfied with great accuracy. Contrary to its fast spread to applications in many different areas, research on finding a general method of handling constraints for PSO has moved at a relatively slow pace.

In this paper, a Newton-like method is proposed to handle constraints for PSO based on the extension of the preliminary work reported in [47]. The proposed mechanism offers the freedom for particles to search spaces and also gives them directions to update their positions. This new method is verified by solving benchmark problems reported in literature [37,48] and is used for solving the LPMIEED problem discussed in Section 2.

3.1. Fundamentals of PSO algorithm

PSO is a population based stochastic optimization technique, inspired by social swarming behavior such as bird flocking or fish schooling. Each particle in the population represents a candidate solution. All the particles start with randomly initialized positions and then "fly" throughout the search space to find the best possible solution to the problem. During the process, the particles communicate with each other and promulgate the best local solutions/positions that each of them has achieved. Then, based on the global and local information obtained, each particle updates its position toward a desired global optimum.

The basic elements of a global version of PSO algorithm are summarized below.

- *Particle*, $X_j(t)$: Each particle is a candidate solution vector containing n optimization variables. $X_j(t)$ is the jth particle at time t, and it can be described as:

$$X_j(t) = [x_{j,1}(t), x_{j,2}(t), \ldots x_{j,n}(t)]^T \quad (13)$$

This particle vector is said to describe the particle's "position" within the solution space.
- *Population*, $Popu(t)$: It is a set consisting of m particles at time t, i.e., $Popu(t) = [X_1(t), X_2(t), \ldots X_m(t)]^T$.
- *Particle velocity*, $V_j(t)$: The velocity of the jth particle at time t in the n-dimensional search space can be represented as:

$$V_j(t) = [v_{j,1}(t), v_{j,2}(t), \ldots v_{j,n}(t)]^T \quad (14)$$

The velocity of the particle indicates its relative change within the solution space with respect to its current position vector. For each time increment, a particle's velocity represents the time rate of change of the particle's solution vector.

- *Personal best*, $X_{j,\,pbest}(t)$: It is the best position that the jth particle has achieved so far at time t. Each particle saves its best position throughout the whole searching procedure.
- *Global best*, $X_{gbest}(t)$: It is the best position (or solution) that has been achieved so far among all the particles. The information of global best is known to each and every particle in the population through communication among particles.

The original PSO algorithm is implemented as follows:

- *Initialization*: At the starting point $t = 0$, all particles are initialized with a randomly assigned position and velocity value.
- *Velocity updating*: During each iteration cycle, the particle velocity is updated based on the following formula:

$$\begin{aligned}V_j(t) = w(t)V_j(t-1) + c_1r_1[X_{j,pbest}(t-1) - X_j(t-1)]\\ + c_2r_2[X_{gbest}(t-1) - X_j(t-1)]\end{aligned} \quad (15)$$

where $w(t)$ is the inertia weighting factor, c_1 and c_2 are two positive constants, and r_1 and r_2 are uniform random numbers in the range of [0, 1].
- *Position updates*: After updating its velocity, each particle changes its position (or solution) according to the following simple formula:

$$X_j(t) = X_j(t-1) + V_j(t) \quad (16)$$

Table 1
Newton-like method based PSO.

Random Initialization
Do
For *each particle*
PSO Velocity Update $\rightarrow V_j(t)$
PSO Position Update $\rightarrow X_j(t)$
Find the Jacobian matrix $J_j(t)$
$dX_j(t) = -pinv(J_j(t))H(X_j(t))$ (19)
$X_j(t+1) = X_j(t) + dX_j(t)$ (20)
Evaluate objective function value
Update individual best
End For
Update global best
While (stop criteria not met)

3.2. Newton's method for solving nonlinear equations

Newton's method, also called Newton–Raphson's method, is one of the most commonly used techniques for solving nonlinear equations [49]. The iterative procedure can be described as

$$X(t+1) = X(t) - J^{-1}(t)F(X(t)) \tag{17}$$

where $\boldsymbol{X}(t)$ is the N-dimensional variable vector at the tth step, $\boldsymbol{F}$ is the N-dimensional function vector, and $\boldsymbol{J}$ is the Jacobian matrix.

For a set of underdetermined nonlinear equations (i.e., the number of variables is larger than the number of consistent equations), a Newton-like method can be used to find a solution with minimum norm by using the pseudoinverse [49]. A similar iterative formula to (12) can be used as follows:

$$X(t+1) = X(t) - pinv(J(t))F(X(t)) \tag{18}$$

where *pinv* represents the pseudoinverse operation. In this case, $J(t)$ is an $M \times N$ matrix, i.e. not a square matrix, i.e. $M \neq N$. M is the number of equations, N is the number of variables, and $M < N$.

Newton's method is fast and it can achieve quadratic convergence. It is a common application to combine Newton's method with other methods in a hybrid format to achieve numerical global convergence [49].

3.3. Newton-like method based PSO

In general, the group of equality constraints such as those given in (5) is a set of underdetermined equations, which should have a set of solutions. Otherwise, there is either no solution to the optimization problem or there is no need to carry out the optimization study if only the equality constraint set itself can determine the solution of the problem.

The idea of using a Newton-like method to solve a set of underdetermined nonlinear equations can be applied to guide particles in a population to change their velocities and positions to meet the equality constraints. Fig. 1 shows the flow chart of the proposed Newton-like PSO algorithm. The implementation pseudo code of the new PSO is given in Table 1.

In (19), $dX_j(t)$ is the incremental change of particle X_j at time t, H is the equality constraint vector, and J_j is the Jacobian matrix of particle X_j.

Fig. 2 shows a graphic illustration of using the Newton-like method to handle equality constraints for PSO. Suppose that there are several particles searching in a 3-D space for an optimal solution with some given objective function. In this example, the objective function is subjected to a sphere equality constraint surface, i.e., $x_1^2 + x_2^2 + x_3^2 = 1$.

As shown in the figure, particles X_j and X_k are flying in the search space and updating their positions based on their current velocities (V_j and V_k), which are merely determined by (15). In the original PSO algorithm, X_j and X_k do not know explicitly where the constraint surface is and how to satisfy the constraint. With the help from the Newton-like method, an additional position adjustment, determined by (19), is added to each particle to push it toward the constraint surface. As shown in Fig. 2, dX_j, for example, is added to change the next position of X_j so that X_j will be pulled toward the sphere surface to satisfy the equality constraint.

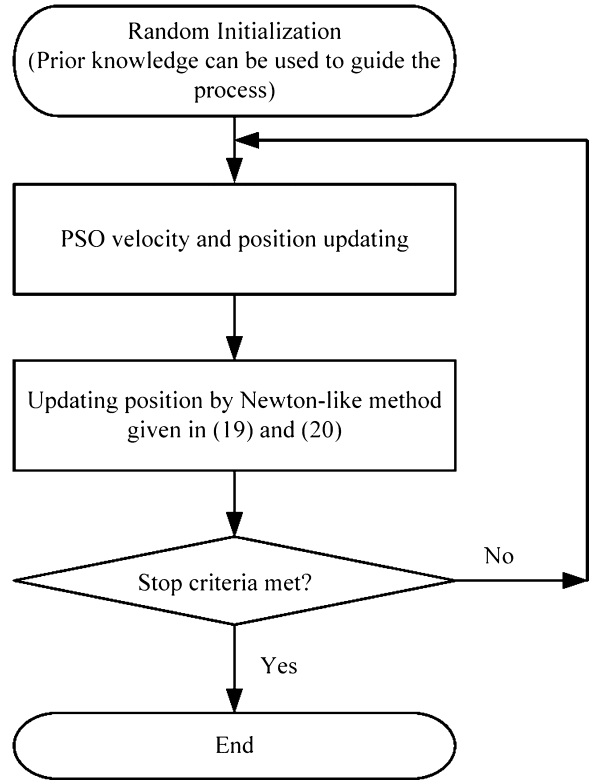

Fig. 1. Flow chart of the proposed Newton-like PSO algorithm.

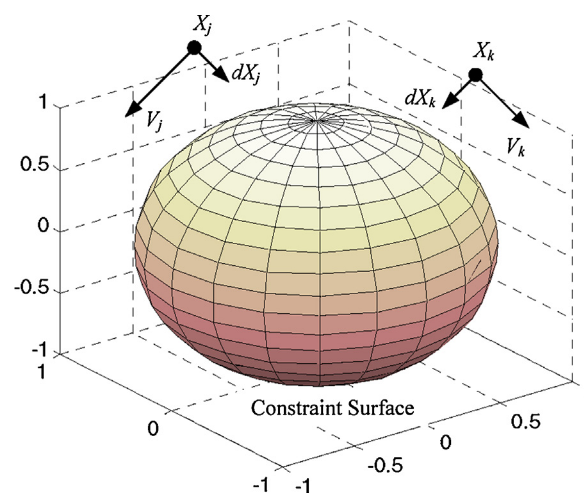

Fig. 2. Graphic illustration of handling equality constraints for PSO using Newton's method.

3.4. Illustrative examples of the Newton-like method based PSO

The proposed Newton-like method based PSO has been tested on the benchmark problems reported in the literature [37,48]. Three of those benchmark problems have been chosen as illustrative examples to show the effectiveness of the proposed method. The details of the test problems are given in Appendix. For each

Table 2
TEST results of the PSO methods.

The proposed PSO method			
Problem	*g01*	*g02*	*g03*
Best	−47.7210036744	961.715171	193.73785137869
Worst	−47.5590286644	961.715546	193.79098756201
Mean	−47.6433222857	961.71521	193.78661571604
Median	−47.6483333260	961.715183	193.78819883169
STD	0.041543549703	7.44336E−5	0.0092241458052
FR	100%	100%	100%
SR	100%	100%	100%
Regular PSO method			
FR	76.67%	93.33%	0%
SR	0%	33.33%	0%

of the three benchmark problems, the proposed PSO program was run thirty times. The test results are summarized in Table 2, which includes the best, mean, median and worst results of the thirty runs. The standard deviation (STD), feasible rate (FR) and success rate (SR) are also given in the table. Feasible rate is defined as the number of feasible runs (where a feasible solution is found) over the total number of runs. Similarly, success rate is defined as the ratio of the number of successful runs over the total number of runs [48]. A solution is considered feasible when all the constraints are met within a tolerance of 0.001. A successful run is a feasible run that also satisfies the following condition:

$$\left|\frac{f(X)-f(X^*)}{f(X^*)}\right| < 0.1\% \tag{21}$$

where $f(X)$ is the objective function value obtained and $f(X^*)$ is the best known value as reported in [48].

The test results given in Table 2 show that the proposed Newton-like method based PSO algorithm found the global optimal solutions with 100% feasible rate and success rate for those test problems. For the purpose of comparison, the results of using a regular PSO method are also given in Table 2. The regular PSO uses a penalty function to handle equality constraints [44]. The regular PSO algorithm has the same parameters as the proposed method except the steps of (19) and (20) given in Table 1. The comparative results show the effectiveness of the proposed method and indicate the incapability of the original PSO method in handling equality constraints.

The proposed method has also been used to solve the LPMIEED problem discussed in Section 2. The details of the application are given in the following section.

4. Simulation system and simulation results

The load profile management integrated environmental/economic dispatch discussed in Section 2 has been implemented using the proposed Newton-like PSO method. The algorithm was tested on the 73-bus IEEE RTS 96 test system [50]. Shown in Fig. 3, the IEEE RTS 96 system represents a relatively large and complex power system, as it has 73 buses (51 load buses) and 99 generators, and a total of 8550 MW load and 10215 MW generation capacities. The generation capacity originally consists of 900 MW hydro-electric, 2400 MW nuclear, 3822 MW coal, 2853 MW petroleum, and 240 MW petroleum combustion turbine generating units. In order to represent the increase in the use of natural gas units in recent years, 1080 MW petroleum units in the test system were replaced with 1080 MW natural gas units in the numerical simulation studies presented in this paper. The costs and emissions factors for hydro-electric and nuclear were set to zero so that these generators always provide base load during the analyses performed. In other words, these generators (in a total of

Table 3
Generator types in the revised IEEE RTS 96 system.

Fuel type	Generator numbers
Coal	33,4,7,8,21,22,31,32,33,36,37,40,41, 54,55,64,65,66,69,70,73,74,87,88,97,98,99
Natural gas	9,10,11,16,17,18,19,20,42,43,44,49,50,51,52,53, 75,76,77,82,83,84,85,86
Oil	1,2,5,6,12,13,14,34,35,38,39,45,46,47, 67,68,71,72,78,79,80
Hydro and nuclear	15[a],23,24,25,26,27,28,29,30,48[a],56,57,58,59, 60,61,62,63,81[a],89,90,91,92,93,94,95,96
Unit type code	
U12	16,17,18,19,20,49,50,51,52,53,82,83,84,85,86
U20	1,2,5,6,34,35,38,39,67,68,71,72
U50	15[a],25,26,27,28,29,30,48[a],58,59,60,61, 62,63,81[a],91,92,93,94,95,96
U76	3,4,7,8,36,37,40,41,69,70,73,74
U100	9,10,11,42,43,44,75,76,77
U155	21,22,31,32,54,55,64,65,87,88,97,98
U197	12,13,14,45,46,47,78,79,80
U350	33,66,99
U400	23,24,56,57,89,90

[a] Synchronous condensers.

Table 4
Fuel costs and emission factors.

	Coal	Natural gas	Oil
Fuel Cost ($/MMBtu)	2.05	6.30	9.05
Emission Factor (Metric ton/MMBtu)	0.0953	0.0535	0.0735

Table 5
Heat rate parameters.

	$k_{i,2}$	$k_{i,1}$	$k_{i,0}$
U12	0.1582	8.6806	16.8204
U20	0.5471	−7.2019	215.1852
U50	0	0	0
U76	0.0309	7.8650	134.1222
U100	0.0119	7.5097	129.7522
U155	0.0056	7.5464	184.3804
U197	0.0050	7.6571	189.6178
U350	0.0033	7.4330	323.5432
U400	0.0010	8.5880	406.8978

24) will not participate in the environmental/economic dispatch. In addition, there are three synchronous condensers which are solely for reactive power support. The remaining 72 generators can be grouped into three categories based on their fuel types: Coal, natural gas and oil, as given in Table 3. These 72 generators together with the load profile management will be optimized for each hour interval in a day. Hence, the total number of decision variables of the LPMIEED problem is 1752 (i.e., $24 \times 72 + 24 = 1752$). The decision variable vector can be represented as

$$x = [P_{G,1}(1)\cdots P_{G,72}(24), \mu(1)\cdots\mu(24)]^T.$$

4.1. Fuel costs, emission factors and load profile

Table 4 shows the fuel costs and emission factors of generators based on their fuel types. The data are taken from [51] and [52]. The heat rate parameters (i.e., $k_{i,0}$, $k_{i,1}$ and $k_{i,2}$) of different unit types are taken from [50], given in Table 5.

Table 6 lists the hourly load profile in a day, which is similar to the one used in [16] but was scaled up based on the average load demand of the IEEE RTS 96 system.

Simulation studies have been carried out for the LPM integrated power dispatch on the IEEE RTS 96 system with the fuel cost and emission factors given in Table 4 and the load profile in Table 6.

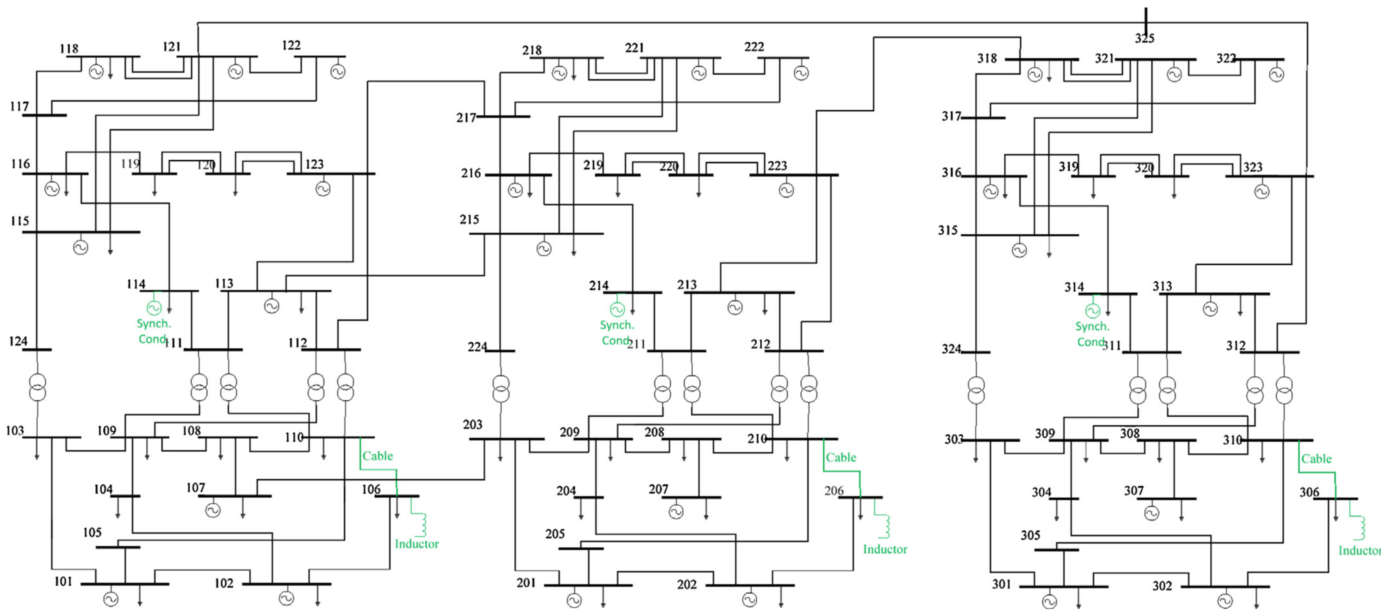

Fig. 3. IEEE RTS 96 System [50].

The results of the different scenarios with different levels of load management are presented, compared and discussed in the next subsections. The proposed Newton-like method based PSO is also compared with the optimization toolbox in MATLAB.

4.2. Simulation results

4.2.1. Constant emission cost factor

Simulation studies are first carried out for a constant emission cost factor (see λ in (12)). λ is chosen as \$5/ton for the simulation studies. Fig. 4 shows the overall generation cost of the system at different levels of load management (i.e., different values of μ_{max} in (7)) in the 24 h simulation period. The case of $\mu_{max} = 0$ represents the scenario when there is no LPM. In this case, the generators are still optimally dispatched, but only on each individual hour interval, not for the whole 24 h period. It can be noted from the figure that the generation cost is reduced since a greater portion of the load is controllable. The results also show that the generation cost savings becomes saturated when the level of controllable load exceeds approximately 30% ($\mu_{max} = 0.30$). Even if more loads were controllable beyond this point, no significant additional cost savings would result. This is mainly because of the load profile (in Table 6) and the cost models (in Table 4) used in the simulation studies. As shown in the figure, the LPM can reduce generation cost by nearly 10%. The CO_2 emission versus load management is also given in Fig. 4. It can be seen that CO_2 emissions remain essentially unchanged under different levels of load management for this uniform emission cost factor case.

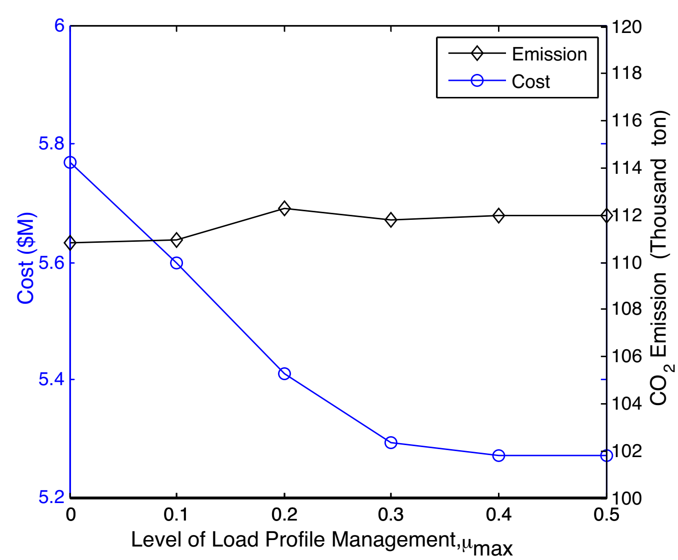

Fig. 4. Cost and emission versus different load management levels with a uniform emission cost factor λ = \$5/ton.

Table 6
Hourly load profile.

Time (h)	Load (MW)	Time (h)	Load (MW)
1	6583.5	13	9234.0
2	6348.4	14	9747.0
3	6305.6	15	9661.5
4	6455.3	16	9533.3
5	6583.5	17	9298.1
6	6626.3	18	9105.8
7	7481.3	19	8699.6
8	9191.3	20	7908.8
9	9832.5	21	7481.3
10	9939.4	22	6840.0
11	9875.3	23	6412.5
12	9725.6	24	9234.0

Fig. 5 shows the total generation profiles over the 24 h simulation period for the case of no load management ($\mu_{max} = 0$) and when $\mu_{max} = 0.20$. This figure demonstrates that the loads at the peak regions have been shifted to the valley zones to make the load more evenly distributed in order to reduce the overall generation cost.

Fig. 6 shows the fuel mixture of the electricity generation over the 24 h simulation period for the case of no load management ($\mu_{max} = 0$) and when $\mu_{max} = 0.20$. It can be seen from the figure that more electricity generation has been shifted from more expensive units (i.e., oil-fired generators) to cheaper generators (i.e., coal and natural gas).

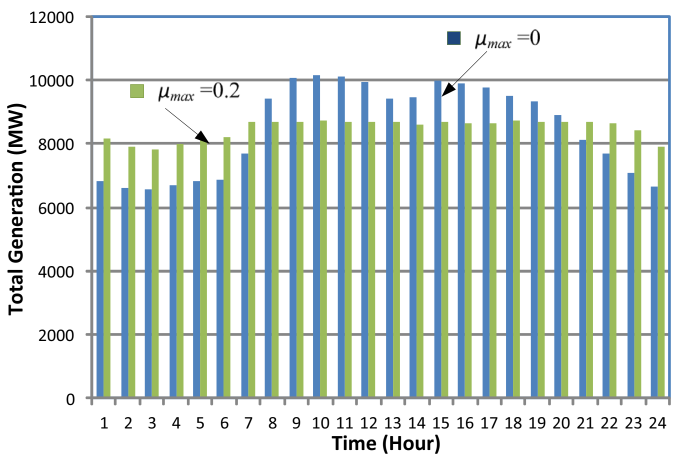

Fig. 5. The overall generation profiles of LPMIEED for the two scenarios of $\mu_{max} = 0$ and $\mu_{max} = 0.2$ with a uniform emission cost factor, $\lambda = \$5$/ton.

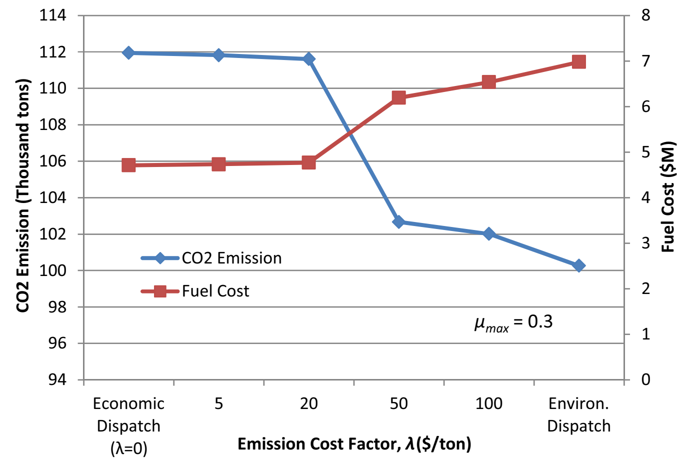

Fig. 7. CO_2 emission and fuel cost versus different emission cost factors with $\mu_{max} = 0.3$.

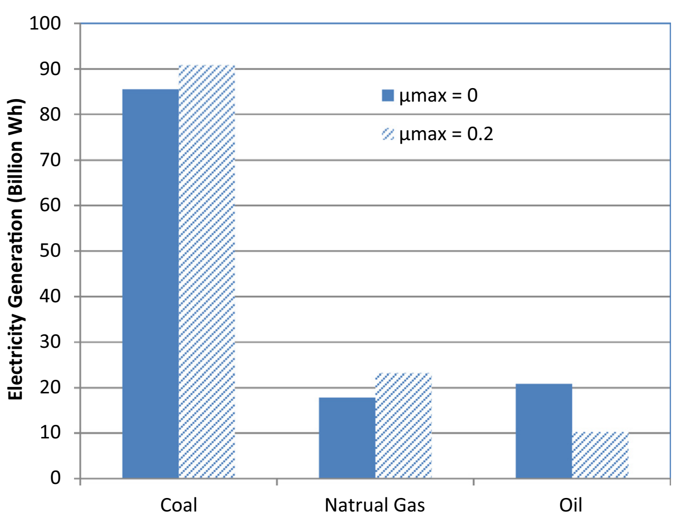

Fig. 6. The fuel mixture of LPMIEED for the two scenarios of $\mu_{max} = 0$, and $\mu_{max} = 0.2$ with an emission cost factor $\lambda = \$5$/ton.

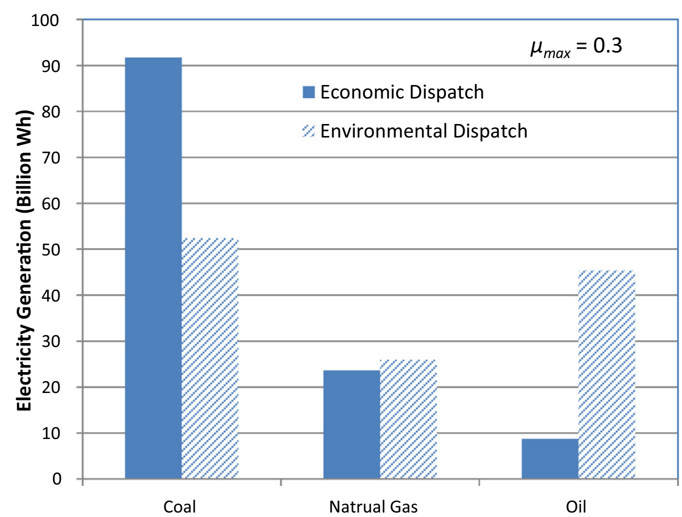

Fig. 8. The fuel mixture of LPMIEED with $\mu_{max} = 0.30$ for the two scenarios: Economic dispatch and environmental dispatch.

4.2.2. Constant load management level

As discussed earlier in this section, there is no significant improvement in cost savings when μ_{max} is over 0.30. Hence, μ_{max} is set at 0.3 for the rest of the simulation studies. The total CO_2 emissions with different emission cost factors and the corresponding fuel costs are presented in Fig. 7. As demonstrated, the total CO_2 emissions are reduced if the emission is given more weight (i.e., a higher emission cost factor) in the optimization model. Compared with the economic dispatch scheme (i.e., $\lambda = 0$), the environmental dispatch (without considering the fuel cost) can reduce the total CO_2 emission by over 10.4%, which is equivalent to a reduction of 11,690 metric tons in a day or a reduction of about 4.3 million metric tons in a year.

Fig. 8 shows the fuel mixture of the economic dispatch and environmental dispatch. It clearly shows that the generation has been shifted from units with higher emission rates (i.e., coal power plants) to generators with lower emission rates (i.e., natural gas and oil) under the environmental dispatch scheme.

It can also be noted from Figs. 3 and 5–7 that the goals of fuel cost saving and emission reduction may not come together at the same optimal point. The LPMIEED with an objective function given in (12) can provide a *Pareto* front, shown in Fig. 9, based on which an optimal tradeoff can be made to balance the fuel cost and emission. Many practical factors will affect the selection of a particular operating point (in the Pareto front) for a given system. As environmental issues gain additional emphasis (e.g. emission reductions to mitigate climate change as suggested in Kyoto and Copenhagen Protocols), the decision may lean more toward emission reduction in the future.

4.2.3. Comparison between the Newton-like PSO and the optimization toolbox in MATLAB

The simulation studies on the IEEE RTS 96 System were carried out on a PC with an Intel(R) Core (TM) i7-3770 3.4 GHz CPU and 8.0 GB memory, running on Microsoft Windows 7. All the testing and simulation programs were coded using MATLAB R2012b.

The parameter settings of the PSO programs are listed in Table 7. The inertia weighting factor, $w(t)$ in (15), is chosen as $w(t) = \alpha_w w(t-1)$, where α_w is the annealing factor. It took about 1 h to obtain a feasible solution using the proposed PSO algorithm on the aforementioned PC.

The *fmincon* function with "*active-set*" algorithm in the MATLAB optimization toolbox was used to implement the same LPMIEED

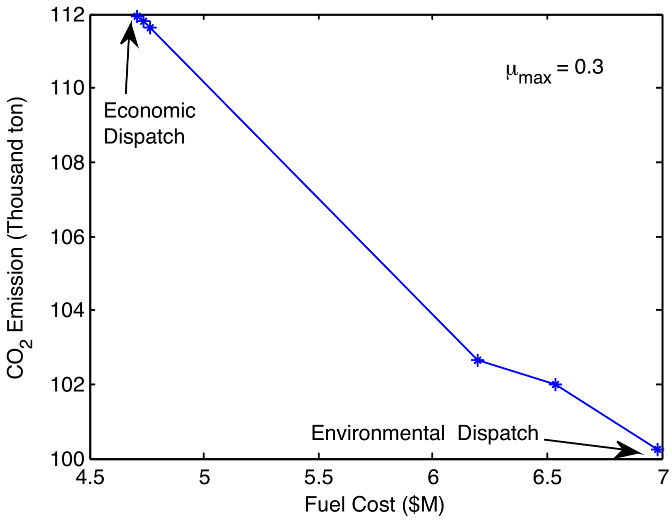

Fig. 9. The Pareto front curve of the LPMIEED with $\mu_{max} = 0.30$.

Table 7
Parameter settings for the PSO algorithms.

Parameter	Memo
$\alpha_w = 0.98$	$w(t) = \alpha_w w(t-1)$, see (15)
$c_1 = 2$	See (15)
$c_2 = 2$	See (15)
$m = 8000$	Total number of particles
$N_{tot} = 200$	Maximum number of total iterations
$N_L = 1000$	Maximum number of iterations since the last update of the best solution

scheme and ran on the same PC. It took about 15 h, but the program still failed to provide a feasible solution. In other words, the *fmincon* optimization program stopped prematurely when the maximum iteration number exceeded the pre-set default value of 175,200. The conventional PSO algorithm also failed to give a feasible solution. The comparison results show that the Newton-like PSO method is an effective tool in solving optimization problems with nonlinear equality constraints.

5. Conclusion

A load profile management integrated environmental/economic dispatch (LPMIEED) algorithm was formulated in this paper. A Newton-like PSO method has been developed for solving the LMPIEED problem. The algorithm was implemented in MATLAB and tested on the IEEE RTS 96 system. The simulation results show that the LPM can reduce system generation costs and emissions by about 10% for the IEEE test system. For the given load profile discussed in the paper, the simulation results also show that the effect of load profile management becomes saturated when the level of load management is over 30% for the IEEE RTS 96 system. Overall, results demonstrate that load management schemes have great potential for reducing emissions.

The proposed Newton-like method was compared with the optimization toolbox function in MATLAB. The illustrative examples, the simulation studies on the IEEE RTS 96 system, and the comparison results show that the proposed PSO technique is effective in finding solutions for optimization problems with equality constraints.

Appendix.

Problem g01 [48]

$$\textbf{Min}\quad f(X) = \sum_{i=1}^{10} x_i \left(c_i + \ln \frac{x_i}{\sum_{j=1}^{10} x_j} \right) \tag{22}$$

s.t.

$$\begin{aligned} h_1(X) &= x_1 + 2x_2 + 3x_3 + x_6 + x_{10} - 2 = 0 \\ h_2(X) &= x_4 + 2x_5 + x_6 + x_7 - 1 = 0 \\ h_3(X) &= x_3 + x_7 + x_8 + 2x_9 + x_{10} - 1 = 0 \end{aligned} \tag{23}$$

where $0 < x_i \le 10$ for $(i = 1, \ldots, 10)$, and $c_1 = -6.089$, $c_2 = -17.164$, $c_3 = -34.054$, $c_4 = -5.914$, $c_5 = -24.721$, $c_6 = -14.986$, $c_7 = -24.1$, $c_8 = -10.708$, $c_9 = -26.662$, $c_{10} = -22.179$. The best known solution is at $X^* = $(0.0406684113216282; 0.147721240492452; 0.783205732104114;0.00141433931889084; 0.485293636780388; 0.000693183051556082; 0.0274052040687766;0.0179509660214818; 0.0373268186859717; 0.0968844604336845) with $f(X^*) = -47.7648884594915$.

Problem g02 [48]

$$\textbf{Min}\quad f(X) = 1000 - x_1^2 - 2x_2^2 - x_3^2 - x_1x_2 - x_1x_3 \tag{24}$$

s.t.

$$\begin{aligned} h_1(X) &= x_1^2 + x_2^2 + x_3^2 - 25 = 0 \\ h_2(X) &= 8x_1 + 14x_2 + 7x_3 - 56 = 0 \end{aligned} \tag{25}$$

Where $0 \le x_i \le 10$ for $(i = 1, 2, 3)$. The optimum solution is $X^* = $(3.51212812611795133; 0.216987510429556135; 3.55217854929179921) with $f(X^*) = 961.715022289961$

Problem g03 [48]

$$\textbf{Min}\quad f(X) = f_1(x_1) + f_1(x_2) \tag{26}$$

where $f_1(x_1) = \begin{cases} 30x_1 & 0 \le x_1 < 300 \\ 31x_1 & 300 \le x_1 < 400 \end{cases}$ and

$$f_2(x_2) = \begin{cases} 28x_2 & 0 \le x_2 < 100 \\ 29x_2 & 100 \le x_2 < 200 \\ 30x_2 & 200 \le x_2 < 1000 \end{cases}$$

s.t.

$$\begin{aligned} h_1(X) &= -x_1 + 300 + \frac{x_3x_4}{131.078}\cos(1.48477 - x_6) + \frac{0.90798x_3^2}{131.078}\cos(1.47588) = 0 \\ h_2(X) &= -x_2 - \frac{x_3x_4}{131.078}\cos(1.48477 + x_6) + \frac{0.90798x_4^2}{131.078}\cos(1.47588) = 0 \\ h_3(X) &= -x_5 - \frac{x_3x_4}{131.078}\sin(1.48477 + x_6) + \frac{0.90798x_4^2}{131.078}\sin(1.47588) = 0 \\ h_4(X) &= 200 - \frac{x_3x_4}{131.078}\sin(1.48477 - x_6) + \frac{0.90798x_3^2}{131.078}\sin(1.47588) = 0 \end{aligned} \tag{27}$$

where $0 \le x_1 \le 400$, $0 \le x_2 \le 1000$, $340 \le x_3$, $x_4 \le 420$, $-1000 \le x_5 \le 1000$ and $0 \le x_6 \le 0.5236$. The best known solution is at $X^* = $(201.784467214523659; 99.9999999999999005; 383.071034852773266; 420; −10.9076584514292652; 0.0731482312084287128) where $f(X^*) = 8853.53967480648$.

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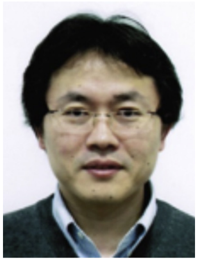

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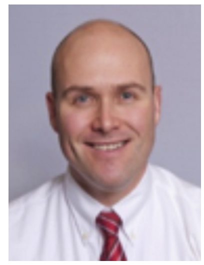

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