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· **Supplementary File** ·

Dynamic economic emission dispatch based on multi-objective pigeon-inspired optimization with double disturbance

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Appendix A Overview of multi-objective pigeon-inspired optimization (MPIO)

Pigeon-inspired optimization (PIO) is a novel swarm intelligence optimizer inspired by the homing behavior of natural pigeons, in which two different operators are designed to simulate the behavior. At the beginning of journey, a map and compass operator is used for pigeons, while in the middle, the navigation of pigeons is switched to a landmark operator. However, the basic PIO is designed for single-objective optimization problem (SOP). For solving multi-objective optimization problem (MOP), Qiu and Duan [1] proposed MPIO based on Pareto sorting scheme and a consolidation operator.

Appendix A.1 Pareto sorting scheme

For MOP, the rank of the pigeons cannot be identified by their fitness values as SOP, and that should be obtained by the classic non-dominated sorting operator. After that, the crowded-comparison operator is used for sorting the pigeons in each rank.

(a) Non-dominated sorting operator

For a minimization MOP, a pigeon $\mathbf{x}_1$ dominates $\mathbf{x}_2$ (written as $\mathbf{x}_1 \prec \mathbf{x}_2$) if and only if both of the following conditions are satisfied:

$$\begin{cases} f_i(\mathbf{x}_1) \le f_i(\mathbf{x}_2), & \forall\, i \in (1,\ldots,k) \\ f_j(\mathbf{x}_1) < f_j(\mathbf{x}_2), & \exists\, j \in (1,\ldots,k) \end{cases} \tag{A1}$$

where f_i denotes the ith function of the k objective functions. Using the fast non-dominated sorting approach [2], the pigeons are sorted into different non-domination levels based on eq. (A1), and the pigeons set in the first rank is known as the Pareto optimal front (POF).

(b) Crowded-comparison operator

In PIO the pigeons unfamiliar with the landmarks (i.e. the inferiorly pigeons) will be eliminated,

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so the pigeons in different sets need to be sorted further to realize the elimination in MPIO. And the crowded-comparison operator is employed to sort the pigeons in each set by comparing their crowing-distance that can be expressed as:

$$\mathrm{Dis}(\mathbf{x}_i)=\sum_{j=1}^{k}\left|\frac{f_j(\mathrm{x}_{i+1})-f_j(\mathrm{x}_{i-1})}{f_j^{\max}-f_j^{\min}}\right|,\ \ i=2,\ldots,n_p-1 \tag{A2}$$

where n_p represents the number of the pigeons in the *p*th set, and $f_j^{\max}$ and $f_j^{\max}$ are the maximum and minimum of the *j*th objective function values, respectively. Both $\mathrm{Dis}(\mathbf{x}_1)$ and $\mathrm{Dis}(\mathbf{x}_{n_p})$ are assigned an infinite value. Obviously, for the diversity preservation the pigeon with larger crowing-distance is superior to the pigeon with smaller one.

After working of the two operators, the pigeons with different non-domination ranks are divided into different sets correspondingly, while in each set the pigeons are arranged in descending order based on their crowding distances.

Appendix A.2 Consolidation operator

In MPIO, the map and compass operator and the landmark operator are merged into one consolidation operator to update the velocity and position of the pigeon:

$$\begin{aligned}
&N_p=N_p-N_{\mathrm{dec}}\\
&\mathrm{MC}=rand_1\cdot(\mathbf{x}_{\mathrm{gbest}}-\mathbf{x}_i(t-1))\\
&\mathrm{LM}=rand_2\cdot(\mathbf{x}_{\mathrm{center}}-\mathbf{x}_i(t-1))\\
&V_i(t)=V_i(t-1)\cdot e^{-R\times t}+tr\cdot(1-\lg_{gm}^{t})\cdot\mathrm{MC}+tr\cdot\lg_{gm}^{t}\cdot\mathrm{LM}\\
&\mathbf{x}_i(t)=\mathbf{x}_i(t-1)+V_i(t)\qquad i=1,\ldots,N_p
\end{aligned} \tag{A3}$$

where MC and LM represents the original map and compass operator and the landmark operator, respectively. N_p denotes the number of the population after *t* iteration loops, *gm* is the maximum number of iterations and N_{dec} denotes the number of eliminated pigeons at each iteration; V_i is the velocity of pigeon $\mathbf{x}_i$, *R* is the map and compass factor, and *tr* is the transition factor which makes the fusion of the two operators smoothly. $\mathbf{x}_{\mathrm{gbest}}$ represents the global best position of the population, which is extracted from an external archive of the nondominated solutions, and $\mathbf{x}_{\mathrm{center}}$ denotes the center position of the pigeons of the POF obtained in last iteration. The detailed procedure for solving $\mathbf{x}_{\mathrm{center}}$ and $\mathbf{x}_{\mathrm{gbest}}$ can be seen in [1].

Appendix B Update Approach for $\mathbf{x}_{\mathrm{pbest}}$

In multi-objective optimization, $\mathbf{x}_{\mathrm{pbest}}$ needs to be redefined based on the Pareto dominance relation between the old and new individual. The method we used to update $\mathbf{x}_{\mathrm{pbest}\_i}$ in each iteration can be described as follows.

Step1. Initialize $\mathbf{x}_{\mathrm{pbest}\_i}$ with the initial value of $\mathbf{x}_i$.

Step2. Update $\mathbf{x}_i$ using eq. (8) of the letter.

Step3. if $\mathbf{x}_i \prec \mathbf{x}_{\mathrm{pbest}\_i}$, update $\mathbf{x}_{\mathrm{pbest}\_i}$ using the current value of $\mathbf{x}_i$; on the contrary, $\mathbf{x}_{\mathrm{pbest}\_i}$ remains unchanged; otherwise, if $\mathbf{x}_i$ and $\mathbf{x}_{\mathrm{pbest}\_i}$ do not dominate each other, $\mathbf{x}_i$ will be selected as the new $\mathbf{x}_{\mathrm{pbest}\_i}$ with the probability of 0.5 for keeping the function of $\mathbf{x}_{\mathrm{pbest}\_i}$ in the later phase of the algorithm.

Appendix C Implementation details of IMPIO-DD to solve DEED

Appendix C.1 Population Initialization

For multi-objective DEED, the output power of each generator at each time period is included in the individual as the decision variable. Therefore, in IMPIO-DD the population consists of N_p pigeons and each pigeon is comprised of NT decision variables, which can be defined as:

$$\mathbf{X} = \{\mathbf{x}_1 \ \mathbf{x}_2 \ \cdots \ \mathbf{x}_{N_p}\} \tag{C1}$$

$$\mathbf{x}_i = \begin{bmatrix} P_{11} & P_{12} & \cdots & P_{1T} \\ P_{21} & P_{22} & \cdots & P_{2T} \\ \vdots & \vdots & \vdots & \vdots \\ P_{N1} & P_{N2} & \cdots & P_{NT} \end{bmatrix} \tag{C2}$$

where N is the number of generating units and T is the number of dispatching periods. P_{ij} is generated randomly between its upper and lower operating limits.

Appendix C.2 Procedures of IMPIO-DD

The implementation of our proposed IMPIO-DD for solving DEED is as follows:

Step1. Initialize the positions $\mathbf{X}$, velocities $\mathbf{V}$, $\mathbf{x}_{\text{gbest}}$ and $\mathbf{x}_{\text{pbest}\_i}$ of the N_p pigeons of the population, and an empty external archive A. Set the iteration counter g by 0.

Step2. Update $\mathbf{V}$ and $\mathbf{X}$ according to eq. (8) of the letter.

Step3. Mutate $\mathbf{X}$ according to eq. (9) of the letter.

Step3. Evaluate the pigeons by Pareto sorting scheme to obtain the POF of the current generation, $\mathbf{X}_{\text{best}}$. Calculate $\mathbf{x}_{\text{center}}$ using $\mathbf{X}_{\text{best}}$ and then add $\mathbf{X}_{\text{best}}$ into A.

Step4. Store the pigeons in A into a temporary archive and clear A. Find the Pareto optimal solutions of the temporary archive, and then store them into A.

Step5. Update $\mathbf{x}_{\text{pbest}\_i}$ and randomly select a pigeon in A as the new $\mathbf{x}_{\text{gbest}}$.

Step6. Increase the generation by $g = g + 1$. If $g < gm$, return to step2, otherwise go to step7.

Step7. Stop the procedure and output the current $\mathbf{X}_{\text{best}}$ or the best compromise solution as the final result.

It should be noted that the fuzzy-based decision making method [3] are employed to extract the best compromise solution from the final POF. Moreover, the constraints handling method used in this paper are based on the dynamic heuristic constraint handling approach [4]. Due to the limited size, the details of the constraints handling and decision making methods are not presented, however, it can be seen in our previous work [5].

Appendix D Simulation results and discussions

Appendix D.1 Case description and parameter settings

Detailed description of the three testing cases are shown in Table D1, where the unit data, power load demand and transmission loss coefficients can be found in the listed references. For all the three testing cases, the parameters of IMPIO-DD are set as follows. The number of eliminated pigeons at each iteration N_{dec} is set to 2 as [1]. The map and compass factor R and the transition factor tr are set to 0.05 and 3, respectively. The disturbance probability p_m and radius r of SPM are set to 0.4 and 0.3, respectively. Due to the elimination of the inferior pigeons in every generation, the population size N_p and the maximum iterations gm of IMPIO-DD are selected as 298 and 100, respectively. Note that the parameters (R, tr, p_m, r, N_p and gm) can be adjusted according to the performance of IMPIO-DD, and the above parameter settings are found to be the best one after various trials. To ensure the fairness of the comparison, parameters of the original MPIO are set to the same values as that of IMPIO-DD. Both of the algorithms are run 20 times independently for all the three cases. The simulation is executed in Matlab R2014b on a PC with i7-6700K CPU @4.00 GHz, 16GB RAM and Windows 7 operation system.

Table D1 Description of testing cases

Case	Number of generators	Number of buses	Number of decision variables	Number of equality constraints	Date sources		
					Unit data	Load demand	Loss coefficients
1	6	30	6×24=144	24	Ref.[6]	Ref.[8]	Ref.[6]
2	14	118	14×24=336	24	Ref.[6]	Ref.[8]	**without loss**
3	14	118	14×24=336	24	Ref.[6]	Ref.[8]	Ref.[7]

Appendix D.2 Simulation results

1) *Case* 1

In this case, the IEEE 30-bus, 6-unit test system with nonlinear transmission loss is solved by the proposed IMPIO-DD and the basic MPIO separately. Based on the above parameter settings, the Pareto optimal fronts obtained in case 1 are shown in Figure D1. The best objective values and the compromise solutions obtained by IMPIO-DD and MPIO are listed in Table D2. Moreover, the results of IMPIO-DD are also compared with other four methods, MAMODE [4], GSOMP [8], MOPSO [8], and NSGA-II [8]. And their corresponding minimal objective values and the best compromise solutions are shown in Table D3 and Table D4, respectively. The detailed information of the best compromise solution obtained by IMPIO-DD in case 1 are listed in Table D5.

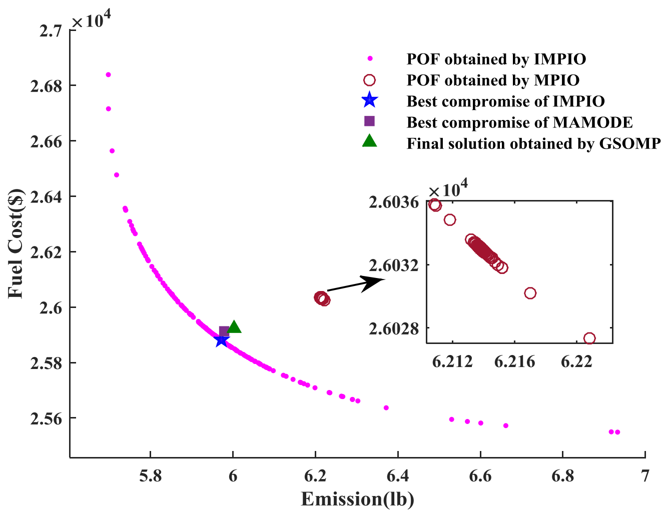

Figure D1 Comparison of POF and compromise solutions in case 1

As shown in Figure D1 and Table D2, it is obvious that the proposed IMPIO-DD obtains a better POF, which has a wider spread and smaller objective values than that of MPIO. The population of MPIO has been trapped into a small search space resulting a very narrow distributed

POF, which can be seen in figure D1. However, the Pareto optimal solutions of IMPIO-DD are uniformly and widely distributed in the objective space demonstrating the feasibility and effectiveness of the ADs and SPM operators in enhancing the global search ability of the population.

Table D2 Results obtained by IMPIO-DD and MPIO in case 1

Method	Objectives	Fuel cost ($)	Emission (lb)
IMPIO-DD	Best cost	**25549.0**	6.9328
	Best emission	26839.0	**5.6976**
	Best compromise	25880.0	5.9720
MPIO	Best cost	**26027.0**	6.2208
	Best emission	26036.0	**6.2108**
	Best compromise	26030.0	6.2170

Table D3 Comparison of the minimum objective values in case 1

	IMPIO-DD	MAMODE [4]	GSOMP [8]	MOPSO [8]	NSGA-II [8]
Fuel cost ($)	25549.0	25732.0	**25493.0**	25633.2	25507.4
Emission (lb)	5.6976	5.7283	**5.6847**	5.6863	5.6881

Table D4 Comparison of the compromise solutions in case 1

	IMPIO-DD	MAMODE [4]	GSOMP [8]
Fuel cost ($)	**25880.0**	25912.89419	25924.45557
Emission (lb)	**5.9720**	5.979548	6.004152

Table D5 The best compromise solution of case 1 obtained by IMPIO-DD (MW)

Hour	P_1	P_2	P_3	P_4	P_5	P_6	ΣP_i	P_L	P_D
1	0.3518	0.4640	0.5592	0.8391	0.7142	0.3595	3.2878	0.0378	3.25
2	0.4750	0.5554	0.7511	0.9143	0.7581	0.5014	3.9553	0.0553	3.90
3	0.3711	0.3963	0.7130	0.8571	0.6969	0.5057	3.5402	0.0402	3.50
4	0.2983	0.3395	0.6433	0.7899	0.5047	0.4534	3.0290	0.0290	3.00
5	0.3408	0.4613	0.6843	0.8625	0.5037	0.5359	3.3886	0.0386	3.35
6	0.4499	0.5159	0.8107	0.9418	0.6820	0.6557	4.0560	0.0560	4.00
7	0.4949	0.6086	1.0292	1.0512	0.9122	0.7264	4.8225	0.0725	4.75
8	0.5319	0.6000	1.1010	1.1043	1.0235	0.7705	5.1312	0.0812	5.05
9	0.6389	0.7224	1.1483	1.1419	1.1371	0.7630	5.5516	0.1016	5.45
10	0.5831	0.7104	1.0988	1.1520	1.0277	0.7186	5.2907	0.0907	5.20
11	0.6452	0.7185	1.1421	1.2069	1.1061	0.7856	5.6044	0.1044	5.50
12	0.6461	0.7864	1.1967	1.2063	1.1566	0.8703	5.8624	0.1124	5.75
13	0.5315	0.6685	1.1203	1.1704	1.0850	0.7612	5.3369	0.0869	5.25
14	0.5704	0.6176	1.0782	1.1447	1.0704	0.7563	5.2376	0.0876	5.15
15	0.5116	0.5333	1.0406	1.1248	0.9891	0.6221	4.8215	0.0715	4.75
16	0.5951	0.7394	1.1081	1.1531	1.0500	0.7493	5.3950	0.0950	5.30
17	0.5747	0.6997	1.0645	1.0990	1.0724	0.7287	5.2391	0.0891	5.15
18	0.7061	0.7959	1.1766	1.1663	1.1766	0.8474	5.8689	0.1189	5.75
19	0.5209	0.6778	1.1492	1.1132	1.1304	0.7435	5.3349	0.0849	5.25
20	0.5570	0.6506	1.1189	1.0650	1.1013	0.8466	5.3394	0.0894	5.25
21	0.4188	0.5788	0.9569	0.9857	1.0253	0.6472	4.6128	0.0628	4.55
22	0.3908	0.4997	0.9695	0.9763	0.8964	0.5699	4.3026	0.0526	4.25
23	0.3979	0.4572	0.9207	0.9895	0.9279	0.6107	4.3039	0.0539	4.25
24	0.3749	0.4361	0.8300	1.0113	0.8656	0.5309	4.0488	0.0488	4.00

In Table D3, both of the minimal objective values obtained by IMPIO-DD are better than those of MAMODE, and not as good as NSGA-II and GSOMP that has the best results of all the five methods. However the differences between the three methods are very small and the values are very close. Moreover, the minimum emission obtained by IMPIO-DD is a little more than that of MOPSO, but its value of minimum fuel cost is less than MOPSO. In addition, the best compromise solution obtained by IMPIO-DD is better than both MAMODE and GSOMP as shown in Figure D1 and Table D4.

For checking whether the twenty-four power balance constraints are satisfied simultaneously, the detailed best compromise solution obtained by IMPIO-DD are listed in Table D5. And it is obvious that in each hour the sum of the generators' outputs can cover the load demand and the power loss precisely.

2) *Case* 2

In this case, the IEEE 118-bus, 14-unit testing system without considering the power loss is employed to verify the performance of the proposed IMPIO-DD in solving high dimensional DEED problem as done in [8].

The Pareto optimal fronts obtained by IMPIO-DD and MPIO in case 2 are shown in Figure D2. And the Table D6 lists the best objective values and the compromise solutions obtained by IMPIO-DD and MPIO. It is clear to see in Figure D2 that the distribution of the Pareto optimal solutions obtained by IMPIO-DD are more broader and more uniform than that of MPIO, which is similar to case 1. Meanwhile, the best values of both objectives obtained by IMPIO-DD are much smaller than that of MPIO. Due to the premature convergence, the POF of MPIO is limited into a small region. Therefore, the ADs and SPM operations in IMPIO-DD expand the searching space of the population and increase the diversity of the population even in the high dimensional decision space.

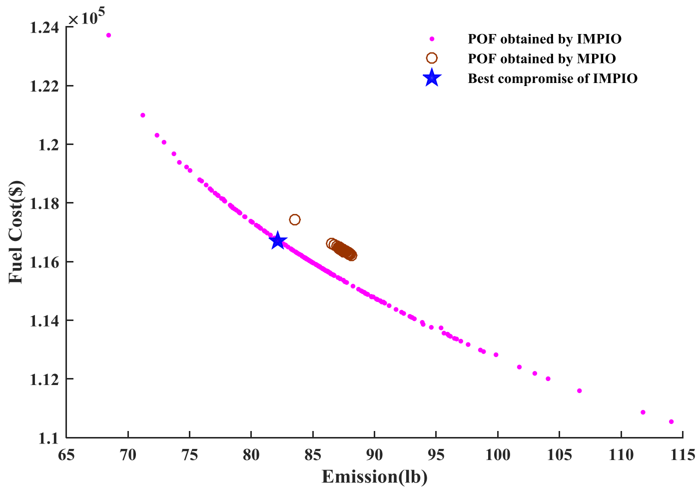

Figure D2 Comparison of POF in case 2

Table D6 Results obtained by IMPIO-DD and MPIO in case 2

Method	Objectives	Fuel cost ($)	Emission (lb)
IMPIO-DD	Best cost	**110550**	114.0744
	Best emission	123720	**68.4313**
	Best compromise	116710	82.1513
MPIO	Best cost	**116220**	88.1546
	Best emission	117440	**83.4975**
	Best compromise	116600	86.5584

In Table D7, the minimum objective values of the proposed IMPIO-DD are listed to compare with other four existing methods [4, 8]. And it is shown that the proposed IMPIO-DD gets the minimum fuel cost and emission, which are much better than that of MAMODE, GSOMP, MOPSO and NSGA-II. In Figure D3, the power balance constraints is checked using the best compromise solution obtained by IMPIO-DD. We can see that the power balance constraints of all the twenty-four dispatch periods are satisfied.

Table D7 Comparison of the minimum objective values in case 2

	IMPIO-DD	MAMODE [4]	GSOMP[8]	MOPSO [8]	NSGA-II [8]
Fuel cost ($)	**110550**	114709.2	142547.2	143218.3	145790.5
Emission (lb)	**68.4313**	70.21	331.23	359.07	348.58

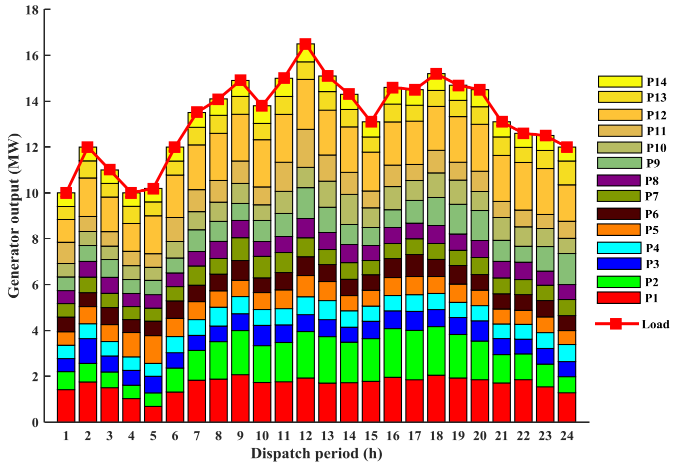

Figure D3 Constraints checking for the best compromise solution of case 2

3) *Case* 3

In this case, the IEEE 118-bus, 14-unit testing system with the power loss is studied to verify the global search ability of the proposed IMPIO-DD in solving DEED problem with highly nonlinear equality constraints. The Pareto optimal fronts obtained by IMPIO-DD and MPIO are shown in Figure D4. The best objective values and the best compromise solutions obtained by IMPIO-DD and MPIO are listed in Table D8. Meanwhile, the results of MAMODE reported in [4] are also listed for comparison. Figure D5 shows the power balance constraints checking of the proposed IMPIO-DD.

As shown in Figure D4, the Pareto optimal solutions obtained by IMPIO-DD spreads widely and uniformly in the objective space, but the POF obtained by MPIO are trapped into a limited region and a local POF may have been obtained. Similar to the previous two cases, the double disturbance mechanism enhances the global search ability of the algorithm indeed making the proposed IMPIO-DD also show a superior performance in solving DEED problem with highly nonlinear equality constraints.

From Table D8, we can clearly see that the proposed IMPIO-DD obtains a much smaller objective values than MPIO. Although the two fuel cost values obtained by IMPIO-DD in the best cost solution and the best compromise solution are more than that of MAMODE, both the corresponding emission values of IMPIO-DD are less than that of MAMODE, which may be preferred to decision makers who care more about the emission release. Moreover, as shown in

Figure D5, the power balance constraint at each dispatch period can be satisfied by IMPIO-DD even when the nonlinear power loss is considered.

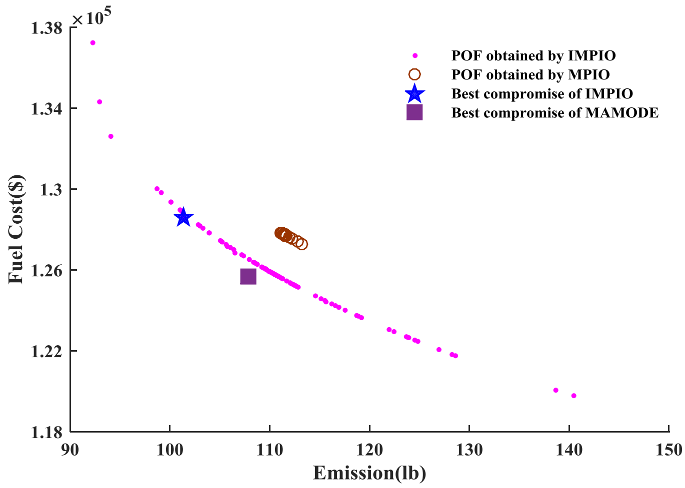

Figure D4 Comparison of POF in case 3

Table D8 Comparison of the simulation results in case 3

Method	Objectives	Fuel cost ($)	Emission (lb)
IMPIO-DD	Best cost	**119780**	140.4679
	Best emission	137240	**92.2827**
	Best compromise	**128580**	**101.3510**
MPIO	Best cost	**127300**	113.2912
	Best emission	127850	**111.0852**
	Best compromise	127550	112.1846
MAMODE[4]	Best cost	**118094.70**	156.481978
	Best emission	134258.849082	**93.597782**
	Best compromise	**125648.735817**	**107.850296**

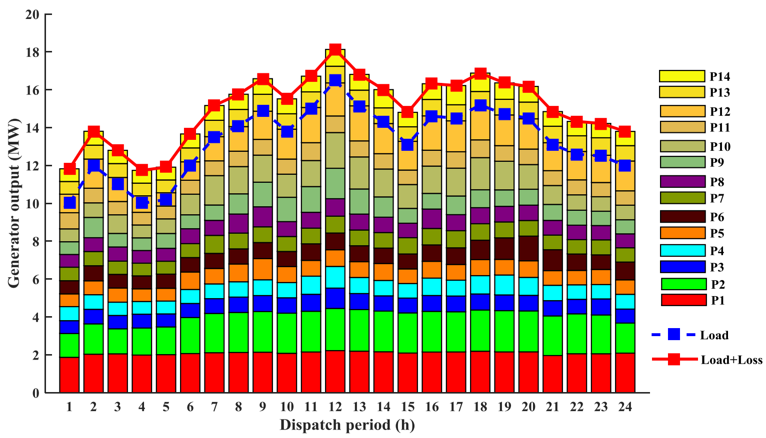

Figure D5 Constraints checking for the best compromise solution of case 3

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