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Optimal active load scheduling in a day-ahead energy market with uncertainty in demand

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ABSTRACT

The existing power loads are continuously increasing and leading to various challenges related to economics and systems constraints. Any uncontrolled fluctuations of the demand over consecutive hours would dramatically complicate the correct management of the power generation. Therefore, this paper provides an effective solution for managing the uncertainty in loads and providing optimal scheduling of the power generation based on active load optimization in the day-ahead energy market. The proposed optimization model relies on operating active loads to encounter any unexpected change in the load pattern with taken into consideration the characteristics of these loads. The objective of the optimization model is to procure the lowest energy bill by reducing operational costs by taking into account the compensation cost in case of operating the active loads. The optimized problem is solved using mixed-integer linear programming through two technical stages. The first stage handles the normal operation of generation and passive demand, while the second stage treats all the uncertainty in stochastic scenarios. The active loads are operated under specific constraints such as the instantaneous min/max amount and the min/max duration over 24-h period of time. Case studies are used to demonstrate the effectiveness of implementing active loads.

1. Introduction

The current power grids around the world need urgent and efficient developments to meet advanced criteria related to security, reliability environment, and economic targets. The transference from old power infrastructure into adequate power systems requires an improvement in all energy sectors, including the demand side to meet the expansion growth of future loads. Smart grid with its technology has been widely introduced to address many challenges in power systems including the concerns of the unexpected variation in demand. Smart grid technology has considered the involvement of end-user customers in providing more solutions to interrupted loads (Liao et al., 2017; Cataliotti et al., 2015; Yang et al., 2016; Unterweger and Engel, 2014). The smart grid in Mortaji et al. (2017) used a load-shedding algorithm to generate an appropriate schedule for a group of customers who owned some intelligent electronic devices. The algorithm of the study was efficient to control selected home appliances and reduce risks of energy shortage. Residential buildings in a smart grid could have the opportunity to participate in the process of scheduling the time and amount of load reductions as discussed by Li et al. (2015). In addition, the smart grid can also serve industrial loads to manage load characteristics by providing optimal price schemes as described by Xu and Lai (2015). Loads in smart grids are reconfigured to more controllable and categorized frameworks to minimize consumers' payments without losing their satisfaction as proposed by Safdarian et al. (2015). The study has clarified how energy cost benefits can be achieved for both energy providers and individual consumers in a smart grid that allows multiple payment methods. Furthermore, smart grids could significantly enhance the profit from energy consumption, provide accurate decisions for retailers on curtailing or shifting loads and take into consideration instant price and weather temperature as explained by Meng and Zeng (2015). Datacenter in the smart grids carefully tracks the variation of loads and gathers all bidding prices to match the optimal energy offers as described in

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Kamyab et al. (2015). One of the attractive features of smart grids to treat the high variations in demand is applying for a demand response program. For example, the study by Roh and Lee (2015) has created a mathematical representation for a demand response program in a smart grid to reflect the behavior of end-user customers during different circumstances. Maximizing social welfare is another advantage of demand response programs as investigated by Gong et al. (2015). The study also proved that incentive-based demand response could effectively guarantee the privacy of end-user customers including sensitive information. The study by Wei et al. (2015) confirmed that the demand response program in a smart grid could significantly decrease the supply cost by almost 10% as compared to the passive loads. Multiple energy carriers in the smart grid can smoothly participate in demand response in both electricity and natural gas markets as demonstrated by Bahrami and Sheikhi (2015). The study showed the relationship and interaction between all energy carriers in the demand response, and how end-user customers could switch between electricity and natural gases.

2. Literature review

Demand response programs in smart grids give opportunities for customers to own on-site generation such as renewable energy resources as presented by Cao et al. (2018). The owner of the on-site generation might submit the expected energy services through the demand response programs and efficiently manage their renewable energy resources. On-site generation and energy storage could reduce the dependency on power plants and help sell energy back to utilities when energy prices are high as discussed by Choobineh and Mohagheghi (2015). The vast increase in electric vehicles has considerably challenged the management of demand response and on-site generation as proposed by Wu et al. (2018). Rassaei et al. (2015) explained how electric vehicles cause high uncertainty in demand and change the patterns of traditional loads. This high uncertainty is mainly due to the randomness of the charging/discharging of the batteries of the electric vehicles, therefore demand response was suggested in the study to solve this issue.

The uncertainty of demand is a major concern in building microgrids on the demand side as explored by Kou et al. (2016). The results of the study were procured after converting the stochastic demand uncertainty into standard programming equations, which facilitate the deterministic of the feasible solution. The effects of the uncertainty between supply and demand through short and long terms were highlighted by Ma et al. (2019). The investigation of the uncertainty in the study was based on a bi-level optimization problem that takes into account the reduction of operational costs and the management of interruptible loads. The uncertainty was further investigated by Käki et al. (2013) to evaluate the unexpected risks for a manufacturing company. The study used generated stochastic scenarios on supply and demand to improve the decisions of the manufacturer and get the best estimation of costs related to risk mitigation. Moreover, considering the uncertainty of demand is a major component in power system planning as highlighted by Giannelos et al. (2018). The study used an algorithm based on Bender Decomposition to examine the effects of the uncertain participation of end-user customers on the investment strategies. Searching for the optimal value of real and reactive power in a microgrid system might be achieved with a high number of errors unless the uncertainty of demand is controlled as explored by Roy and Das (2021). The objective of the study was to achieve the allocation of active/reactive power subjected to constraints of power losses and uncertainty in loads. One of the effective solutions to address the uncertainty of demand is to build battery banks at loads due to their ability to absorb/supply energy within a very short time. For example, the study by Sanjari and Karami (2020) has suggested using integrated battery storage to regulate the energy resource scheduling under uncertain deviation of loads. The uncertainty of demand not only affects the distribution sectors but also has a potential impact on developing the transmission lines as explained by Soroudi (2021).

Active loads have been widely discussed in the literature to enhance the applicability of demand response and encourage end-user customers to change their passive energy usage. For instance, the study by Al-Sumaiti et al. (2020) has explained the positive impact of active loads in scheduling a demand response that is subjected to frequency limitations. The study has reported that when the active loads are in operation, the operational cost was significantly reduced as compared to the passive loads, even though the system was restricted by physical and time constraints. Economic dispatch and unit commitment are adequate techniques to schedule active loads in demand response programs (Le et al., 2021; Kiran AND Kumari, 2016; Howlader et al., 2016; Liu and Tomsovic, 2015). For example, scheduling active loads within an islanded microgrid have been organized through the economic dispatch technique as specified in Jordehi et al. (2020). This technique allows the operator to shed the optimal value of active loads during contingency or when the demand exceeds the defined deviation limits. Mixed-integer linear programming (MILP) and unit commitment are applied by Mohandes et al. (2020) to manage active load participation and control the distributed generation. The reason behind using the MILP in the study was to combine the thermal generations cost and the supplementary cost of active loads in fast mathematical calculation with an acceptable rate of accuracy. On the other hand, non-linear programming NLP was used by Azizipanah-Abarghooee et al. (2016) with a unit commitment to procure wind power generation and the sharing of active loads in demand response, hinting the NLP was particularly used since wind power generation depends on the non-linear output. Also, the benefit of using NLP in the previous study was to operate wind curtailment and enhance the spinning reserve availability from the optimal use of active loads by Lee et al. (2016). A non-linear bidding curve of active loads in demand response has been transferred into a linear curve to accommodate a large number of constraints in a short programming time. However, most of these studies did not consider the specifications and boundaries of active loads when scheduling energy resources during demand uncertainty.

This paper introduces an optimization technique to manage generation units and active loads in a day-ahead energy market. The objective of this study is to evaluate the minimum operational cost of generation and the compensation cost of the active loads. The compensation cost will be only accounted for if the active loads are in operation. The generation, active loads, and passive loads are optimized as MILP to merge all these variables together with the associated sets and constraints within short and accurate programming. The proposed optimization model takes into consideration the uncertainty of demand during the scheduling of the active loads. The stochastic scenarios of the uncertain demand are generated through Gather-Update-Solves-Scatter GUSS, which is an extension tool in GAMS that has been created to support random probability distribution (Bussieck et al., 2012). The optimization problem includes the characteristics and limitations of the active loads during high deviation of uncertain demand. The model splits the optimization problem into two stages to avoid any constraints' interruptions during the stochastic scenarios. The first stage is responsible for finding the optimal value in the base model, whereas all the uncertainties are treated in the second stage. The compensation cost of the active loads is precisely evaluated using a specific linearized curve to make it suitable for the MILP.

3. Problem formulation

3.1. Master function

The objective of the proposed model is to minimize the function provided in Eq. 1. The first part of the master problem in Eq. 1 contains the cost of heating up a generator $\mathcal{H}_{it}$, the cost of cooling down a generator $\mathcal{C}_{it}$ and the instantaneous cost of feeding the required demand, which is $\mathcal{P}_{it} * \mathcal{Q}_{it}$. The binary indicators λ_{it}, γ_{it} and ψ_{it} are defined in the master problem to maintain the operation of the generators and control the start-up and shut-down status. The second part of the master problem is responsible for calculating the compensation cost of the active loads $C_{at}^{\mathcal{AL}}$ involved in the scheduling procedure. The status of the active loads $\in_{at,r}$ is a binary variable. If $\in_{at,r}$ is one, the active load is under operation and $\in_{at,r}$ will be zero otherwise. The determination of the active load cost is described in Eq. 2. The cost of the active loads follows the linear relationship described in Fig. 1. The first part in Eq. 2 presents the consideration of the initial active loads, whereas the second part evaluates every participation of the active loads through specific stages β_a^s. The stages of the active loads are used to specify the number of active loads and are located between ε_a^s and ε_a^{s-1}.

$$min \sum_{t=1}^{NT}\{\sum_{i=1}^{NG}(\mathcal{H}_{it} * \lambda_{it} + \mathcal{C}_{it} * \gamma_{it} + \mathcal{P}_{it} * \mathcal{Q}_{it} * \psi_{it}) + \sum_{a=1}^{NA} C_{at}^{\mathcal{AL}} * \in_{at}\} \tag{1}$$

$$C_{at}^{\mathcal{AL}} = \tau_a^0\, \varepsilon_a^0 \in_a^0 + \sum_{s=1}^{NS} \tau_a^s\, \beta_a^s \in_a^s \tag{2}$$

$$\beta_a^s = \varepsilon_a^s - \varepsilon_a^{s-1} \tag{3}$$

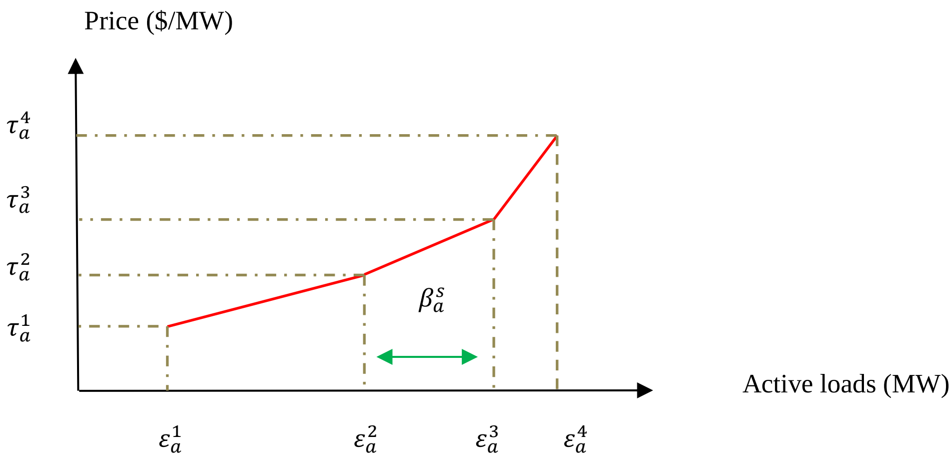

Fig. 1: Active loads curve

3.2. Stage-one constraints

The stage-one constraints are defined in the base model, where all uncertainties are excluded from the optimization problem. The stage-one would concentrate on the energy balance of the system, the boundaries of the transmission lines, the specifications of the generating units, and the required reserve of the system. The flow of the energy through all transmission lines is ensured in

Eq. 4. The hourly flow $\mathcal{FW}_{lt}$ in line l always reflects the instantaneous power supply minus the demand. The phase shift and the reactance of the transmission lines are essential in the calculation of the DC $\mathcal{FW}_{lt}$ as specified in Eq. 5. Constraint (6) provides more security of the transmission lines since the max/min of $\mathcal{FW}_{lt}$ is restricted. The heating-up cost $\mathcal{H}_{it}$ mentioned previously in the master function is only considered if Eq. 7 is satisfied. The $\mathcal{H}_{it}$ is considered if the previous operation status is 0 and the current operation status is 1, which presents the transition of the generator from OFF to ON mode. The fixed heating-up cost $\mathcal{U}_i^{up}$ is varying according to the prime mover of each generator. The instantaneous power supply is accomplished through Eq. 8, where ϱ_i^{min} presents the minimum capacity at initial of each generator and P_{jt} presents the power of each stage j. The instantaneous power is always positive and forced to operate within the defined limits as shown in Eq. 9. One of the most important factors of the generating units is the ramping ability over specific time duration, which has been considered in Eqs. 10-11. The increase of the power supply over the time duration $\mathcal{P}_{it} - \mathcal{P}_{i(t-1)}$ must be less than the ramping-up limit ξ_i^{UP}. Similarly, the decrease of the power supply over the time duration $\mathcal{P}_{i(t-1)} - \mathcal{P}_{it}$ must be less than the ramping-down limit ξ_i^{DN}.

The shut-down or turn-on operation of a generator needs a certain time to cover specific requirements related to manufacturing, and this has been taken into consideration in Eqs. 12-13. The operating hours of a generator are tracked and nominated by $\mathcal{T}_{i(t-1)}^{on}$ and should not exceed the min on-time defined as $\mathcal{N}_i^{on}$. In contrast, the duration of the shut-down $\mathcal{T}_{i(t-1)}^{off}$ must match the min off-time limit defined as $\mathcal{N}_i^{off}$.

$$\sum_{i=1}^{NG} \mathcal{P}_{it} - dm_{bt} = \sum_{l=1}^{NL} \mathcal{FW}_{lt} \tag{4}$$
$$\mathcal{FW}_{lt} = \frac{1}{x_l}(\vartheta_{ln} - \vartheta_{lm}) \tag{5}$$
$$\mathcal{FW}_{lt}^{min} \leq \mathcal{FW}_{lt} \leq \mathcal{FW}_{lt}^{max} \tag{6}$$
$$\mathcal{H}_{it} \geq \mathcal{U}_i^{up}(\psi_{it} - \psi_{i(t-1)}) \tag{7}$$
$$\mathcal{P}_{it} = \varrho_i^{min}\,\psi_{it} + \sum_{j=1}^{NJ} P_{jt} \tag{8}$$
$$\mathcal{P}_i^{min} \leq \mathcal{P}_{it} \leq \mathcal{P}_i^{max} \tag{9}$$
$$\mathcal{P}_{it} - \mathcal{P}_{i(t-1)} \leq \left(1 - \psi_{it}(1 - \psi_{i(t-1)})\right) * \xi_i^{UP} + \psi_{it}(1 - \psi_{i(t-1)}) * \mathcal{P}_i^{min} \tag{10}$$
$$\mathcal{P}_{i(t-1)} - \mathcal{P}_{it} \leq \left(1 - \psi_{i(t-1)}(1 - \psi_{it})\right) * \xi_i^{DN} + \psi_{i(t-1)}(1 - \psi_{it}) * \mathcal{P}_i^{min} \tag{11}$$
$$(\mathcal{T}_{i(t-1)}^{on} - \mathcal{N}_i^{on})(\psi_{i(t-1)} - \psi_{it}) \geq 0 \tag{12}$$
$$\left(\mathcal{T}_{i(t-1)}^{off} - \mathcal{N}_i^{off}\right)(\psi_{it} - \psi_{i(t-1)}) \geq 0 \tag{13}$$

3.3. Stage-two constraints

Now all uncertainties of the stochastic scenarios are considered in the optimization problem through GUSS. The energy balance from supply to demand in all stochastic scenarios is maintained as described in Eq. 14, where r presets the number of stochastic scenarios and $\rho_i^G(r)$ presents the availability of generations in the scenarios. Similarly, the outage status of the transmission lines $\rho_i^L(r)$ is included in the calculation of the power flow in the random scenarios as shown in Eq. 15. The new power flow in the stochastic scenarios is restricted according to the previous definition of the transmission limitations as illustrated in Eq. 16. The selection of the active loads is achieved through the linear curve of the cost and amount of the active loads as demonstrated previously in Fig. 1. The active load a at time t in scenario r is the combination of the segments β as displayed in Eq. 17. The collection of all segments of the active loads must be less than the maximum limit $\mathcal{A}_{a,\beta}^{Max}$ as specified in Eq. 18. The hourly active loads are operating according to the boundaries defined in Eq. 19. The aggregated active loads over the complete period of time NT must not exceed the maximum limit $\mathcal{Y}^{Max}$ as shown in Eq. 20. This constraint provides more control over the maximum daily limit of the active loads in each scenario. For efficient operation of the active loads over a certain consecutive period of time, the constraints (21)-(24) are defined. The operator of the active loads is obligated to change the level of the active loads over two consecutive hours in all stochastic scenarios according to the assigned maximum and minimum limits q_a^{Max} and q_a^{Min}, respectively as defined in Eqs. 21-22. Similarly, the change of the active loads over the time $t-1$ and t is totally controlled through Eqs. 23-24. The overall operating time for the active loads in each random scenario is restricted to be less than the r^{Max} and maximum than the limit r^{Min} as described in Eq. 25 and Eq. 26, respectively.

The location of the active load a on the power network is important and must be determined in all random scenarios. Therefore, the incident matrix $\Lambda_{at,r}$ is defined, which clarifies the participation of the active loads on each bus of the system as illustrated in Eq. 27. The results of the multiplication of the $\Lambda_{at,r}$ and the active load $\mathcal{A}_{at,r}$ gives the exact allocation of the active loads $\mathcal{L}_{bt,r}$ on bus b. Finally, the total hourly demand is simply calculated through Eq. 28, which is the hourly uncertain load $HL_{bt,r}$ subtracted by the active loads on buses $\mathcal{L}_{bt,r}$.

$$\sum_{i=1}^{NG} \rho_i^G(r)\,\mathcal{P}_{it,r} - dm_{bt,r}^T = \sum_{l=1}^{NL} fw_{lt,r} \tag{14}$$
$$fw_{lt,r} = \rho_i^L(r)\left(\frac{1}{x_l}(\vartheta_{ln,r} - \vartheta_{lm,r})\right) \tag{15}$$
$$\mathcal{FW}_{lt}^{min} \leq fw_{lt,r} \leq \mathcal{FW}_{lt}^{max} \tag{16}$$
$$\mathcal{A}_{at,r} = \sum_{\beta=1}^{N\beta} \beta_{a,r}^s \in_{at,r} \tag{17}$$
$$\beta_{a,r}^s \leq \mathcal{A}_{a,\beta}^{Max} \tag{18}$$
$$\in_{at,r} \mathcal{A}_a^{Min} \leq \mathcal{A}_{at,r} \leq \mathcal{A}_a^{Max} \in_{at,r} \tag{19}$$
$$\sum_{t=1}^{NT} \mathcal{A}_{at,r} \leq \mathcal{Y}^{Max} \tag{20}$$
$$\mathcal{A}_{at,r} - \mathcal{A}_{a(t-1),r} \leq q_a^{Max} \tag{21}$$
$$\mathcal{A}_{at,r} - \mathcal{A}_{a(t-1),r} \geq q_a^{Min} \tag{22}$$
$$\mathcal{A}_{a(t-1),r} - \mathcal{A}_{at,r} \leq z_a^{Max} \tag{23}$$
$$\mathcal{A}_{a(t-1),r} - \mathcal{A}_{at,r} \geq z_a^{Min} \tag{24}$$
$$\sum_{t=1}^{NT} \in_{at,r} \leq r^{Max} \tag{25}$$
$$\sum_{t=1}^{NT} \in_{at,r} \leq r^{Min} \tag{26}$$
$$\mathcal{L}_{bt,r} = \sum_{r=1}^{NR} \sum_{a=1}^{NA} \Lambda_{at,r} * \mathcal{A}_{at,r} \tag{27}$$
$$dm_{bt,r}^T = HL_{bt,r} - \mathcal{L}_{bt,r} \tag{28}$$

4. Results and discussion

The optimization of the proposed model and the operation of the active loads are examined using the 10-generators test model obtained (Saravanan et al., 2016; Alqunun et al., 2020). The data of the generators including amount and costs are depicted in Table 1. The function of the supply cost is transferred into linearized stages to present the power of each generator with its related cost in the MILP. The optimization problem is run using GAMS/Cplex software on a personal computer. Two case studies are applied to inspect the effectiveness of the active loads.

Table 1: The characteristics of the generating units

Unit	$\mathcal{P}_i^{min}$ (MW)	$\mathcal{P}_i^{max}$ (MW)	a_i	b_i	c_i	$\mathcal{N}_i^{on}$(h)	$\mathcal{N}_i^{off}$(h)	$\mathcal{H}_{it}$($)	$\mathcal{C}_{it}$($)	ξ_i^{UP} (MW)	ξ_i^{DN} (MW)
1	150	455	1000	16.19	0.00048	8	8	4500	9000	80	80
2	150	455	917	17.26	0.00031	8	8	5000	10,000	60	60
3	20	130	700	16.60	0.00200	5	5	550	1100	40	40
4	20	130	680	16.50	0.00211	5	5	560	1120	40	40
5	25	162	450	19.70	0.00398	6	6	900	1800	50	50
6	20	80	370	22.26	0.00712	3	3	170	340	30	30
7	25	85	480	27.74	0.00079	3	3	260	520	30	30
8	10	55	660	25.92	0.00413	1	1	30	60	15	15
9	10	55	665	27.27	0.00222	1	1	30	60	15	15
10	10	55	770	27.79	0.00173	1	1	30	60	10	10

4.1. Case 1: Power generation scheduling with uncertainty in demand

The target of the power network operator is to satisfy the variation of the demand with the least operating cost with respect to all the defined system constraints. The normal distribution function is used in the stochastic simulation to specify the forecasting errors of the demand. The deviation of the uncertainty in demand is considered to be 10% of the hourly rated loads. A large number of scenarios is generated, then a scenario reduction tool is used to reduce the number of scenarios into 10 scenarios as depicted in Fig. 2. The minimum demand is 579 MW at hour 2 in scenario 7, whilst the maximum demand has reached 1644 MW at hour 12 in scenario 8. The accumulative daily loads of the scenarios vary between 25,230 MWh and 27,763 MWh. The generating units have many challenges to cover the high variation of the demand such as the ramping-up/down capabilities and maximum power capacity. The power dispatch schedule starts with the generating units with low production cost, then any sudden increase in the demand will be immediately supplied by certain generating units with flexible on/off generating units regardless of the production cost. To investigate the effect of the uncertainty in demand on the power schedule, the hourly power dispatch of all scenarios has to be investigated. For example, the power dispatch schedule of scenario 8 is illustrated in Table 2. It can be noticed from Table 2 that the power dispatch is mainly dependent on units 1-5 to cover the majority of the demand, while units 6-10 have limited commitment due to their high production cost and low supply capacity. In addition, the comparison of the unit commitment schedule between base demand and scenario 8 is shown in Table 3. One means the generator is supplying the demand and zero otherwise, where the change of the dispatch status from base demand to scenario 8 is represented by bold style. For example, the total operating hours of unit 5 is 21 hours in the base demand, however, this number is significantly decreased to 15 hours in scenario 8. The variation of the operating hours amongst all the scenarios leads to the variation in the hourly production cost. Fig. 3 illustrated the hourly production cost of the committed generating units in scenario 8. The maximum daily production cost is $569,204 in scenario 10, whilst the minimum is $504,406 in scenario 4. The uncertainty of the passive loads in all scenarios has challenged the generating units in terms of security and economic, which requires the need to involve active loads operation in the scheduling optimization problem.

4.2. Case 2: Active loads impact on demand uncertainty

20% of the passive loads are now converted into active loads. The converted active loads would follow the structure of the demand segments and cost segments during the hourly operation. Also, the defined constraints of the active loads are considered in this case to provide complete control during the generation schedule. The power network operator, with full control of the active loads, has the ability to shut down the low-priority loads with taking into consideration the compensation cost of these loads. The data of the active loads are given in Table 4. The power dispatch has completely changed after the participation of the active loads in all scenarios. Fig. 4 demonstrates the hourly power dispatch in scenario 10 with and without the active loads' operation. The scheduling of the active loads started at hour 3 by curtailing 41.5 MW and ended at hour 22 by curtailing 243 MW.

The operation of the active loads is concentrated on the peak hours to maximize the benefits of these loads within the specified limit and to avoid operating expensive generating units. The total active loads' participation has satisfied the maximum limit over the 24-hour period of time. The active loads in scenario 10 have a significant reduction in the power dispatch scheduling. Only units 1, 2, and 4 are dispatching to supply the demand, while the rest are totally off.

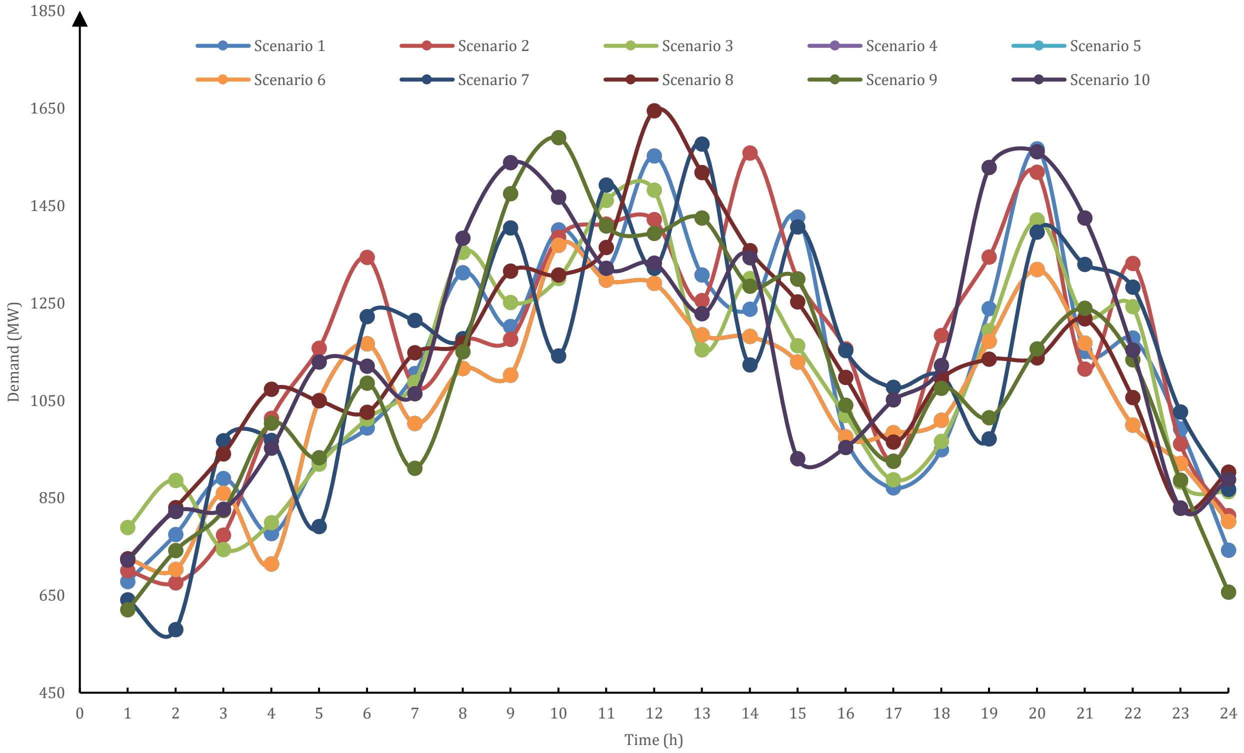

Fig. 2: Hourly demand of the power network (all scenarios)

Table 2: Power dispatch schedule in scenario 8 (MW)

	No. of units										
h	1	2	3	4	5	6	7	8	9	10	Demand
1	455	244.31			25						724.31
2	455	349.76			25						829.76
3	455	455			30.198						940.2
4	455	455			152.46			10			1072.5
5	455	455			138.88						1048.9
6	455	455			115.62						1025.6
7	455	455		130	107.41						1147.4
8	455	455		130	128.1						1168.1
9	455	455	130	130	145.34						1315.3
10	455	455	130	130	137.26						1307.3
11	455	455	130	130	162	31.778					1363.8
12	455	455	130	130	162	80	85	55	55	37.527	1644.5
13	455	455	130	130	162	80	50.497	55			1517.5
14	455	455	130	130	161.88		25				1356.9
15	455	455	130	130	81.812						1251.8
16	455	381.85	130	130							1096.8
17	455	249.43	130	130							964.43
18	455	379.37	130	130							1094.4
19	455	419.36	130	130							1134.4
20	455	422.03	130	130							1137
21	455	455	130	130				47.053			1217.1
22	455	340.58	130	130							1055.6
23	455	373.12									828.12
24	455	447.57									902.57

Fig. 5 presents the active loads' operation in all scenarios with uncertainty in demand. 9.5% of the active loads are operating at hour 12 over all the stochastic scenarios. The active loads have effectively reduced the production cost in all of the stochastic scenarios. Fig. 6 demonstrates the positive impact of the active loads on the hourly production cost in scenario 4 as compared to Case 1. For example, the production cost at hour 10 was $28,278 in Case 1, however, this cost is remarkably reduced to $17,234. It can be noticed from Fig. 6 that the active loads have dramatically smoothed the hourly cost, particularly at hours 5-21. In addition, the hourly compensation cost of the active loads is small compared to the high production cost. The min/max compensation costs of the active loads are $777 and $6526 at hours 16 and 22, respectively. The total production cost is less in this case as compared to Case 1, even though the compensation cost of the active loads is considered.

5. Conclusion

This paper presented an optimization procedure to manage generation and active load scheduling in a day-ahead energy market. The model considered the uncertainty of demand through stochastic scenarios. The aim of the work was to seek the minimum operational cost besides the consideration of the compensation cost when active loads are in charge.

Table 3: Comparison of the unit commitment schedule between base demand and scenario 8

	Base										Scenario 8									
	No. of units										No. of units									
h	1	2	3	4	5	6	7	8	9	10	1	2	3	4	5	6	7	8	9	10
1	1	1	0	0	1	0	0	0	0	0	1	1	0	0	1	0	0	0	0	0
2	1	1	0	0	1	0	0	0	0	0	1	1	0	0	1	0	0	0	0	0
3	1	1	0	0	1	0	0	0	0	0	1	1	0	0	1	0	0	0	0	0
4	1	1	0	0	1	0	0	0	0	0	1	1	0	0	1	0	0	1	0	0
5	1	1	0	0	1	0	0	0	0	0	1	1	0	0	1	0	0	0	0	0
6	1	1	0	1	1	0	0	0	0	0	1	1	0	0	1	0	0	0	0	0
7	1	1	0	1	1	0	0	0	0	0	1	1	0	1	1	0	0	0	0	0
8	1	1	0	1	1	0	0	0	0	0	1	1	0	1	1	0	0	0	0	0
9	1	1	1	1	1	0	0	0	0	0	1	1	1	1	1	0	0	0	0	0
10	1	1	1	1	1	1	0	0	0	0	1	1	1	1	1	0	0	0	0	0
11	1	1	1	1	1	1	0	1	0	0	1	1	1	1	1	1	0	0	0	0
12	1	1	1	1	1	1	0	1	1	0	1	1	1	1	1	1	1	1	1	1
13	1	1	1	1	1	1	0	0	0	0	1	1	1	1	1	1	1	1	0	0
14	1	1	1	1	1	0	0	0	0	0	1	1	1	1	1	0	1	0	0	0
15	1	1	1	1	1	0	0	0	0	0	1	1	1	1	1	0	0	0	0	0
16	1	1	1	1	1	0	0	0	0	0	1	1	1	1	0	0	0	0	0	0
17	1	1	1	1	1	0	0	0	0	0	1	1	1	1	0	0	0	0	0	0
18	1	1	1	1	1	0	0	0	0	0	1	1	1	1	0	0	0	0	0	0
19	1	1	1	1	1	0	0	0	0	0	1	1	1	1	0	0	0	0	0	0
20	1	1	1	1	1	1	0	0	0	0	1	1	1	1	0	0	0	0	0	0
21	1	1	1	1	1	1	0	0	0	0	1	1	1	1	0	0	0	1	0	0
22	1	1	0	1	0	1	0	0	0	0	1	1	1	1	0	0	0	0	0	0
23	1	1	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0
24	1	1	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0

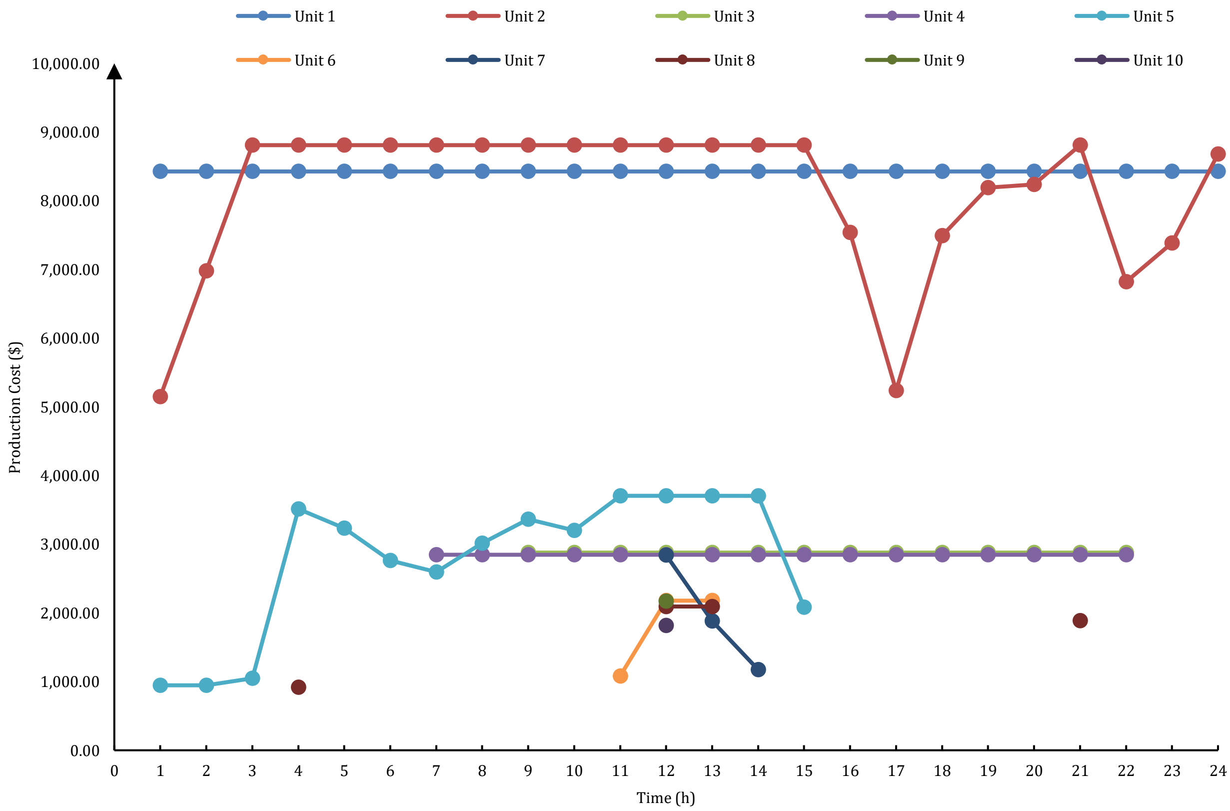

Fig. 3: Hourly production cost of the generating units (scenario 8)

Table 4: Active loads characteristics

Segment NO.	1	2	3	4	5
Amount (MW)	1084	2168	3252	4336	5420
Cost ($/MW)	10	11	12	13	14

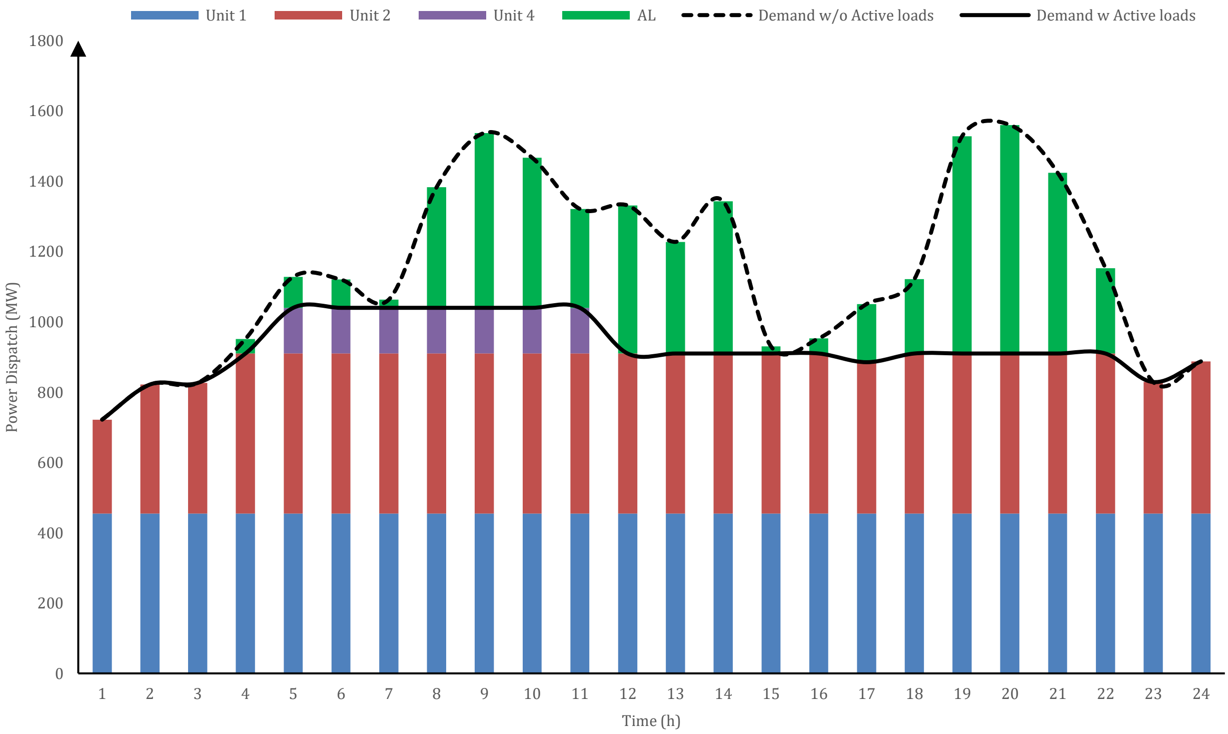

Fig. 4: Power dispatch in scenario 10 (with and without active loads)

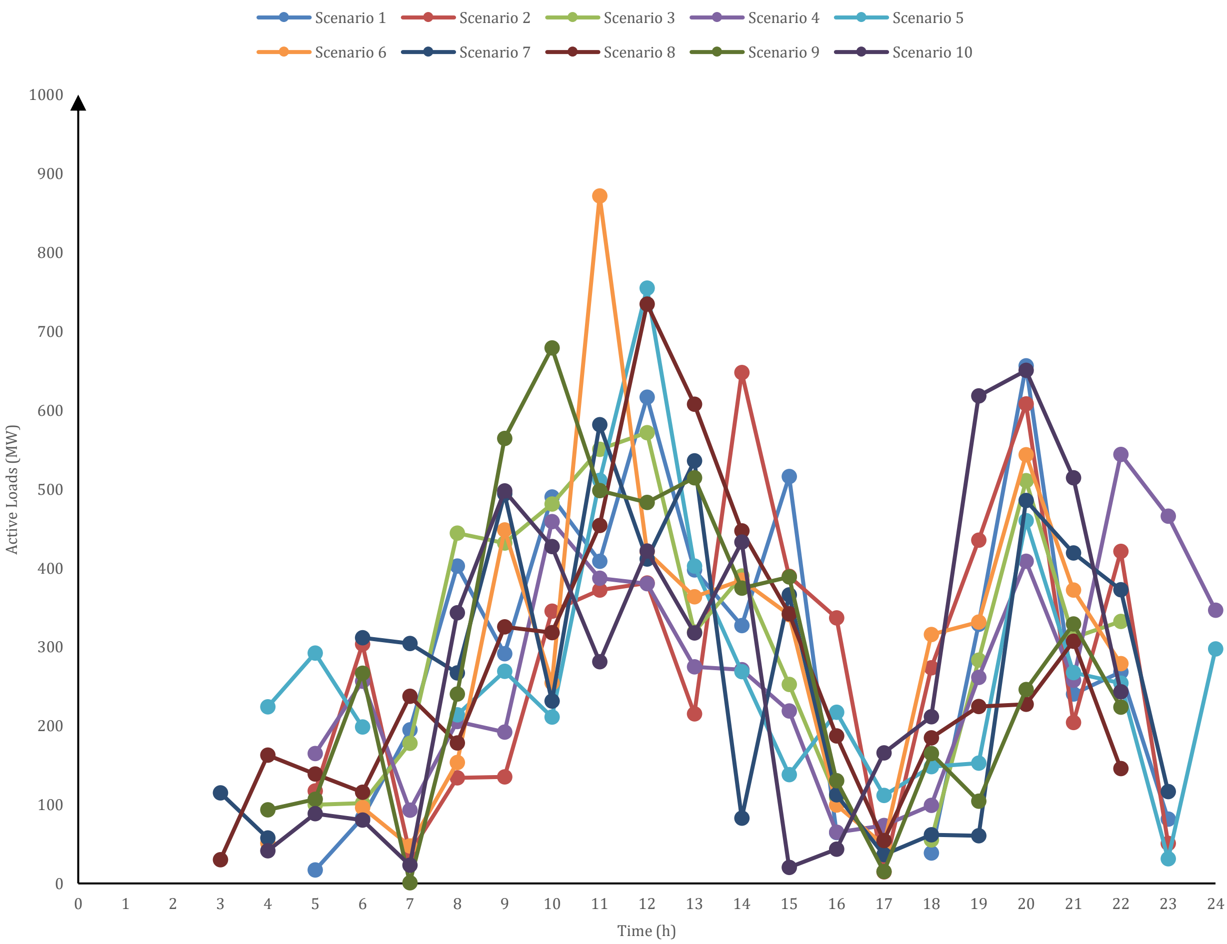

Fig. 5: Hourly active loads operation in all scenarios

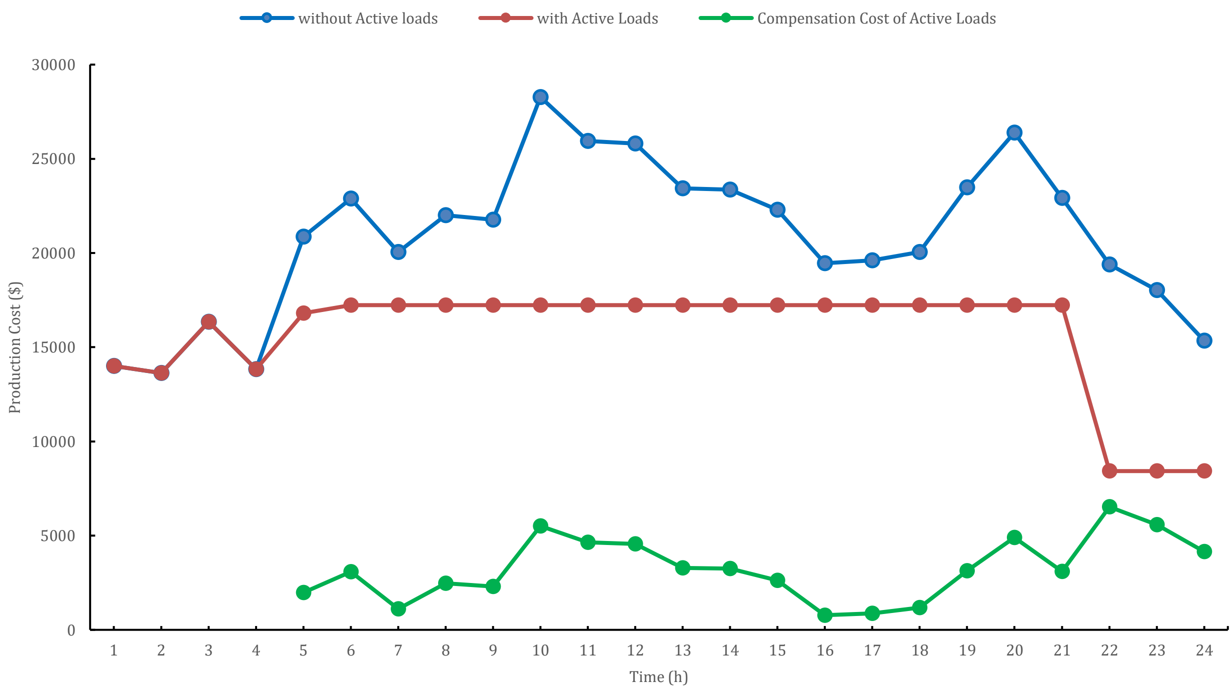

Fig. 6: Hourly production cost of scenario 4

Two stages have been designed to accumulate the optimal scheduling of generation and active loads during normal passive demand and uncertain demand. The active loads' operation was examined through ten-generating units with respect to the constraints of the transmission lines. Case 1 explained the effects of all passive loads on the operational cost in both base mode and stochastic scenarios. In some scenarios, the fluctuation of the passive demand was high, which dramatically increases the generation cost. However, part of the passive loads has been converted into active loads in Case 2 to examine the effects on the generation cost. The active loads have a positive impact on regulating the high fluctuation of the uncertain demand even though the compensation cost of the active loads was considered. The results of active loads operation demonstrated that the generation cost in some scenarios can be significantly reduced by 39% as compared to operating only passive loads.

List of symbol

Indices

i	Index for generators
t	Index for time
a	Index for active load
β	Index for active load segments
S	Index for number of active load segments
l	Index for transmission line
j	Index for power generation segment
b	Index for bus
r	Index for scenario

Parameters

$\mathcal{Q}_{it}$	Operating cost of generator i at time t
τ_a^s	Cost of active load a in the active load curve
β_a^s	Active load amount of active load a
ε_a^s	Active load points in the active load curve
dm_{bt}	Hourly demand on bus b at time t
$\mathcal{U}_i^{up}$	Heat-up cost of generator i
ϱ_i^{min}	Minimum power supply at initial of generator i
$\mathcal{P}_i^{min}$	Minimum power capacity of generator i
$\mathcal{P}_i^{max}$	Maximum power capacity of generator i
ξ_i^{UP}	Maximum ramping-up of generator i
ξ_i^{DN}	Maximum ramping-down of generator i
$\mathcal{N}_i^{on}$	Minimum on-time generator i
$\mathcal{N}_i^{off}$	Minimum off-time generator i
$\mathcal{X}_l$	Reactance of transmission line l
$\mathcal{A}_{a,\beta}^{Max}$	Maximum capacity in the active load curve
$\mathcal{A}_a^{Max}$	Maximum limit of the hourly active load a
$\mathcal{A}_a^{Min}$	Minimum limit of the hourly active load a
$\mathcal{Y}^{Max}$	Maximum amount of daily active loads
q_a^{Max}	Maximum change of the active load between t and $(t-1)$
q_a^{Min}	Minimum change of the active load t and $(t-1)$
z_a^{Max}	Maximum change of the active load between $(t-1)$ and t
z_a^{Min}	Minimum change of the active load between $(t-1)$ and t
r^{Max}	Maximum operating hours of the active loads
r^{Min}	Minimum operating hours of the active loads
$\Lambda_{at,r}$	Incident matrix (active loads and buses) at time t in scenario r
$HL_{bt,r}$	Hourly stochastic demand on bus b at time t in scenario r

Variables

$\mathcal{H}_{it}$	Heat-up cost of generator i at time t
$\mathcal{C}_{it}$	Cooling-down cost of generator i at time t
$\mathcal{P}_{it}$	Instantaneous power supply of generator i at time t
$\mathcal{FW}_{lt}$	Power flow of line l at time t
$C_{at}^{\mathcal{AL}}$	Compensation cost of the active load a at

	time t
ϑ_{ln}	Voltage phase angle of line l at bus n
ϑ_{lm}	Voltage phase angle of line l at bus m
P_{jt}	Power supply of stage j at time t
$\mathcal{T}_{it}^{on}$	Operating duration of generator i at time t
$\mathcal{T}_{it}^{off}$	Shut-down duration of generator i at time t
$dm_{bt,r}^{T}$	Total hourly demand on bus b at time t in scenario r
$fw_{lt,r}$	Power flow of line l at time t in scenario r
$\mathcal{A}_{at,r}$	Hourly active load a at time t in scenario r
$\mathcal{L}_{bt,r}$	Active loads participation on bus b at time t in scenario r

Binary variables

λ_{it}	Start-up indicator of generator i at time t
γ_{it}	Turn-off indicator of generator i at time t
ψ_{it}	Operation status of generator i at time t
$\in_{at}$	Active load status of load a at time t
$\rho_i^G(r)$	Availability of generator i in scenario r
$\rho_i^L(r)$	Availability of transmission line l in scenario r

Compliance with ethical standards

Conflict of interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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