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Event-triggered multi-agent optimization for two-layered model of hybrid energy system with price bidding based demand response

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***Abstract*—Due to uncertainty and dynamic characteristics from intermittent energy and load demand response (DR), it brings great challenge to optimal operation of hybrid energy system. This paper proposes an event-triggered multi-agent coordinated optimization strategy with two-layered architecture. Firstly, price-bidding based DR model is proposed with different stakeholders, and it also deduces optimal bidding price with Nash equilibrium theory. Then, four agents are designed to control different kind of energy resources, Agent 1 mainly analyzes the uncertainty or randomness caused by intermittent power, Agent 2 takes charge of dynamic economic dispatch (DED) within thermal units, Agent 3 manages the optimal scheduling of energy storage, and Agent 4 mainly undertakes load shifting strategy from consumers. In the upper-layer level, all agents coordinate together to ensure the stability of hybrid energy system with event-triggered mechanism, the intelligent control approach mainly depends on switching on/off power generators or curtailing system load, and consensus algorithm is utilized to optimize subsystem problem in lower-layer level. Furthermore, simulation results can further verify the efficiency of proposed method, and it also reveals that event-triggered multi-agent optimization strategy can be a promising way for solving hybrid energy system problem.**

***Index Terms*—event-triggered, coordinated optimization, demand response, intelligent control, hybrid energy system.**

I. INTRODUCTION

WITH increasing penetration of renewable energy resources, it can gradually become a great challenge for hybrid energy management due to randomness or uncertainty of power generation, bi-direction energy flow and price-responsive loads, etc [1]. Effective optimization strategy for hybrid energy management can be necessary to ensure energy utilization to the maximum extent, especially with deterministic model or without considering demand response [2]. However, stochastic nature of intermittent energy and demand requirement brings great challenge on both dynamic hybrid energy management and optimization methodology [3], [4], [5]. With consideration of uncertainty of intermittent energy, stochastic optimization (SO) [6], [7], fuzzy optimization [8], [9] and robust optimization (RO) strategy [10], [11] are employed to get rid of potential risk to hybrid energy system. Stochastic programming approach depends on probability density function by data sampling, which may cause large deviation when data source is limited. Fuzzy approach determines membership mainly by decision-makers' personal experience, optimal scheme can be subjective. RO can achieve optimal scheme without excessive information, but it can be conservative for exchanging economic expense to robustness.

Besides, demand response (DR) can be another important part in hybrid energy system, it can be dynamic and unpredictable, which also motivates further research on modeling and methodology with DR. With considering benefit of DR, literature [12] evaluates the impact market design and DR on reducing wind power forecast error, while literatures [13], [14] investigates positive benefit on short-term trading of wind power producers. Literature [15] employs one DR program with critical peak price, and investigates the optimal value according to load serving entity that sells wind energy to market. For properly managing demand side requirement, multi-agent architecture has been widely used. The intelligent bidding strategy based continues double auction allows consumers to participate DR programs, and agent-based architecture is developed to manage power with considering DR [16]. With multiple micro-grids including DR and distributed storage, an agent-based approach is utilized to reduce system peak demand and minimize electricity cost [17]. Literature [18] has proposed a two-level architecture of multi-agent system for multiple micro-grids, naive auction algorithm is employed to simulate the biding action of market agents that participate real-time bidding. Those literatures can deal with dynamic characteristics of micro-grids system with DR and bidding problem with considering consumers' behavior, but it lacks effective way for potential risk in optimal operation.

This paper involves coordinated optimization with switching strategy to avoid potential risk in a positive and co-

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ordinated way, event-triggered mechanism is proposed for positive action from power supply and load demand side. Generally, event-triggered coordination approach can be considered as control theory with network communication [19], [20], [21], [22], [23], [24]. Though literature [24] has been successfully implemented in power system, event-triggered strategy still depends network communication. Here, event-triggered based multi-agent optimization is proposed to optimize hybrid energy system with considering DR, event-triggered mechanism is designed to avoid potential risk caused by uncertainty from intermittent energy and system load, the structure of proposed optimization is shown in Fig.1. The main contribution of this paper can be summarized as follows:

(1) From stakeholders' view, all stakeholders pursuit profit for themselves, electricity price changes with all players' bidding actions, this paper firstly makes price bidding strategy with Nash equilibrium theory, and deduces optimal price for trade-off scheme.

(2) For properly managing different energy resources and system load, Four agents are designed as it is shown in Fig.1. Agent 1 analyzes uncertainty of intermittent energy resource with uncertainty parameter, Agent 2 mainly assigns optimal output of thermal units to minimize fuel cost, Agent 3 ensures the stability of hybrid energy system with charging/discharging behavior, Agent 4 makes proper load shifting scheme for consumers to minimize switching cost.

(3) On the basis of multi-agent system, an event-triggered optimization strategy is proposed with considering potential risk caused by intermittent energy. Combined with coordination of different energy resources, power generators are switched to keep stability of hybrid energy system as well as load curtailment.

(4) In the subsystem, alternating direction method of multipliers is utilized to achieve consensus of thermal units, optimal solutions can be deduced with several iterative algorithms. Finally, simulation results can prove the feasibility and priority of event-triggered multi-agent optimization method.

In comparison to other optimization strategy, the proposed algorithm is dynamic and systemic, which also means that it can be robust while exempting potential risk with coordination between power supply and system load side, and further keep the stability of hybrid energy system.

II. PRICE BIDDING STRATEGY OF DEMAND RESPONSE

The electricity price mainly depends on bidding among different stakeholders, which are market participants with pursuing profit for themselves. Each stakeholder can be considered as a player during price biding, generation cost and purchasing cost are considered for each player. The profit function of the $q(q = 1, 2..., Q)$th player can be described as:

$$Maximize f(x_{q,b,t}, P_{q,i}) \tag{1a}$$

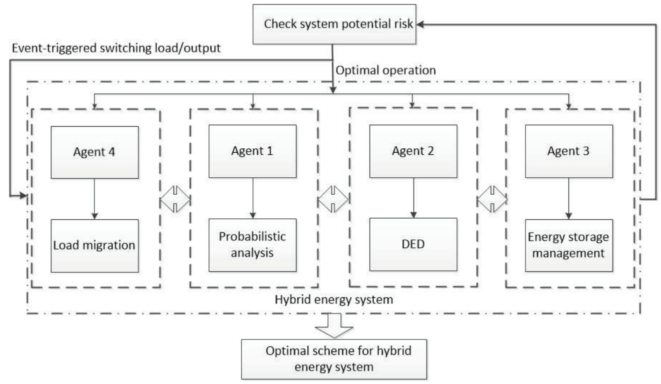

Fig. 1. The structure of event-triggered multi-agent optimization for hybrid energy system

$$\begin{cases} f_q(x_{q,b,t}, P_{q,i}(t)) = \\ \sum_{t \in T} [\gamma_{q,t}(P_{q,i}(t) - \underline{P_q}(t) - \sum_{b \in B} x_{q,b,t}) - C_{q,cost}] \end{cases} \tag{1b}$$

$$C_{q,cost} = \sum_{t \in T} \sum_{i \in I} [\alpha_{q,1i} + \alpha_{q,2i} P_{q,i}(t) + \alpha_{q,3i} P_{q,i}^2(t)] \tag{1c}$$

where $\gamma_{q,t}$ is market price, $\underline{P_q}(t)$, $\overline{P_q}(t)$ are minimum and maximum load, B is the blocking set, $x_{q,b,t} > 0$ is consumption assigned at bth block of tth time period, the size of each block is $\frac{\overline{P_q}(t) - \underline{P_q}(t)}{B}$, $C_{q,cost}$ presents the operational cost of hybrid energy system, $\alpha_{q,1i}$,$\alpha_{q,2i}$,$\alpha_{q,3i}$ are cost coefficients, $P_{q,i}(t)$ is power output, I is the set of all energy resources respectively. Some constraints should be properly satisfied:

$$0 \leq B * x_{q,b,t} \leq \overline{P_q}(t) - \underline{P_q}(t), \tag{1d}$$

$$\underline{P_{q,i}} \leq P_{q,i}(t) \leq \overline{P_{q,i}}, \tag{1e}$$

$$\underline{P_q}(t) + \sum_{b \in B} x_{q,b,t} - \underline{P_q}(t-1) - \sum_{b \in B} x_{q,b,t-1} \leq R_{q,up,t}, \tag{1f}$$

$$\underline{P_q}(t-1) + \sum_{b \in B} x_{q,b,t-1} - \underline{P_q}(t) - \sum_{b \in B} x_{q,b,t} \leq R_{q,dn,t} \tag{1g}$$

where $R_{q,up,t}$,$R_{q,dn,t}$ are ramp up and ramp down of total load. The Lagrangian function can be constructed with several penalty functions as follows:

$$\begin{aligned} & Ł_q(x_{q,b,t}, P_{q,i}) = f_q(x_{q,b,t}, P_{q,i}) + \lambda_{q1}^-(B x_{q,b,t} - \overline{P_q}(t) + \underline{P_q}(t)) \\ & + \lambda_{q2}^+(\underline{P_{q,i}} - P_{q,i}(t)) + \lambda_{q2}^-(P_{q,i}(t) - \overline{P_{q,i}}) + \\ & \lambda_{q3}^+(\underline{P_q}(t) + \sum_{b \in B} x_{q,b,t} - \underline{P_q}(t-1) - \sum_{b \in B} x_{q,b,t-1} + R_{q,dn,t}) + \\ & \lambda_{q3}^-(\underline{P_q}(t) + \sum_{b \in B} x_{q,b,t} - \underline{P_q}(t-1) - \sum_{b \in B} x_{q,b,t-1} - R_{q,up,t}) \end{aligned} \tag{2}$$

Once all players complete biding instead of corporation, Nash equilibrium optima means that there is no better scheduling scheme than current scheme $P_{q,i}^*$ by adjusting its own generation and bidding scheme. On the basis of Nash

Equilibrium condition, it can obtain the iteration optimization algorithm as follows:

$$\frac{\partial L_q}{\partial P_{q,i}(t)} = \gamma_{q,t} - (\alpha_{q,2i} + 2\alpha_{q,3i}P_{q,i}(t)) - \lambda_{q2}^{+} + \lambda_{q2}^{-} \quad (3)$$

$$\frac{\partial L_q}{\partial x_{q,b,t}} = -\gamma_{q,t} + B\lambda_{q1}^{-} + \lambda_{q3}^{+} - \lambda_{q3}^{-} \quad (4)$$

The parameters λ_{q1}^{-}, λ_{q2}^{+}, λ_{q2}^{-}, λ_{q3}^{+} and λ_{q3}^{-} can be iterated with following equations:

$$\begin{cases} \lambda_{q1}^{-} = \lambda_{q1}^{-} + \beta_{q1}[Bx_{q,b,t} - \overline{P_q}(t) + \underline{P_q}(t)]^{-} \\ \lambda_{q2}^{+} = \lambda_{q2}^{+} + \beta_{q2}^{+}[\underline{P_{q,i}} - P_{q,i}(t)]^{+} \\ \lambda_{q2}^{-} = \lambda_{q2}^{-} + \beta_{q2}^{-}[P_{q,i}(t) - \overline{P_{q,i}}]^{-} \\ \lambda_{q3}^{+} = \lambda_{q3}^{+} + \beta_{q3}^{+}[\underline{P_q}(t) + \sum_{b\in B} x_{q,b,t} - \\ \underline{P_q}(t-1) - \sum_{b\in B} x_{q,b,t-1} + R_{q,dn,t}]^{+} \\ \overline{\lambda_{q3}^{-}} = \lambda_{q3}^{-} + \beta_{q3}^{-}[\underline{P_q}(t) + \sum_{b\in B} x_{q,b,t} - \\ \underline{P_q}(t-1) - \sum_{b\in B} x_{q,b,t-1} - R_{q,up,t}]^{-} \end{cases} \quad (5)$$

where β_{q1}, β_{q2}^{+}, β_{q2}^{-}, β_{q3}^{+}, $\beta_{q3}^{-} \in \Re^{+}$. When According to equation(5), the optimal scheme can satisfy the minimum and maximum constraints after several iterations. The bidding price of the qth micro-grid can be presented as:

$$\gamma_{q,t} = \alpha_{q,2i} + 2\alpha_{q,3i}P_{q,i}(t) \quad (6)$$

The market trading price is generally the highest bidding price among all the stakeholders, electricity price of the tth period γ_t can be obtained as:

$$\gamma_t = max\{\gamma_{q,t}, q = 1, 2, ..., Q\} \quad (7)$$

According to price biding, electricity market can have unified electricity price at tth period, the deduced bidding price can be taken for calculating switching cost in load shifting model.

III. Upper level problem: Event-triggered multi-agent coordinated optimization with switching mechanism

A. Definition of four agents

For properly managing hybrid energy system, four agents are defined to control different energy resources. Agent 1 for intermittent energy resources, agent 2 for thermal energy resource, agent 3 for energy storage, agent 4 for system load demand.

1) Agent 1: Intermittent power system model. It mainly consists wind power and solar power, wind power follows Weibull distribution [25] and normalized solar power follows Beta distribution [26]. For simplicity, intermittent power output P_{Ijt} can be described as:

$$\begin{cases} P_{Ijt} = \overline{P_{Ijt}} + r_{Ijt}\widetilde{P_{Ijt}} \\ \widetilde{P_{Ijt}} \in [\underset{\sim}{P_{Ijt,min}}, \underset{\sim}{P_{Ijt,max}}] \end{cases} \quad (8)$$

where $j \in J$ is the intermittent power index, J is the number of intermittent energy resources, $\overline{P_{Ijt}}$ represents the estimated intermittent power output,$r_{Ijt} \in [0, 1]$ denotes adjustable parameter for each intermittent energy resource, $\widetilde{P_{Ijt}}$ represents power disturbance of intermittent energy, $\underset{\sim}{P_{Ijt,min}}$ and $\underset{\sim}{P_{Ijt,max}}$ denote lower and upper bounds of power disturbance.

2) Agent 2: Thermal power system model. Thermal units generate power output $P_{ck}(t)$ with consuming fuel, it is a economic issue [27], [28], economic cost can be presented as:

$$\begin{cases} minF_1 = \sum_{k\in K} f_{ck} = \sum_{k\in K}\sum_{t\in T} H_{kt}(a_k + \\ b_kP_{ck}(t) + c_kP_{ck}^2(t)) \\ minF_2 = \sum_{k\in K}\sum_{t\in T} u_{ck}H_{kt} \end{cases} \quad (9)$$

where f_{ck} is the economic cost of $k \in K$th thermal unit,$H_{kt} \in 0, 1$ represents turn on/off state of thermal unit, a_k,b_k,c_k,d_k,e_k are the coefficients of economic cost of kth thermal unit, $P_{ck,min}$ is minimal output of kth thermal unit, u_{ck} is efficient of switching cost. It also subjects to several constraints as follows:

$$\begin{cases} P_{ck,min} \le P_{ck}(t) \le P_{ck,max} \\ DR_{ck} \le P_{ck}(t) - P_{ck}(t-1) \le UR_{ck} \end{cases} \quad (10)$$

where $P_{ck,max}$ is maximal output of $k \in K$th thermal unit, DR_{ck}, UR_{ck} are the down-ramp and down-ramp limits of kth thermal unit.

3) Agent 3: Energy storage model. For simplicity, battery energy storage system represents the whole energy storage of hybrid energy system, it supplements intermittent power to ensure the stability of whole power system. The charging and discharging output must satisfy some constraints [29]:

$$\begin{cases} minF_3 = \sum_{l\in L} f_l^{store} = \sum_{l\in L}\sum_{t\in T}[\alpha_{l1} + \\ \alpha_{l2}P_l^{store}(t) + \alpha_{l3}(P_l^{store}(t))^2] \\ V_l^{store}(t+1) = V_l^{store}(t) + \eta_l P_l^{store}(t) * \Delta T \\ V_{l,min}^{store} \le V_l^{store}(t) \le V_{l,max}^{store} \\ P_l^{store}(t) = P_l^{cha}(t), if P_l^{store}(t) \ge 0 \\ P_l^{store}(t) = -P_l^{dis}(t), if P_l^{store}(t) < 0 \\ 0 \le P_l^{dis}(t) \le P_{l,max}^{dis} \\ 0 \le P_l^{cha}(t) \le P_{l,max}^{cha} \\ V_l^{store}(0) = V_{l,initial}^{store} \end{cases} \quad (11)$$

where f_l^{store} denotes the economic cost of $l \in L$th energy storage, $P_l^{store}(t)$ represents charging/discharging output of lth battery at tth period, $V_l^{store}(t)$ is the storage of lth battery at tth time period,α_{l1},α_{l2},α_{l3} are coefficients of economic cost , ΔT is the time period length, $V_{l,min}^{store}$, $V_{l,max}^{store}$ are the minimum and maximum storage of the lth battery, $P_l^{dis}(t), P_l^{cha}(t)$ are the output of discharging and charging state,$P_{l,max}^{dis}$,$P_{l,max}^{cha}$ are the maximum discharging and charging output at $l \in L$th battery at tth time period. $\eta_l \in (0, 1]$ is efficiency factor of charging or discharging state.

4) Agent 4: Load shifting model. On the demand side, DR model can be generally classified as: incentive-based model and price-based model, here it chooses price-based model to describe the state of load requirements. System load can be divided into two parts: fixed load $\overline{P_{load}}(t_i)$ and controllable load $\widetilde{P_{load}}(t_i)$ as:

$$P_{load}(t_i) = \overline{P_{load}}(t_i) + \widetilde{P_{load}}(t_i), t_i \in T \tag{12}$$

In the power system, controllable load can be adjusted to keep the system load balance when power supply cannot meet load requirement from demand side, then some load must be cut down through switching off them, it can be described as:

$$\widetilde{P_{load}}(t_i) = \sum_{s \in S} B_{s,t_i} P_s(t_i) \tag{13}$$

Generally, system load cannot be adjusted, it brings switching cost as:

$$minF_4 = \sum_{t_i \in T} \gamma_{t_i} \sum_{s \in S} (1 + B_{s,t_i}) P_s(t_i) \tag{14}$$

Subject to

$$\widetilde{P_{load}}(t_i) = \sum_{s \in S} \Big(\sum_{t_j \in T, t_j \neq t_i} P_{st_j t_i} - \sum_{t_j \in T, t_j \neq t_i} P_{st_i t_j} \Big) \tag{15}$$

$$P_s(t_i) = \sum_{t_j \in T} P_{st_j t_i} - \sum_{t_j \in T, t_j \neq t_i} P_{st_i t_j} \geq 0 \tag{16}$$

$$\sum_{t_i \in T} P_s(t_i) = M_s \geq 0 \tag{17}$$

$$P_{s,min} \leq P_{st_i t_j} \leq P_{s,max}, \forall t_i, t_j \in T, t_i \neq t_j \tag{18}$$

where B_{s,t_i} is binary number of each consumer$s$, S represents the number of consumers, P_s is the consumption of consumer in one day, it can be assumed that it is an invariant, $P_{st_i t_j}$ means that consumer s moves load consumption from t_i period to t_j period, M_s is a real number, which means that electricity consumption of each consumer is certain, $P_{s,min}$ and $P_{s,max}$ are the minimum and maximum value for moving load consumption.

B. Event-triggered optimization of hybrid energy system with probabilistic risk

In hybrid energy system, power supply must meet the requirement from demand side, but when power generation cannot satisfy the system load, some controllable load will be cut down, system load topology of agent 4 can be switched to a different one, which greatly increase the difficulty for optimizing hybrid energy system. Here, event-triggered method is utilized to judge switching model with probabilistic risk, which is mainly caused by imbalance between power supply and load demand. Thus, it is assumed that the expected value of total power output approximates system load as follows:

$$E(P_{total,t}) \rightarrow P_{load}(t) \tag{19}$$

where $P_{total,t}$ denotes the summation of power output of all energy resources. For ensuring that power generation meets load requirement, the probability of above formula needs to satisfy:

$$Prob(|P_{total,t} - P_{load}(t)| \leq \epsilon_t) \geq \delta_t \tag{20}$$

where $Prob()$ denotes the probability operator, $\epsilon_t \in R^+$ represents the deviation error, $\delta_t \in (0,1)$ means the smallest permitted probability, it can also be converted into other form as follows:

$$Prob(|P_{total,t} - P_{load}(t)| \geq \epsilon_t)) \leq 1 - \delta_t \tag{21}$$

With considering system load balance, it can obtain:

$$\begin{aligned} & Prob(|\sum_{j \in J} r_{Ijt} \widetilde{P_{Ijt}} - [P_{load}(t) - \sum_{j \in J} \overline{P_{Ijt}} - \sum_{k \in K} P_{ck}(t) \\ & - \sum_{l \in L} P_l^{store}(t)]| \geq \epsilon_t)) \leq 1 - \delta_t \end{aligned} \tag{22}$$

Suppose that parameters r_{Ijt} are independent variables, it can obtain inequality with Chebyshev inequality as follows:

$$\frac{Var(\sum_{j \in J} r_{Ijt} \widetilde{P_{Ijt}})}{\epsilon_t^2} \leq 1 - \delta_t \tag{23}$$

It can deduce the permitted deviation error:

$$\epsilon_t^* = \sqrt{\frac{Var(\sum_{j \in J} r_{Ijt} \widetilde{P_{Ijt}})}{1 - \delta_t}} \tag{24}$$

The deviation can guide switching scheme of multi-agent system for controlling both power supply and load demand. Once generated power cannot meet load requirement (calculated deviation ϵ_t is larger than ϵ_t^*), it needs to cut off some controllable load or turn off some power generators to keep the balance. Here, an efficient switching scheme is proposed to coordinate different agent-based subsystems as follows:

Algorithm 1 Event-triggered based coordinated optimization

```
procedure S(w)itching scheme for power balance
    Check balance |P_{total,t} − P_{load}(t)|
    if ε_t < ε_t^* then
        switch on thermal unit P_{ck}
        For k = ξ : K
        P_{total,t} = P_{total,t} + P_{ck}
        Until P_{load}(t) ∈ Range(P_{total,t})
        if Maxtotal_t < P_{load}(t) then
            switch off controllable load P_s
            For s = 1 : η
            P_{load}(t) = P_{load}(t) − P_s
            Until Maxtotal_t ∈ Range(P_{load}(t))
        end if
    end if
end procedure
```

where ϵ is the number of current thermal units turned on, $Range()$ denotes the possible interval,$Maxtotal_t$ represents current maximum output of all energy resources at tth period, η is current number of consumers using the electricity. After switching scheme for power balance is made, coordinated optimization strategy is also made to optimize multi-agent system as follows:

Algorithm 2 Event-triggered based coordinated optimization

```
1: procedure C(o)ordination scheme of hybrid energy system
2:     Agent 4: Making load shifting scheme
3:     Agent 1: Probabilistic analysis in small intervals
4:     P_load(t) = P_load(t) − P_Intermittent,t
5:     if P_load(t) < Maxtotal_t then
6:         Agent 2: DED on thermal units
7:         goto End
8:     end if
9:     P_load(t) = P_load(t) − Maxtotal_t
10:    Agent 3: Energy storage management
11: end procedure
```

where $P_{Intermittent,t}$ represents the total output of intermittent energy resources at tth time period.

IV. Lower level problem: Convex optimization for multi-agent subsystem

In upper level, event-triggered switching mechanism and coordination strategy have been made, but subsystem of each agent still needs to be properly optimized. Here, several optimization approaches are utilized for solving above problems. Agent 1 mainly analyzes probabilistic characteristics of intermittent energy resources with statistical methods, it doesn't need optimization. Actually, optimization for Agent 3 cannot be a big problem, it can arrange energy storage from big capacity to small capacity until system load is properly satisfied, which can also save switching cost. Here, it focus on the optimization of subsystems in Agent 4 and Agent 2. In Agent 4, Lagrangian relaxation approach is utilized to obtain the iterated algorithm, which can deduce the optimal load shifting scheme. Since problem formulation of Agent 2 can be a DED problem, consensus algorithm can be a better way, consensus algorithm with ADMM is utilized to assign output for each thermal unit.

A. Lagrangian relaxation approach for load shifting in Agent 4

The load shifting model reflects consumers' action with disturbance of electricity price, but consumers shift load from one time to another one with shifting cost, so how to make shifting scheme for consumers can be a big problem. Here, Lagrangian relaxation approach is utilized to optimize this problem. Firstly, combine with Lagrangian relaxation operator, it can obtain Lagrangian function as follows:

$$\begin{aligned} L_{load} = F_4 + \sum_{t_i \in T} [\lambda^+_{s,t_i} (\sum_{t_j \in T} P_{st_j t_i} - \sum_{t_j \in T, t_j \neq t_i} P_{st_i t_j})] \\ + \sum_{s \in S} \lambda_s (\sum_{t_i \in T} P_s(t_i) - M_s) + \sum_{t_i \in T} \sum_{t_j \in T, t_j \neq t_i} [\lambda^+_{s,t_i,t_j} \\ (P_{s,min} - P_{st_i t_j}) - \lambda^-_{s,t_i,t_j} (P_{st_i t_j} - P_{s,max})] \end{aligned} \tag{25}$$

where λ_{s,t_i^+}, λ_s, λ^+_{s,t_i,t_j} and λ^-_{s,t_i,t_j} are Lagrangian parameters. It can obtain following equations:

$$\begin{cases} \dfrac{\partial L_{load}}{\partial P_{st_i t_j}} = -\sum_{t_i \in T} \gamma_{t_i} \sum_{s \in S} (1 + B_{s,t_i}) + \lambda^+_{s,t_i} + \\ \lambda_s + \sum_{t_i \in T} \sum_{t_j \in T, t_j \neq t_i} (\lambda^-_{s,t_i,t_j} - \lambda^+_{s,t_i,t_j}) \\ \dfrac{\partial L_{load}}{\partial \lambda^+_{s,t_i}} = \sum_{t_j \in T} P_{st_j t_i} - \sum_{t_j \in T, t_j \neq t_i} P_{st_i t_j} \geq 0 \\ \dfrac{\partial L_{load}}{\partial \lambda_s} = \sum_{t_i \in T} P_s(t_i) - M_s \\ \dfrac{\partial L_{load}}{\partial \lambda^+_{t_i,t_j}} = P_{st_i t_j} - P_{s,min} \geq 0 \\ \dfrac{\partial L_{load}}{\partial \lambda^-_{t_i,t_j}} = P_{s,max} - P_{st_i t_j} \geq 0 \end{cases} \tag{26}$$

With above equations, the best $P_{st_i t_j}$, λ_{s,t_i^+}, λ_s, λ^+_{s,t_i,t_j} and λ^-_{s,t_i,t_j} can be deduced after several iterations, so optimal load shifting scheme can be properly made.

B. Consensus with regularization algorithm for DED in Agent 2

Combined with Lagrangian operator, since switching strategy has been made from upper-level mechanism, it merely needs to take fuel cost into consideration, it can be converted into following mathematical model:

$$\begin{aligned} L_{ck} = \sum_{k \in K} f_{ck} + \lambda_{c1}(P_{ck}(t) - P_{ck,min} - d_1) + \\ \lambda_{c2}(P_{ck,max} - P_{ck}(t) - d_2) + \lambda_{c3}(P_{ck}(t) \\ - P_{ck}(t-1) - DR_{ck} - d_3) + \lambda_{c4}(UR_{ck} + \\ P_{ck}(t-1) - P_{ck}(t)) \end{aligned} \tag{27}$$

where $\lambda_{c1}, \lambda_{c2}, \lambda_{c3}, \lambda_{c4}$ represent the Lagrangian parameters. For accelerating search ability, it is converted into a distributed way with consensus theory. With equal increment criterion, it can obtain:

$$\frac{\partial f_{ck}}{\partial P_{ck}(t)} = -\lambda_{c1} + \lambda_{c2} - \lambda_{c3} + \lambda_{c4} \tag{28}$$

For output of each thermal unit, it can be deduced:

$$P^*_{ck}(t) = (\lambda_{c2} - \lambda_{c1} - \lambda_{c3} + \lambda_{c4} - b_k)/(2c_k) = z \tag{29}$$

where $P^*_{ck}(t)$ is the utopia optima of $P_{ck}(t)$, z is common global variable. Combined with alternating direction method of multipliers (ADMM) algorithm [30], equal increment criterion can be treated as constraint limit, regularization operator is taken in iterations to achieve synchronization, it can obtain following iterative procures:

$$\begin{cases} P^{n+1}_{ck} := \arg\min_{P_{ck}} [L_{ck} + (\rho/2) || P_{ck} - z^n + \mu^n_{ck} ||^2_2] \\ z^{n+1} := \arg\min_{z} [g(z) + (K\rho/2) || z - \bar{P_c}^{n+1} - \bar{\mu_c}^n ||^2_2] \\ \mu^{n+1}_{ck} := \mu^n_{ck} + P^{n+1}_{ck} - z^{n+1} \end{cases} \tag{30}$$

where n is iteration number, μ^n_{ck} represents scaled dual variable, $\rho > 0$ is augmented Lagrangian parameter, $\bar{P}_c$ is

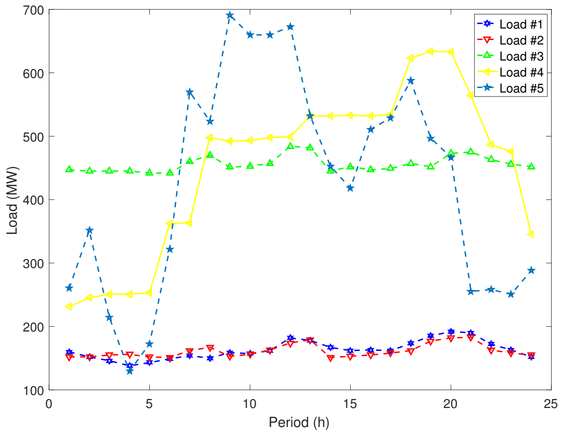

Fig. 2. System load before load shifting strategy

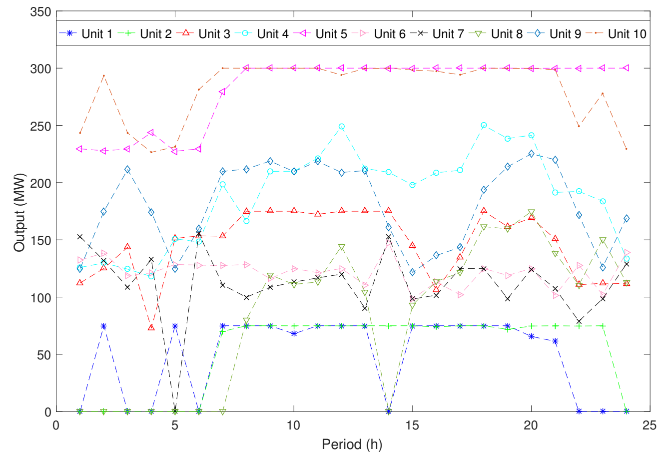

Fig. 3. The Output of ten thermal units for minimizing economic cost

average value of thermal units, $\bar{\mu_c}$ is average value of μ_{ck}. Since L_{ck} and $g(z)$ are differentiable and KKT conditions can be properly satisfied, the $argmin[\cdot]$ operator here is mainly implemented with derivation to deduce the extreme value of P_{ck} and z, which are taken as P_{ck}^{n+1} and z^{n+1} for iterations. With consideration of feasibility of iterations, the procedure is implemented as follows:

$$P_{ck}^{n+1} = \begin{cases} \overline{P_{ck}} & P_{ck}^{n} > \overline{P_{ck}} \\ \underline{P_{ck}} & P_{ck}^{n} < \underline{P_{ck}} \end{cases} \tag{31}$$

where $\overline{P_{ck}}$ and $\underline{P_{ck}}$ represent upper bound and lower bound of feasible domain. The convergence can be ensured with satisfying two assumptions in literature [31]: (1) f_{ck} and $g(z)$ (actually $g(z) = 0$ when it is implemented) are both closed, proper and convex; (2) The function L_{ck} has at least one saddle point, because f_{ck} is monotonically increasing function. Once the above iteration converges, it means $P_{ck}^{n+1} \rightarrow P_{ck}^{*}$, optimal scheme can be made for dispatch problem of thermal units.

V. Case Study

For verifying feasibility and efficiency of proposed algorithm, it is implemented in two test systems: hybrid energy system without switching mode and hybrid energy system with switching model. Test system 1 can be considered as traditional optimal operation without considering DR, and event-triggered multi-agent optimization is not involved. While in test system 2, all factors are taken into consideration, and comparison with test system 1 can reflect the priority of event-triggered multi-agent optimization for hybrid energy system.

A. Test system 1: hybrid energy system without switching mode

This test system includes 4 wind farms, 3 photovoltaic fields, 10 thermal units and 4 energy storage, all details can be found in literature [32], [33]. The wind power

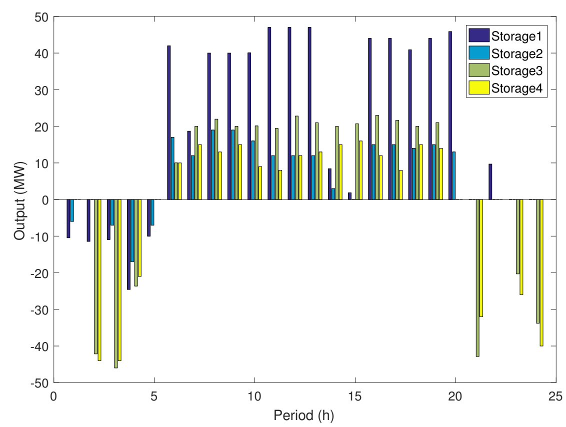

Fig. 4. The charging and discharging process of energy storage

can calculated with wind speed, and photovoltaic power is closely related to illumination intensity. The predicted wind and PV power output at least 85% confidence interval are presented in Table.I and Table.II, which list upcoming output interval for 24 hours. The system load includes five different kinds of load: Load #1, Load #2, Load #3, Load #4 and Load #5, which can be found in Fig.2. For minimizing the expected value of total economic cost, it needs to find optimal scheme of ten thermal units and 4 energy storage, here it is presented in Fig.3 and Fig.4. Since state of thermal units is closely related to capacity with considering on/off cost, most thermal units always be turned on except Unit 1, Unit 2, Unit 7 and Unit 8, and Unit 5 and Unit 10 almost keep maximum output during 24 hours. In Fig.3, permitted minimum output of thermal units does not equal to 0MW, it means that thermal unit is turned off when the output achieve 0 MW, and it is also the same for energy storage. In Fig.4, energy storage is frequently utilized to keep the stability of hybrid energy system, which also means that it will generate more economic cost.

TABLE I
85% CONFIDENCE INTERVAL OF WIND POWER GENERATION

period	wind 1	wind 2	wind 3	wind 4	period	wind 1	wind 2	wind 3	wind 4
00:00-00:59	[32, 45]	[30, 42]	[30, 40]	[25, 34]	12:00-12:59	[16, 22]	[15, 21]	[12, 16]	[13, 19]
01:00-01:59	[35, 45]	[35, 41]	[32, 38]	[29, 35]	13:00-13:59	[20, 26]	[20, 26]	[17, 23]	[17, 23]
02:00-02:59	[35, 44]	[34, 40]	[30, 36]	[25, 43]	14:00-14:59	[25, 31]	[22, 30]	[22, 28]	[21, 27]
03:00-03:59	[29, 35]	[27, 35]	[23, 29]	[18, 24]	15:00-15:59	[30, 38]	[28, 36]	[27, 35]	[25, 33]
04:00-04:59	[20, 28]	[20, 26]	[16, 24]	[12, 18]	16:00-16:59	[26, 34]	[24, 32]	[24, 30]	[22, 28]
05:00-05:59	[15, 21]	[13, 19]	[12, 18]	[10, 18]	17:00-17:59	[24, 30]	[22, 26]	[20, 26]	[19, 25]
06:00-06:59	[18, 26]	[15, 23]	[13, 20]	[13, 20]	18:00-18:59	[22, 28]	[19, 25]	[18, 24]	[17, 23]
07:00-07:59	[22, 28]	[19, 25]	[17, 23]	[14, 22]	19:00-19:59	[15, 20]	[17, 23]	[15, 21]	[15, 21]
08:00-08:59	[22, 30]	[22, 28]	[20, 24]	[17, 23]	20:00-20:59	[22, 28]	[23, 29]	[20, 26]	[19, 25]
09:00-09:59	[20, 26]	[18, 24]	[15, 23]	[15, 21]	21:00-21:59	[25, 32]	[28, 34]	[25, 33]	[23, 29]
10:00-10:59	[17, 23]	[15, 19]	[12, 18]	[12, 18]	22:00-22:59	[31, 39]	[27, 35]	[25, 33]	[23, 30]
11:00-11:59	[17, 23]	[15, 21]	[12, 18]	[12, 16]	23:00-23:59	[33, 43]	[32, 40]	[30, 38]	[27, 35]

TABLE II
85% CONFIDENCE INTERVAL OF PV OUTPUT

period	PV 1	PV 2	PV 3	period	PV 1	PV 2	PV 3
00:00-00:59	[0, 0]	[0, 0]	[0, 0]	12:00-12:59	[28, 36]	[24, 32]	[26, 34]
01:00-01:59	[0, 0]	[0, 0]	[0, 0]	13:00-13:59	[25, 35]	[23, 29]	[27, 33]
02:00-02:59	[0, 0]	[0, 0]	[0, 0]	14:00-14:59	[23, 29]	[20, 24]	[23, 29]
03:00-03:59	[2, 4]	[0, 0]	[1, 3]	15:00-15:59	[20, 24]	[16, 20]	[20, 24]
04:00-04:59	[4, 6]	[1, 3]	[2, 6]	16:00-16:59	[15, 19]	[14, 18]	[15, 21]
05:00-05:59	[8, 12]	[6, 10]	[7, 11]	17:00-17:59	[10, 14]	[11, 15]	[10, 14]
06:00-06:59	[11, 15]	[10, 14]	[8, 12]	18:00-18:59	[6, 8]	[8, 12]	[6, 10]
07:00-07:59	[15, 21]	[13, 19]	[12, 16]	19:00-19:59	[1, 3]	[3, 5]	[4, 6]
08:00-08:59	[16, 22]	[17, 23]	[17, 23]	20:00-20:59	[0, 0]	[0, 0]	[0, 2]
09:00-09:59	[20, 26]	[20, 26]	[17, 23]	21:00-21:59	[0, 0]	[0, 0]	[0, 0]
10:00-10:59	[23, 29]	[22, 28]	[20, 24]	22:00-22:59	[0, 0]	[0, 0]	[0, 0]
11:00-11:59	[23, 29]	[25, 31]	[24, 30]	23:00-23:59	[0, 0]	[0, 0]	[0, 0]

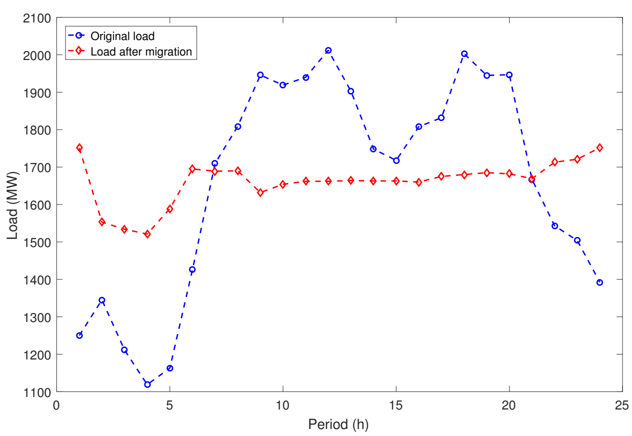

Fig. 5. The original load and load after load migration

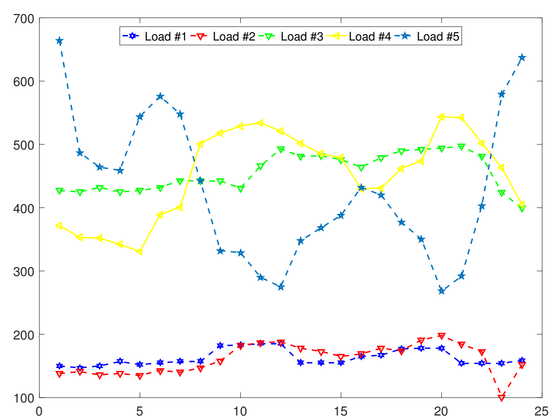

Fig. 6. System load after load shifting strategy

B. Test system 2: hybrid energy system with event-triggered switching mode

Test system 1 can be taken as a traditional case for optimizing hybrid energy system without DR, it is static and simple case but widely used in real-world application. Here, on the basis of test system 1, this test system takes all above factors into consideration, the comparison with robust optimization in Literature [2] and multi-agent optimization in literature [18] are taken in Table.III, it can be seen that the proposed method has minimal total cost with less time consumption, and it can also ensure the safety of hybrid energy system with high average confidence degree. Since load migration is taken into consideration, consumers can arrange proper timing for electricity consumption, it can be seen in Fig.5, in which system load can be more stable, electric peak has been curtailed and electricity trough has been supplemented in comparison to original load, five kinds of system load after shifting have been presented in Fig.6, and load shifting process of each system load has been listed in Table.IV, Table.V, Table.VI, Table.VII and

TABLE III
THE COMPARISON WITH OTHER OPTIMIZATION METHODS

Methods	Literature [2]	Literature [18]	The proposed method
Fuel cost($)	33463	31766	30071
On/off cost($)	7382	7124	7233
Charging/discharging cost($)	10531	6254	5677
Load shifting cost($)	0	1011	2135
Total cost($)	51376	46155	45116
Time (s)	68	59	56
Average confidence degree(%)	87	82	91

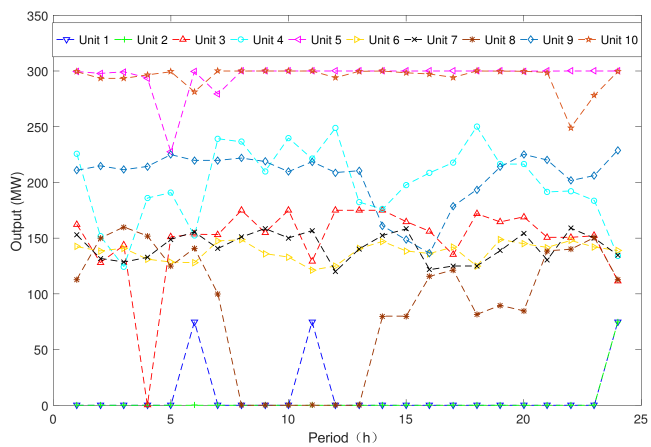

Fig. 7. The output of thermal units with event-triggered mechanism

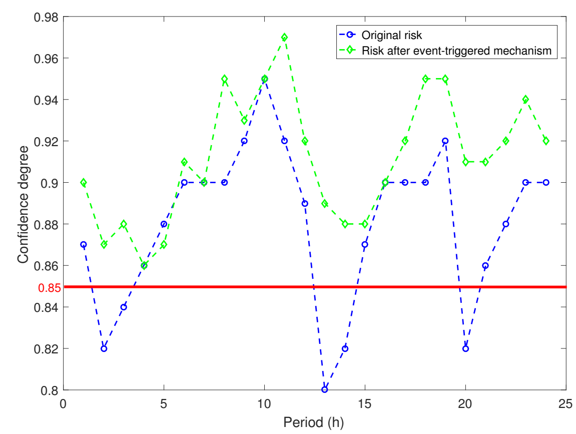

Fig. 9. The confidence degree for exempting potential risk

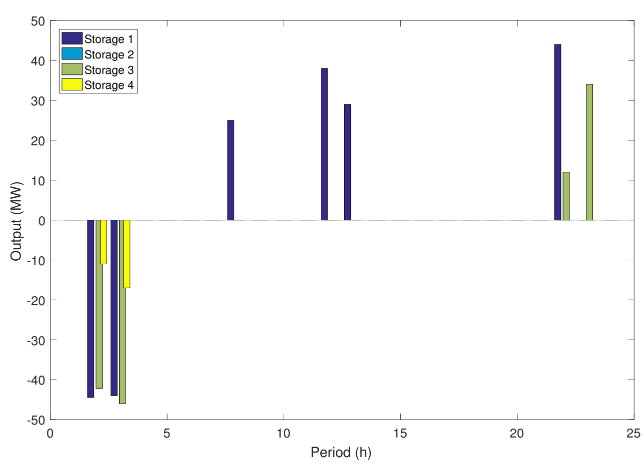

Fig. 8. The charging and discharging of energy storage with event-triggered mechanism

Table. VIII. The obtained output of thermal units has been presented in Fig.7, it can be found that Unit 1 and Unit 2 are almost turned off during the whole period, which can save total economic cost better than that in test system 1. With considering charging and discharging cost, energy storage can be used merely when other power generation cannot meet load requirement in Fig.8, obviously energy storage is seldom used in comparison that in test system 1. It can be noted that there are three key periods, where energy storage has been used. Actually, it adjusts potential risk to minimum extent, which can be found in Fig.9. Here, δ_t can be set as 0.85, once confidence degree is smaller than it, event-triggered switching mechanism can be utilized to decrease the potential risk or improve the confidence degree. As it is shown in Fig.9, there are five dangerous periods with low confidence level in original load, but they are improved after utilizing event-triggered switching mechanism, which also proves the feasibility of proposed method. In subsystem level, consensus with ADMM is employed to optimize economic dispatch of ten thermal units, those obtained results are listed in Table.IV. It can be found that total cost has been greatly reduced especially charging and discharging cost in comparison to test system 1. In addition, convergence process has also been analyzed in comparison to DP and QP methods in Fig.10, though DP and QP have good performance before 50 iterations, QP fall into premature problem after 100 iterations and search ability is still not good enough. With above comparison and analysis, four designed agents can work properly in hybrid energy system, the proposed event-triggered switching mechanism based multi-agent optimization can improve optimal efficiency for reducing the total economic cost as well as decreasing potential risk, which can ensure the reliability of hybrid energy system.

VI. Conclusion

Due to the strong uncertainty and coupled complexity of hybrid energy system, optimal operation has become a

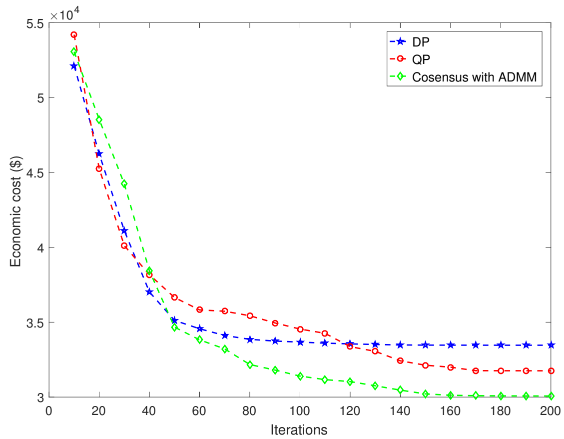

Fig. 10. The comparison of convergence ability with DP and QP

great challenge for both system modeling and optimization methodology. This paper proposes a two-layered multi-agent optimization with event-triggered switching mechanism. After simulation on two test systems, some merits can be concluded as follows:

(1) Since different energy resources have different characteristics, four agents are designed for different purposes. Agent 1 analyzes probabilistic characteristics and provides the probability interval for power dispatch. Agent 2 assigns output of thermal units to minimize fuel cost and on/off cost. Agent 3 manages energy storage with minimizing the charging and discharging cost. Agent 4 provides load shifting/migration model for consumers' consumption in DR.

(2) In upper level, event-triggered switching mechanism is proposed to decrease potential risk caused by intermittent energy, the switching of power supply's on/off state and load curtailment can be controlled to properly arrange power generator state or load curtailment. For proper coordination among different energy resources, some norms are designed for properly optimizing of four subsystems.

(3) In lower level, ADMM is developed with regularized consensus algorithm to optimize DED model in subsystem. Combined with equal increment criterion, different power generators can achieve a utopia optima after several iterations.

Finally, those obtained simulation results can support above view points, and it also reveals that the proposed event-triggered multi-agent optimization can be a viable and promising approach for optimal operation of hybrid energy system.

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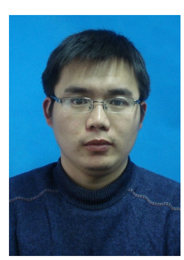

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TABLE IV
LOAD SHIFTING PROCESS OF LOAD #1

period	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
1	-	0	0	0	0	0	0	0	0	0	10	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	-	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5
3	0	0	-	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	-	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	-	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	0	0	0	0	0	-	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	-	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	-	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	-	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0	0	-	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0	0	-	0	0	0	0	0	0	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0	0	0	0	0	-	0	0	0	0	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	23	0	0	0	-	0	0	0	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0	8	0	0	-	0	0	0	4	0	0	0	0	0	0
15	0	0	0	1	0	6	0	0	0	0	0	0	0	0	-	0	0	0	0	0	0	0	0	0
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-	0	0	0	0	0	0	0	0
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-	0	0	0	0	0	0	0
18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-	0	0	0	0	0	0
19	0	0	0	0	0	0	0	7	0	0	0	0	0	0	0	0	0	0	-	0	0	0	0	0
20	0	0	4	0	0	0	3	0	0	0	5	0	0	0	0	0	0	0	0	-	0	0	0	2
21	0	0	0	0	0	0	0	0	0	26	0	3	0	0	0	2	5	0	0	0	-	0	0	0
22	0	0	0	18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-	0	0
23	0	0	0	0	9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-	0
24	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-

TABLE V
LOAD SHIFTING PROCESS OF LOAD #2

period	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
1	-	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	10	0	0
2	0	-	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	11	0	0	0	0	0
3	0	0	-	0	0	0	0	0	0	0	0	0	0	0	0	0	19	0	0	0	0	0	0	0
4	0	0	0	-	0	0	0	0	0	18	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	-	0	0	0	0	0	0	0	0	0	0	0	0	0	0	16	1	0	0	0
6	0	0	0	0	0	-	0	0	0	8	0	0	0	0	0	0	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	-	0	0	0	0	0	0	22	0	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	-	0	0	0	0	0	0	8	0	0	12	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	-	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0	0	-	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0	0	-	0	0	0	0	0	0	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0	0	0	0	0	-	0	0	0	0	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0	0	0	0	-	0	0	0	1	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0	-	0	0	0	0	0	0	0	0	0	0
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-	0	0	0	0	0	0	0	0	0
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-	0	0	0	0	0	0	0	0
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-	0	0	0	0	0	0	0
18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-	0	0	0	0	0	0
19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-	0	0	0	0	0
20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-	0	0	0	0
21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-	0	0	0
22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-	0	0
23	0	0	0	0	0	0	0	0	5	0	24	14	0	0	0	14	0	0	0	0	0	0	-	0
24	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	-

TABLE VI
LOAD SHIFTING PROCESS OF LOAD #3

period	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
1	-	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	20	0	0	0	0
2	0	-	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	20	0	0	0	0	0
3	0	0	-	0	0	0	0	0	0	0	0	0	0	0	0	0	13	0	0	0	0	0	0	0
4	0	0	0	-	0	0	0	0	0	0	0	0	0	0	0	0	0	0	20	0	0	0	0	0
5	0	0	0	0	-	0	0	0	0	0	0	0	0	0	15	0	0	0	0	0	0	0	0	0
6	0	0	0	0	0	-	0	0	0	0	0	0	0	0	0	0	10	0	0	0	0	0	0	0
7	0	0	0	0	0	0	-	0	0	0	0	0	0	0	0	17	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	-	0	0	0	0	0	0	9	0	0	19	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	-	0	9	0	0	0	0	0	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0	0	-	0	0	0	0	0	0	0	0	0	0	22	0	0	0
11	0	0	0	0	0	0	0	0	0	0	-	0	0	0	0	0	0	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0	0	0	0	0	-	0	0	0	0	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0	0	0	0	-	0	0	0	0	0	0	1	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0	-	0	0	0	0	0	0	0	0	0	0
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-	0	0	0	0	0	0	0	0	0
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-	0	0	0	0	0	0	0	0
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-	0	0	0	0	0	0	0
18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-	0	0	0	0	0	0
19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-	0	0	0	0	0
20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-	0	0	0	0
21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-	0	0	0
22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-	0	0
23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	14	0	0	0	18	-	0
24	0	0	0	0	0	0	0	0	0	0	0	9	0	37	0	0	7	0	0	0	0	0	0	-

TABLE VII
LOAD SHIFTING PROCESS OF LOAD #4

period	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
1	-	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	-	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	0	0	-	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	-	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	-	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	0	0	0	0	0	-	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	-	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	-	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	-	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0	0	-	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0	0	-	0	0	0	0	0	0	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0	0	0	0	0	-	0	0	0	0	0	0	0	0	0	0	0	0
13	0	0	0	0	0	27	0	3	0	0	0	0	-	0	0	0	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	37	0	0	0	0	0	0	-	0	0	0	0	0	0	0	10	0	0
15	0	0	0	0	0	0	0	0	13	0	36	0	0	0	-	0	0	0	0	0	0	5	0	0
16	0	0	0	0	78	0	0	0	0	24	0	0	0	0	0	-	0	0	0	0	0	0	0	0
17	0	0	0	91	0	0	0	0	0	12	0	0	0	0	0	0	-	0	0	0	0	0	0	0
18	0	0	101	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-	0	0	0	0	0	60
19	141	19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-	0	0	0	0	0
20	0	89	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-	0	0	0	0
21	0	0	0	0	0	0	0	0	0	0	0	22	0	0	0	0	0	0	0	0	-	0	0	0
22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-	0	0
23	0	0	0	0	0	0	0	0	13	0	0	0	0	0	0	0	0	0	0	0	0	0	-	0
24	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-

TABLE VIII
LOAD SHIFTING PROCESS OF LOAD #5

period	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
1	-	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	-	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	0	0	-	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	-	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	-	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	0	0	0	0	0	-	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
7	0	21	0	0	0	0	-	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8	0	0	81	0	0	0	0	-	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
9	2	0	0	0	0	0	0	0	-	0	0	0	0	0	0	0	0	0	0	0	0	0	8	349
10	0	0	0	330	1	0	0	0	0	-	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11	0	0	0	0	370	0	0	0	0	0	-	0	0	0	0	0	0	0	0	0	0	0	0	0
12	398	0	0	0	0	0	0	0	0	0	0	-	0	0	0	0	0	0	0	0	0	0	0	0
13	2	0	0	0	0	0	0	0	0	0	0	0	-	0	0	0	0	0	0	0	37	145	0	0
14	0	85	0	0	0	0	0	0	0	0	0	0	0	-	0	0	0	0	0	0	0	0	0	0
15	0	30	0	0	0	0	0	0	0	0	0	0	0	0	-	0	0	0	0	0	0	0	0	0
16	2	0	22	0	0	55	0	0	0	0	0	0	0	0	0	-	0	0	0	0	0	0	0	0
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-	0	0	0	0	0	109	0
18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-	0	0	0	0	211	0
19	0	0	147	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-	0	0	0	0	0
20	0	0	0	0	0	199	0	0	0	0	0	0	0	0	0	0	0	0	0	-	0	0	0	0
21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-	0	0	0
22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-	0	0
23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-	0
24	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-