Two-stage optimal operation strategy of isolated power system with TSK fuzzy identification of supply-security

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***Abstract*—Due to the uncertainty of intermittent energy and system load, it is a big challenge to optimally operate an isolated power system. This paper proposes a two-stage optimal operation strategy with a Takagi-Sugeno-Kang (TSK) fuzzy system to address the supply-security under uncertainty circumstance. For proper analysis of the uncertainty characteristics, adjustable uncertainty parameters of intermittent energy resource and system load are taken as fuzzy sets, with consideration of the robustness of these uncertainty parameters on isolated power system, it creates supply-security identification model with TSK fuzzy approach under RBF neural network, and deduces optimal weight values with a recursive least square (RLS) method. For properly avoiding potential risks, security index is classified into several degrees, each degree of risk can switch a different operation model, which can ensure the supply-security of an isolated power system. For properly solving the optimization model, gradient descent based multi-objective cultural differential evolution (GD-MOCDE) is employed to minimize economic cost and emission rate simultaneously. With simulations on isolated regional network, the obtained results reveal that the proposed method can be a viable alternative for optimal operation in isolated power systems.**

***Index Terms*—optimal operation, intermittent energy, TSK fuzzy approach, uncertainty, potential risk.**

NOMENCLATURE

$\alpha(n)$ The gain parameter of RLS algorithm
α_{k0}, α_{k1}, α_{k2} The cost coefficients of the kth thermal unit
ΔT The time period length
ϵ_t The valve of supply security
$\eta_l \in (0,1]$ The efficiency factor of the charging or discharging state
$\gamma_{cut,s}$ The cost parameter of the cut-off load
γ_{k0}, γ_{k1}, γ_{k2} The emission coefficients of the thermal units
$\gamma_{swi,bl}$ The cost price of switching on/off energy storage
$\gamma_{swi,ck}$ The cost price of switching on/off thermal units
κ_j The control parametero RBF function
μ_{ij} The membership function
Ω The number of power generators
$\overline{P_{Ij}}$ The estimated output of intermittent energy resource
$\overline{P_{load}}$ Estimated load from the demand side
ρ The control parameter of RLS algorithm
τ_{con} The number of controllable load with on state after switching
τ_c The number of thermal units with on state after switching
τ_i The firing degree of rule i
τ_{store} The number of energy storage with on state after switching
$\widetilde{P^{[k]}_{Ij,max}}$ The upper bounds of the kth small interval of the power output
$\widetilde{P_{Ij,max}}$ The maximum disturbance of intermittent power output
$\widetilde{P^{[k]}_{Ij,min}}$ The lower bounds of the kth small interval of the power output
$\widetilde{P_{Ij,min}}$ The minimum disturbance of intermittent power output
$\widetilde{P_{Ij}}$ The output disturbance of intermittent energy resource
$\widetilde{P^{[k]}_{load,max}}$ The upper bounds of the kth small interval of the system load
$\widetilde{P_{load,max}}$ The maximum disturbance of system load
$\widetilde{P^{[k]}_{load,min}}$ The lower bounds of the kth small interval of the system load
$\widetilde{P_{load,min}}$ The minimum disturbance of system load
$\widetilde{P_{load}}$ Load disturbance from the demand side
$A_{i1}, A_{i2}, ...A_{iN}$ The fuzzy sets
b_{ij} The width of fuzzy set A_{ij}
c_j,d_i The parameters of RBF network
$f()$ The output function
H_{bl} The on/off state of the lth energy storage
H_{bl} The on/off state of the energy storage units
H_{ck} The on/off state of thermal unit
$H_{con,s}$ The on/off state of sth controllable load
I The identity matrix
k The current sample index

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K_j The number of small intervals of intermittent power
K_{load} The number of small intervals of load
m_{ij} The center of fuzzy set A_{ij}
N_b The number of energy storage units
N_{con} The number of controllable loads
N_c The number of thermal units
N_R The number of rules
p The RLS order
P_{bl} The output of the lth energy storage unit
$P_{ck,max}$ The maximum output of thermal unit
$P_{ck,min}$ The minimum output of thermal unit
P_{ck} The output of the kth thermal unit at the tth time period
$P_{con,s}$ The sth a controllable load
P_{fix} The fixed part of the system load
P_{Ij} The output of intermittent energy resource
$P^{cha}_{l,max}$ The maximum charging output at the $l \in L$th battery at the tth time period
$P^{dis}_{l,max}$ The maximum discharging output at the $l \in L$th battery at the tth time period
P_{load} System load from the demand side
P_{loss} The transmission loss
$P^{cha}_{l}(t)$ The output of charging state
$P^{dis}_{l}(t)$ The output of discharging states
P^{store}_{l} The charging/discharging power
$P_{tot}(t)$ The total output of power generation
$Q(n)$ The matrix parameter
r_{Ij} Control parameters of output uncertainty
r_{load} Control parameters of load uncertainty
S_0 The number set of load
$T^{off}_{ck,min}$ The minimum off-line time period
$T^{on}_{ck,min}$ The minimum on-line time period
$T^{off}_{ck,t-1}$ Off-line time period until the $t-1$ period
$T^{on}_{ck,t-1}$ On-line time period until the $t-1$ period
$V^{store}_{l}(t)$ The storage of the lth battery at the tth time period
$V^{store}_{l,max}$ The maximum storage of the lth battery
$V^{store}_{l,min}$ The minimum storage of the lth battery
w_{ij} The weight of the network
x_j The jth input variable
y_i The output of rule consequent of rule i
Y_n The output of the nth sample data

I. Introduction

WITH thigh penetration of renewable energy resources, the great challenge is to adapt the uncertain operating conditions of power generation and system load [1]. Generally, the objective of optimal operation is to minimize economic cost while satisfying different constraints, including the system load balance, the output limit, spinning reserve constraints and the ramp rate limit. In the literature [2] emphasis is put on the energy storage system and spinning reserve in the economic dispatch model of micro-grids. Also, [3] proposes a distributed economic dispatch strategy for microgrids with multiple energy storage systems, which overcomes the challenges of dynamic couplings among all decision variables and stochastic variables in a centralized dispatching formulation. Besides economic factors, environmental issues can also plays a role. [4] optimizes economic cost and emission rate caused by thermal units simultaneously, and produces a set of Pareto optimal schemes. In most instances, the uncertainty or randomness of intermittent energy resources can be considered a tough problem. There are mainly three approaches: 1) Fuzzy optimization, 2) Stochastic optimization and 3) Robust optimization (RO). The first one depends mainly on the membership function of the decision-makers' experience, which can be subjective and not suitable for real-world applications [5], [6]. Stochastic optimization requires probabilistic information, which is difficult to obtain or not accurate enough for optimization [7], [8]. RO can deal with the uncertainty problem objectively, as well as with less probabilistic information, but somehow it may lead to a conservative problem [9], [10]. For avoiding this problem, this paper adopts a robustness condition with flexible control parameters, which has been deduced in literature [11]. The uncertainty of intermittent energy and system load can also lead to a potential risk in isolated power system. Security is also an important issue in the optimal operation of isolated power system, especially isolated power system. Some researchers focuses on the security assessment and evaluation in distributed systems, including distributed power generators [12], [13], [14], [15], [16]. Usually, the security issue is not taken into consideration at the planning stage, or it exists merely in the communication network. A novel efficient security analysis approach is proposed for overcoming the drawbacks of high computational cost in classical N-k-induced cascading contingency analysis [17]. In the literature [18] approaches are presented for clustering active distribution systems into a set of microgrids with optimized reliability and supply-adequacy indexes. [19] proposes a novel robust security-constrained optimal power flow method to balance the economy, combined with the security requirements under the uncertainties associated with renewable generation and load demand. This paper adopts supply-security to describe the reliability of isolated power system, and the relationship between supply-security and fuzzy sets of power generation and system load is modeled with a TSK fuzzy system, which has been a hot issue for system identification [20], [21], [22], [23], [24], [25]. In the literature [20], an interactively recurrent self-evolving fuzzy neural network is proposed for prediction and identification of dynamic systems. [21] discusses a knowledge-leverage-based fuzzy system from the perspective of transfer learning, which not only make full use of data from the current scene, but also effectively leverage the existing knowledge from reference scenes. [23] utilizes a system identification-based framework to develop monotone fuzzy If-Then rules for formulating monotone zero-order TSK fuzzy inference systems. [24] presents a novel application of a hybrid learning approach to optimize membership functions of a newly developed interval type-2 intuition fuzzy logic system of TSK fuzzy inference with

a neural network learning capacity. This paper proposes a two stage optimal operation strategy with TSK fuzzy identification to optimize isolated power system, TSK fuzzy identification approach is utilized to identify the relationship between those uncertainty parameters and supply-security, and then a two-stage optimization strategy with switching mechanism is presented to minimize economic cost and emission rate simultaneously. The main contribution of this paper can be summarized as:
(1) The uncertainty of power generation and system load can lead supply security problem, but the relationship between them can not be clearly presented. In this paper, the uncertainty variables of intermittent energy resources and system load are converted into fuzzy sets, the robustness of these parameters on isolated power system is taken into the identification model, a TSK fuzzy approach is employed to identify nonlinear relationships between uncertainty variables and supply-security index with recursive least square (RLS) method under an RBF neural network.
(2) Due to the uncertainty and complexity of isolated power system, a two stage framework of optimal operation is proposed to optimize the whole system model, the potential risk of supply security is divided into three different degrees: excellent, good and bad, each degree can switch a different operation model and improve system security, which can decrease the potential risk to some extent.
(3) For properly solving those switched optimal operation models, gradient descent based multi-objective cultural differential evolution (GD-MOCDE) is utilized to optimize the economic cost and emission rate simultaneously. The gradient decent based mutation operator enhances the convergence ability, which can further improve the optimization efficiency for optimizing the optimal operation model.

The structure of this paper can be arranged as follows: the TSK fuzzy system is presented in Section II and the problem formulation in Section III. The system identification and two stage optimal operation strategy are proposed in Section IV, and the main results are shown in Section V. Finally, the conclusions follow in Section VI.

II. Takagi-Sugeno-Kang fuzzy system with recursive least square for identification

Generally, a TSK fuzzy system can be considered as a typical nonlinear and dynamic system [26], consisting of several rules that can be expressed as follows:

$$\begin{aligned} &Rule\ i: IF(x_1 \in A_{i1}) AND ... AND (x_N \in A_{iN}) \\ &THEN \quad y_i = f_i(x_1, ..., x_N) \quad i = 1, 2..., N_R \end{aligned} \tag{1}$$

The membership functions are employed to produce membership degree with a Gaussian function as follows:

$$\mu_{ij} = exp[-\frac{(x_j - m_{ij})^2}{b_{ij}^2}] \tag{2}$$

For each rule i, its firing degree τ_i can be considered as "AND" operators for all membership $\mu_{ij} (j = 1, 2, ..., N)$, which can obtain:

$$\tau_i = \prod_{j=1,2..,N} \mu_{ij} = exp[-\sum_{j=1,2,...,N} \frac{(x_j - m_{ij})^2}{b_{ij}^2}] \tag{3}$$

Combined with a weighted average method, it can obtain an output of this fuzzy model as follows:

$$y = \frac{\sum_{i=1}^{N_R} \tau_i y_i}{\sum_{i=1}^{N_R} \tau_i} \tag{4}$$

Since the output function can be expressed with a nonlinear style, RBF neural network is employed to approximate it with consideration of two reasons: (1) The RBF has good universal approximation ability; (2) RBF networks are more stable because each individual RBF unit operates only on selected input patterns [27].

$$f_i(X) = \sum_{j=1}^{N} w_{ij} \phi(||X - c_j||) + d_i \tag{5}$$

where $X = (x_1, x_2, ..., x_N)$, $\phi()$ denotes an RBF function, which can be presented with inverse multi-quadratics as:

$$\phi(||X - c_j||) = \frac{1}{\sqrt{||X - c_j||_2^2 + \kappa_j^2}} \tag{6}$$

Since system load can be a dynamic process with online sampling data, a recursive model can be taken into consideration here. For all recent training sample data, it needs to minimize the global objective as follows:

$$J(\theta_1, \theta_2, ..., \theta_N) = \sum_{n=k-p+1}^{k} (y_n - \sum_{j=1}^{N} \theta_j \phi(||X_n - c_j||))^2 \tag{7}$$

where $X_n = [x_{n-j+1} \ y_{n-j+2} \ ... \ y_j]^T$ is an input vector of the nth sample data. For simplicity, the above equation can be rewritten as:

$$J(\mathbf{\Theta}) = ||Y_n - \mathbf{\Phi}\mathbf{\Theta}||_2^2 \tag{8}$$

where the weight vector $\mathbf{\Theta} = [\theta_1 \ \theta_2 \ ... \ \theta_N]^T$, output vector $Y_n = [y_{n-p+1} \ y_{n-p+2} \ ... \ y_n]^T$, network function vector $\mathbf{\Phi} = [\phi]_{nj}$. To minimize this global objective, the RLS is utilized with several recursive equations as follows:

$$\begin{cases} \mathbf{\Theta}(n) = \mathbf{\Theta}(n-1) + \alpha(n) G(n) \\ \alpha(n) = Y(n) - \mathbf{\Phi}(n)^T \mathbf{\Theta}(n-1) \\ G(n) = Q(n-1)\mathbf{\Phi}(n)[\rho + \mathbf{\Phi}(n)^T Q(n-1)\mathbf{\Phi}(n)]^{-1} \\ Q(n) = \rho^{-1} Q(n-1) - G(n)\mathbf{\Phi}(n)^T \rho^{-1} Q(n-1) \end{cases} \tag{9}$$

The initial conditions of the above parameters can be set as follows:

$$\begin{cases} \mathbf{\Theta}(0) = \mathbf{0} \\ X(n) = X_n = 0, \ n = -p, -p+1, ..., -1 \\ Y(n) = y_n = 0, \ n = -p, -p+1, ..., -1 \\ Q(0) = \delta I, \delta \in R \end{cases} \tag{10}$$

Since RLS can be considered as a rolling optimization approach, it can revise the weight value $\mathbf{\Theta}$ as time goes, which can finally achieve a global optima when the time step ends.

III. Problem formulation: risk degree based isolated power system with different switching models

A. Uncertainty analysis of intermittent energy resources and system load

Since intermittent energy resources and system load have great uncertainty, it can bring a potential risk for hybrid energy system stability. The intermittent power output and system load can be expressed as follows:

$$\begin{cases} P_{Ij} = \overline{P_{Ij}} + r_{Ij}\widetilde{P_{Ij}} \\ P_{load} = \overline{P_{load}} + r_{load}\widetilde{P_{load}} \\ \widetilde{P_{Ij}} \in [\widetilde{P_{Ij,min}}, \widetilde{P_{Ij,max}}] \\ \widetilde{P_{load}} \in [\widetilde{P_{load,min}}, \widetilde{P_{load,max}}] \\ r_{Ij}, r_{load} \in [0,1] \end{cases} \tag{11}$$

For further analysis on uncertainty, the uncertainty interval can be divided into several small intervals as:

$$[\widetilde{P_{Ij,min}}, \widetilde{P_{Ij,max}}] = \bigcup_{k=1}^{K_j} [\widetilde{P_{Ij,min}^{[k]}}, \widetilde{P_{Ij,max}^{[k]}}] \tag{12}$$

$$[\widetilde{P_{load,min}}, \widetilde{P_{load,max}}] = \bigcup_{k=1}^{K_{load}} [\widetilde{P_{load,min}^{[k]}}, \widetilde{P_{load,max}^{[k]}}] \tag{13}$$

For simplicity, suppose that $K_j = K_{load} = K$, it can be labeled as:

$$\begin{cases} x_j = \widetilde{P_{Ij}}, \quad j = 1, 2..., J-1 \\ x_J = \widetilde{P_{load}} \\ A_{jk} = [\widetilde{P_{Ij,min}^{[k]}}, \widetilde{P_{Ij,max}^{[k]}}], \quad j = 1, 2..., J-1 \\ A_{Jk} = [\widetilde{P_{load,min}^{[k]}}, \widetilde{P_{load,max}^{[k]}}] \\ \theta_j = r_{Ij}, \quad j = 1, 2..., J-1 \\ \theta_J = -r_{load} \end{cases} \tag{14}$$

where $x = [x_1, x_2, ..., x_J]$, $A = [A_{jk}]_{J\times K}$, $\theta = [\theta_1, \theta_2, ..., \theta_J]$, those small intervals are equally divided.

B. Economic dispatch model with uncertainty degree in isolated power system

The economic issue is crucial in power systems. It consists of different kinds of economic cost, i.e. power generation cost and benefit, load cut-off cost, on/off cost, and simultaneously it also produces emission pollution from thermal units, which can be expressed as follows:
(1) Power generation cost: Generally, the power generation cost can be described with quadratic functions of power output. Here, the on/off state of each thermal units is also taken into consideration, then it can be expressed as:

$$C_{gen} = \sum_{k=1}^{N_c} H_{ck}(\alpha_{k0} + \alpha_{k1}P_{ck} + \alpha_{k2}P_{ck}^2) \tag{15}$$

(2) Emission volume: Since thermal units can produce emission pollutant during power generation, emission issue can also be taken into consideration, which can be presented as:

$$E = \sum_{k=1}^{N_c} H_{ck}(\gamma_{k0} + \gamma_{k1}P_{ck} + \gamma_{k2}P_{ck}^2) \tag{16}$$

(3) Load cut-off cost: Some system load can be controllable, it can be cut-off to ensure the system balance, but it needs to compensate consumers, which can generate cut-off cost as:

$$C_{cut} = \sum_{s\in S_0} \gamma_{cut,s}P_{con,s} \tag{17}$$

$$S_0 = \{s | H_{con,s} = 0\} \tag{18}$$

If it is on, $H_{con,s} = 1$, otherwise, $H_{con,s} = 0$.
(4) Switching on/off cost: The on/off operation of thermal units and energy storage can bring economic cost, the switching cost can be presented as:

$$C_{swi,thermal} = \sum_{k=1}^{N_c} \gamma_{swi,ck}|H_{ck}(t) - H_{ck}(t-1)| \tag{19}$$

$$C_{swi,store} = \sum_{k=1}^{N_b} \gamma_{swi,bl}H_{bl}|P_l^{store}| \tag{20}$$

$$C_{swi} = C_{swi,thermal} + C_{swi,store} \tag{21}$$

Its total cost F can be expressed with three parts as:

$$F = C_{gen} + C_{cut} + C_{swi} \tag{22}$$

(5) Power system transmission loss: In this paper, the isolated power system consists of thermal units, intermittent energy sources and energy storage units. Since different energy resources are widely distributed, it exists transmission loss among them.

$$P_{tot} = P_{load} + P_{loss} = P_{fix} + \sum_{s=1}^{N_{con}} H_{con,s}P_{con,s} + P_{loss} \tag{23}$$

$$P_{loss} = \sum_{i,j\in\Omega} B_{ij}P_iP_j + \sum_{j\in\Omega} B_{0j}P_j + B_{00} \tag{24}$$

$$P_{tot} = \sum_{j=1}^{J-1} P_{Ij} + \sum_{k=1}^{N_c} H_{ck}P_{ck} + \sum_{l=1}^{N_b} H_{bl}P_{bl} \tag{25}$$

(6) Thermal power generation constraints: During thermal power generation, it needs to satisfy maximum and minimum output limits. With consideration of equipment management issue, each thermal unit can not be with on/off state permanently, its on/off time must be limited as:

$$\begin{cases} P_{ck,min} \le P_{ck} \le P_{ck,max} \\ (T_{ck,t-1}^{on} - T_{ck,min}^{on})(H_{ck}(t-1) - H_{ck}(t)) \ge 0 \\ (T_{ck,t-1}^{off} - T_{ck,min}^{off})(H_{ck}(t) - H_{ck}(t-1)) \ge 0 \end{cases} \tag{26}$$

(7) Energy storage constraints: Energy storage is a supplementary energy resource for intermittent energy, it has

storage limits and charging/discharging limits, all these constraints can be presented as follows:

$$\begin{cases} V_l^{store}(t+1) = V_l^{store}(t) + P_{bl}(t) * \Delta T \\ P_{bl}(t) = \eta_l P_l^{store}(t) \\ V_{l,min}^{store} \leq V_l^{store}(t) \leq V_{l,max}^{store} \\ P_l^{store}(t) = P_l^{cha}(t), if\ P_l^{store}(t) \geq 0 \\ P_l^{store}(t) = -P_l^{dis}(t), if\ P_l^{store}(t) < 0 \\ 0 \leq P_l^{dis}(t) \leq P_{l,max}^{dis} \\ 0 \leq P_l^{cha}(t) \leq P_{l,max}^{cha} \\ V_l^{store}(0) = V_{l,initial}^{store} \end{cases} \tag{27}$$

IV. Fuzzy system based two stage optimization strategy

A. TSK fuzzy system identification of supply-security in isolated power system

The confidence degree of active power supply-security can be considered as an important issue in isolated power system, since it is mainly affected by both power supply and demand uncertainty, but the relationship between these is still uncertain. For properly dealing with this problem, a TSK fuzzy system is employed to build up the relationship, an RBF neural network approximates the nonlinear function, and the robustness constraint is also satisfied for avoiding potential risk. The confidence degree can be considered as the output of a fuzzy system, which is a function of the adjustable parameter θ_j and input variables with an RBF neural network approach as:

$$y = f(X) = \sum_{j=1}^{J} \theta_j \phi(||X - c_j||) \tag{28}$$

Combined with the introduced fuzzy system model in Section II, the robustness constraint is also taken into consideration with an RLS approach, those recursive iterations can be updated with several procedures. For proper analysis on uncertainty, the system load balance can be rewritten as:

$$\sum_{j=1}^{J} \theta_j x_j = \overline{P_{load}} - \sum_{j=1}^{J-1} \overline{P_{Ij}} - \sum_{k=1}^{N_c} P_{ck} - \sum_{l=1}^{L} P_l^{store} \tag{29}$$

Moreover, system robustness can also be taken into consideration for avoiding the worst case, which has been referred to in [11]. Then, the following constraint should be satisfied:

$$\sum_{j=1}^{J-1} \theta_j - \theta_J \leq \delta \tag{30}$$

where $\delta \in [0, J]$ represents the uncertainty degree. Here, it satisfies:

$$\delta \geq \sqrt{-2Jln\xi} \tag{31}$$

where $1-\xi \in (0, 1]$ denotes the probability of satisfying the constraints requirement. Since the robustness constraint is added into the fuzzy system model, it can be converted into a constrained problem. With consideration of the correlation among sequences, taking forgetting factors also into consideration, the Lagrange function can be presented as follows:

$$L(\boldsymbol{\Theta}_n) = ||Y_n^{'} - \boldsymbol{\Phi}_n^{'} \boldsymbol{\Theta}_n||_2^2 + \lambda(I_0 \boldsymbol{\Theta}_n - (\delta - \delta^{'})ee^T)^2 \tag{32}$$

where $0 << \zeta < 1$ represents the forgetting factor, $I_0 = [1\ 1\ \cdots\ 1\ \ -1]$, $0 \leq \delta^{'} \leq \delta$, $e = [1\ 0\ \cdots\ 0\ 0]$. Here, $X_n^{'} = [\zeta^{j-1} x_{n-j+1}\ \zeta^{p-2} x_{n-j+2}\ \cdots\ x_n]^T$, and the matrix $\boldsymbol{\Phi}_n^{'}$ can also be updated as:

$$\begin{pmatrix} \phi_{11}^{'} & \phi_{12}^{'} & \cdots & \phi_{1J}^{'} \\ \phi_{21}^{'} & \phi_{22}^{'} & \cdots & \phi_{2J}^{'} \\ \vdots & \vdots & \vdots & \vdots \\ \phi_{p1}^{'} & \phi_{p2}^{'} & \cdots & \phi_{pJ}^{'} \end{pmatrix} \tag{33}$$

The RBF of the neural network can be updated with $\phi_{nj}^{'}$, which can be rewritten as:

$$\phi_{nj}^{'} = \phi(||X_n^{'} - c_j||) = \frac{1}{\sqrt{||X_n^{'} - c_j||_2^2 + \kappa_j^2}} \tag{34}$$

The relationship between $X_n^{'}$ and $X(n)$ can be expressed as:

$$X_n^{'} = \boldsymbol{B} X_n \tag{35}$$

where $\boldsymbol{B}$ can be defined as:

$$\begin{pmatrix} \zeta^{j-1} & 0 & 0 & 0 \\ 0 & \zeta^{j-2} & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & \cdots & 1 \end{pmatrix} \tag{36}$$

Define an exponentially-weighted covariance matrix $\boldsymbol{U}_n$ and vector $\boldsymbol{V}_n$, then it can be expressed as:

$$\begin{cases} \boldsymbol{U}_n = X_n^{'}(X_n^{'})^T = \zeta^2 \boldsymbol{U}_{n-1} + x_n x_n^T \\ \boldsymbol{V}_n = X_n^{'} Y_n^{'} = \zeta \boldsymbol{V}_{n-1} + y_n x_n \end{cases} \tag{37}$$

For optimizing the above Lagrange function, a relaxation approach is utilized with Lagrange multipliers. $\boldsymbol{\Theta}_n$ can be calculated as:

$$\boldsymbol{\Theta}_n = (\boldsymbol{U}_n + \lambda I_0^T I_0)^{-1}(\boldsymbol{V}_n + \lambda(\delta - \delta^{'}) I_0^T) \tag{38}$$

To decrease the cumulative error caused by iterations, it needs to update $\boldsymbol{\Theta}$ with experienced information:

$$I_0 \boldsymbol{\Theta}_n = \delta - \delta^{'} \tag{39}$$

With those above iterations, the weight vector $\boldsymbol{\Theta}_n$ can be deduced with several samples, which also means that the nonlinear relationship between the confidence degree of the system balance and the uncertainty sets can be approximated.

B. Switching mechanisms under confidence degree of supply-security

For proper description of supply-security as well as convenience for collecting output value from samples, the confidence degree is defined as:

$$Security_{con} = Prob(\sum_{i \in N_{node}} \beta_i |P_{tot,i} - P_{load,i} - P_{loss,i}| < \epsilon) \tag{40}$$

where N_{node} represents the number of nodes in isolated power system, β_i is state parameter of ith node, $P_{tot,i}$, $P_{load,i}$ and $P_{loss,i}$ denote total power output, load demand and transmission loss respectively. The confidence degree is in the mainly range $[0, 1]$, with safe when it approaches 1. If the confidence degree cannot be properly satisfied, it needs to take some measures to improve it, energy storage can be turned on to supplement it, and even cut off some controllable load in the worst case. Since the probability of real-world supply security is unknown, the confidence degree can be easily obtained from samples, confidence degree of each sample can be collected by frequency of same events, and then it can be taken as the output value of TSK fuzzy model. Moreover, within total power generation, thermal power bears 80% of system load to ensure stable power supply. The confidence degree can be classified at three levels: Excellent, good and bad, and each level will switch on different adjusting scheme. An excellent level of confidence degree is in the range $[0.9, 1]$, which means that the system balance has been completely satisfied, then its goal is merely to minimize economic cost. A good level of confidence degree is in the range $[0.8, 0.9)$, which indicates that the energy storage should be turned on to decrease the uncertainty for ensuring system balance. A bad level of confidence degree is mainly in the range $[0, 0.8)$, then some controllable load can also be cut off to the keep system balance. For each time period, the confidence degree must achieve an excellent level, then it can be optimized. From both a security and economic view, the adjusting procedures can be presented in Algorithm 1.

Algorithm 1

procedure S(w)itched adjusting scheme under different levels of confidence degree
  Evaluate confidence degree y
Case 1:
  if $y \geq 0.9$ **then**
    Goto optimize ED problem
  end if
Case 2:
  if $0.8 \leq y < 0.9$ **then**
    Turn on energy storage
    For $l = 1 : L$
    $H_l = 1$
    $\delta = \delta - 0.1$
    Evaluate confidence degree y
    if $y \geq 0.9$ **then**
      Goto Case 1
    end if
  end if
Case 3:
  if $y < 0.8$ **then**
    Turn on energy storage
    For $l = 1 : L$
    $H_l = 1$
    $\delta = \delta - 0.1$
    Evaluate confidence degree y
    if $y < 0.9$ **then**
      switch off controllable load
      For $s = 1 : N_{con}$
      $H_{con,s} = 0$
      $\delta = \delta - 0.1$
      Evaluate confidence degree y
      if $y \geq 0.9$ **then**
        Goto Case 1
      end if
    end if
  end if
end procedure

C. GD-MOCDE approach for optimizing the economic dispatch problem of isolated power

Combined with above procedures, the potential risk has been properly avoided and all the on/off or cut-off states of all power generators and controllable load becomes a certain state, the remaining problem can be considered as a classical economic dispatch problem. Without loss of generality, the optimal operation model can be converted as follows:

$$\begin{cases} minF_1, minF_2 = E \\ P_{ck,min} \leq P_{ck} \leq P_{ck,max} \\ V_l^{store}(t+1) = V_l^{store}(t) + P_{bl}(t) * \Delta T \\ V_{l,min}^{store} \leq V_l^{store}(t) \leq V_{l,max}^{store} \\ P_l^{store}(t) = P_l^{cha}(t), if\ P_l^{store}(t) \geq 0 \\ P_l^{store}(t) = -P_l^{dis}(t), if\ P_l^{store}(t) < 0 \\ 0 \leq P_l^{dis}(t) \leq P_{l,max}^{dis} \\ 0 \leq P_l^{cha}(t) \leq P_{l,max}^{cha} \\ V_l^{store}(0) = V_{l,initial}^{store} \\ H_{ck} = 1, H_{bl} = 1, H_{con,s} = 1, \\ k = 1, 2...\tau_c, l = 1, 2...\tau_{store}, s = 1, 2...\tau_{con} \end{cases} \tag{41}$$

Here, the GD-MOCDE algorithm is utilized to solve the above problem, the output of the thermal unit and the charging/discharging output of the energy storage units are taken as decision variables. In the framework of the cultural algorithm, a differential evolution strategy promotes the evolution of the population space. In the differential evolution, the mutation operator of DE/rand/1/bin can be expressed as:

$$R_{r,G+1} = Q_{r,G} + \beta[(Q_{r1,G} - Q_{r2,G}) + (Q_{r3,G} - Q_{r4,G})] \tag{42}$$

where $Q_{r,G}$, $Q_{r1,G}$, $Q_{r2,G}$, $Q_{r3,G}$ and $Q_{r4,G}$ are selected from the current population set and it also satisfies $r1 \neq r2 \neq r3 \neq r4 \neq r$, G denotes the generation index, $R_{r,G+1}$ is a trial vector, and β is a mutation parameter. For improving the optimization efficiency, the gradient decent mechanism can be obtained with two spaces Ω^+ and Ω^-, which can be presented as:

$$\begin{cases} \Omega^+ = d \in R^m | \bigtriangledown g(z)^T d > 0 \\ \Omega^- = d \in R^m | \bigtriangledown g(z)^T d < 0 \end{cases} \tag{43}$$

where $g(z) = [g_1(z), g_2(z), \ldots, g_m(z)]^T$ represents the objective function vector, $z = [z_1, z_2, \ldots, z_n]$ denotes the variable, d is an arbitrary vector, and $\bigtriangledown g(z)$ can be considered as a Jacobi matrix as follows:

$$\begin{pmatrix} \frac{\partial g_1(z)}{\partial z_1} & \frac{\partial g_1(z)}{\partial z_2} & \cdots & \frac{\partial g_1(z)}{\partial z_n} \\ \frac{\partial g_2(z)}{\partial z_1} & \frac{\partial g_2(z)}{\partial z_2} & \cdots & \frac{\partial g_2(z)}{\partial z_n} \\ \vdots & \vdots & \vdots & \vdots \\ \frac{\partial g_m(z)}{\partial z_1} & \frac{\partial g_m(z)}{\partial z_2} & \cdots & \frac{\partial g_m(z)}{\partial z_n} \end{pmatrix} \tag{44}$$

It also means that the deviation between Q_{G+1} and Q_G can be described as:

$$Q_{G+1} - Q_G = -\Upsilon_G \sum_{i \in m} \chi_i \frac{\bigtriangledown g_i(z)}{|| \bigtriangledown g_i(z)||} \tag{45}$$

With consideration of a discrete version, if it is a bi-objective optimization problem, and it can be converted as:

$$Q^j_{G+1} = Q^j_G + \psi_1(Q_{r1,G} - Q_{r2,G}) + \psi_2(Q_{r3,G} - Q_{r4,G}) \tag{46}$$

where ψ_1 and ψ_2 are two control parameters, which can be presented as:

$$\begin{cases} \psi_1 = -\frac{\Upsilon_G \chi_1 sgn(g_1(Q_{r1,G}) - g_1(Q_{r2,G}))}{(Q_{r1,G} - Q_{r2,G})^2 \sqrt{\sum_{j \in n} \frac{1}{(Q_{r1,G} - Q_{r2,G})^2}}} \\ \psi_2 = -\frac{\Upsilon_G \chi_2 sgn(g_2(Q_{r3,G}) - g_2(Q_{r4,G}))}{(Q_{r3,G} - Q_{r4,G})^2 \sqrt{\sum_{j \in n} \frac{1}{(Q_{r3,G} - Q_{r4,G})^2}}} \\ \Upsilon_G = \Upsilon_0[(G_{max} - G + 1)/G_{max}]^p \end{cases} \tag{47}$$

where Υ_G, χ_i, ψ_1 and ψ_2 are control parameters, G_{max} denotes the maximum generation number. By replacing the classic mutation operator with the above gradient descent operator, the convergence speed can be improved. Moreover, since there are some inequality and equality constraints in the model, an embedded constraint-handling technique is employed to deal with them especially those equality constraints, the details can be found in literature [28]. The whole procedure of the GD-MOCDE for economic dispatch can be presented in Algorithm 2. In the above algorithm, $Size$ represents the current size of the archive set, $|B|$ means the size of the archive set, $violation$ denotes the total violation of the equality constraints.

Algorithm 2

```
procedure G(D)-MOCDE algorithm for economic dispatch in isolated power system
    Initialize population set Q and archive set B
    G = 0, B = ∅, Size = 0
    while G < G_max do
        Check total constraint violation
        if violation > ϵ then
            Embedded constraint handling strategy
        end if
        GD based mutation operator
        Crossover operator
        Selection operator
        Store non-dominated solutions in archive set B
        Size = Size + 1
        if Size > |B| then
            Truncate archive set B
        end if
        G = G + 1
    end while
end procedure
```

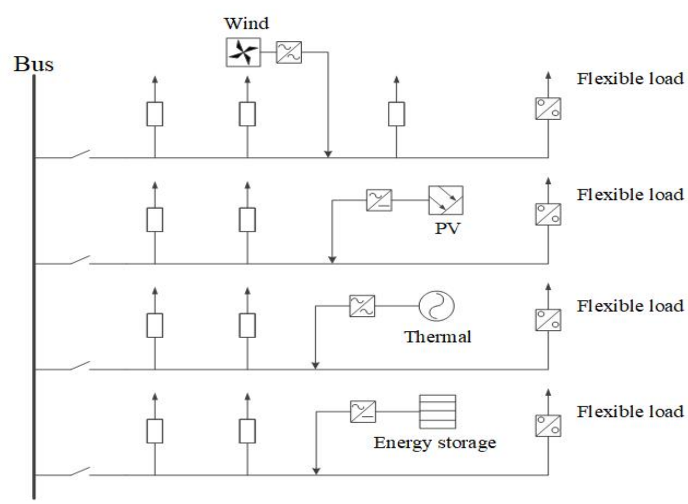

Fig. 1. The structure of isolated power system

V. CASE STUDY

The isolated power system consists of 4 wind farms, 3 photovoltaic fields, 10 thermal units and 4 energy storage units, its structure has been shown in Fig.1, related details can be found in [29], [30]. The system load includes a fixed load and a controllable load, which can be cut off when necessary. The output of wind power and photovoltaic power can be obtained with wind speed and illumination intensity prediction shown in Table 1 and Table 2, system load interval and controllable load are shown in Fig. 2. The outputs of wind power, solar power and system load can be considered as fuzzy sets, which can be calculated by dividing the output interval into four parts. Here, four typical periods are selected for verifying the efficiency of both fuzzy identification and optimal operation. It includes 00:00-02:00, 06:00-08:00, 10:00-12:00 and 19:00-21:00, which represent the key periods in one day.

A. Fuzzy system identification with intermittent energy resources and system load

The fuzzy system has $4^4 * 4^3 * 4 = 65536$ possible fuzzy sets and the output value can be calculated with a membership function. Combined with the sampling data, the relationship between the uncertainty variables and supply-security can be identified, and then optimal schemes can be properly applied. A static model can be converted into a dynamic one due to its on-line identification approach. With the consideration of constraints robustness, the lower bound of the uncertainty budget can be calculated as 6.0697, which also means that the uncertainty budget can only

TABLE I
THE OUTPUT 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
THE OUTPUT INTERVAL OF PV FIELDS

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]

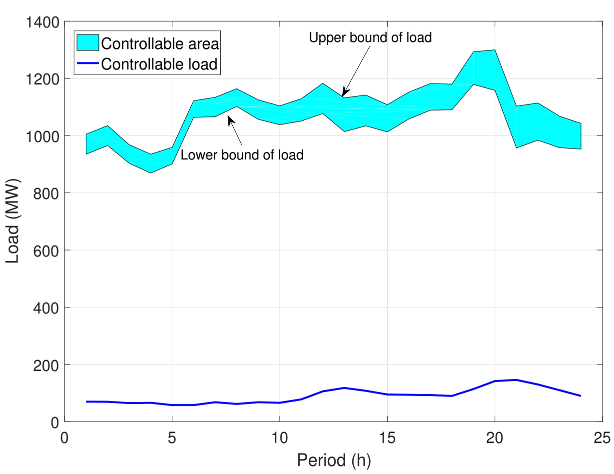

Fig. 2. Controllable load and system load with lower and upper bounds

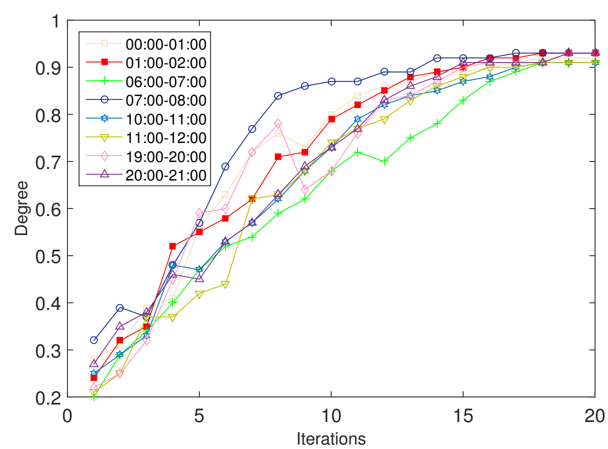

Fig. 3. The convergence analysis of supply-security in some typical periods

range between $[6.0697, 8]$. The uncertainty budget for 24 periods are listed in Table.3, because the uncertainty is mainly caused by intermittent power generation and system load, the uncertainty budget can be large in some periods where huge intermittent power generation or system load requirement occurs. For each time period, the potential degree of supply-security can be evaluated with the TSK fuzzy approach, and then two-stage optimization strategy is utilized to optimize the isolated power system with comparison with RO. The convergence process of TSK identification in some typical periods are shown in Fig.3. It can be seen that identification in different typical periods converges in less than 20 iterations to reach an excellent degree (larger than 0.9), the identification is completed after the switching mechanism, which also means that all the power generators, even system load, work together to improve the supply-security. In Fig.4, the comparison between RO and proposed two stage optimization method is presented, it can be seen that two stage approach can improve the confidence degree, which can avoid the potential risk of supply security to certain extent.

TABLE III
THE UNCERTAINTY BUDGET OF 24 TIME PERIODS

period	1	2	3	4	5	6	7	8	9	10	11	12
δ	7.342	7.123	6.775	6.642	6.5321	7.221	7.327	7.452	7.4631	7.462	7.4853	7.514
period	13	14	15	16	17	18	19	20	21	22	23	24
δ	7.631	7.642	7.454	7.535	7.498	7.346	7.245	7.524	7.511	7.201	7.132	7.265

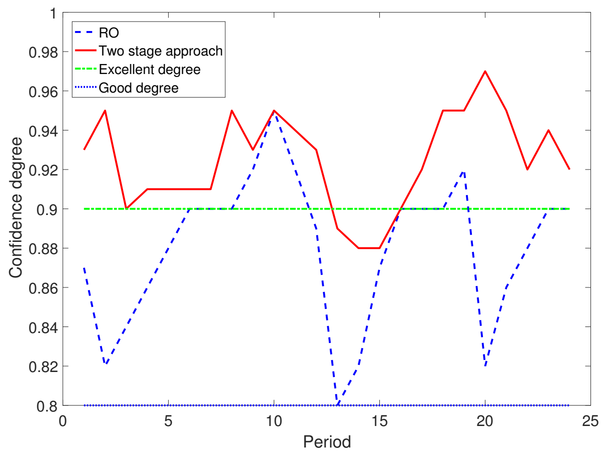

Fig. 4. The confidence degree between RO and two stage approach

B. Optimal operation of an isolated power system with a two-stage optimization strategy

Once the supply-security has been identified for each period, optimal schemes can be calculated with a switching mechanism and GD-MOCDE algorithm. Since 00:00-02:00, 06:00-08:00, 10:00-12:00 and 19:00-21:00 can be taken a four typical periods for the system load in one day, the analysis below focus on the results of these four periods. Since economic cost and emission rate can be taken as two objectives, 20 Pareto schemes are obtained by GD-MOCDE and multi-objective differential evolution (MODE)[31]. The results in some typical periods have been presented in Fig. 5. It can be clearly observed that those Pareto optimal schemes obtained by MODE are disorder, and the GD-MOCDE has both better convergence ability and diversity distribution. For better analysis on optimization results, the 10th scheme of those Pareto optimal schemes is taken as a compromise scheme, which has been labeled in Fig.5. According to different confidence degree, different switching mechanisms have been turned on, the on/off state of all power generators and energy storage units in 24 hours are listed in Table.IV. It can be seen that Unit 1 and Unit 2 are almost turned off in the whole day, energy storage 2 is always turned off, the controllable load is not turned off, and thermal power is still taken as the main power source. Further analysis is taken on those typical periods, the obtained economic cost and emission rate are presented in Table V, in which the proposed two stage approach achieves better results than RO. All the evaluation indexes are presented in Table VI, fuel cost, on/off cost of thermal units, charging/discharging cost, cut-off load cost, total cost, total emission, average confidence degree and average transmission loss are listed, it can be revealed that the proposed two stage approach has better results than RO. Since energy storage is seldom used, the switching cost can be expensive. In those typical periods, the outputs of all power generators and energy storage units are shown in Fig. 6, where U1, U2,...,U10 represent Unit 1, Unit 2,..., Unit 10, S1, S2, S3 and S4 represent energy storage 1, energy storage 2, energy storage 3 and energy storage 4. With above analysis, optimal operation with supply-security identification is a complicated problem. The system model can be uncertain, multi-objective and complex-coupled, hence this paper proposes a two stage optimization approach with supply-security identification. The TSK fuzzy approach can properly identify the relationship between uncertainty parameters and supply-security, and a two-stage optimization strategy can switch on/off power generators to improve the security degree according to three levels of confidence degree, then optimizes the economic dispatch problem with the known on/off state of the power generators and energy storage units with the GD-MOCDE algorithm, those obtained results can reveal that the proposed method can be an effective way for solving isolated power system problem.

VI. CONCLUSION

The uncertainty and complexity of the optimal operation in isolated power system pose a great challenge optimization. This paper proposes a two-stage optimization strategy with a TSK fuzzy identification of supply-security. According to the obtained results, the merits can be concluded as follows:

(1) Supply-security can be considered as an important issue in isolated power system, and it is mainly affected by the uncertainty of power generation and system load. For better dealing with uncertainty problem and decreasing potential risk, this paper proposes a TSK fuzzy model for identifying the relationship between uncertainty parameters and confidence degree of supply security with TSK fuzzy model under RBF neural network.

(2) Due to the complexity coupled characteristics of the system model, a two-stage optimization strategy is proposed to optimize the operation model. Combined with different confidence degree of supply security, a switching mechanism is made before economic dispatch to ensure the security degree. It adjusts the on/off state of power generators, energy storage devices and even cut off system load to keep the balance until the security degree achieves an "excellent" degree.

(3) After obtaining the on/off state of power generators, energy storage devices and system load, the GD-MOCDE

TABLE IV
THE ON/OFF STATE OF POWER GENERATORS AND SYSTEM LOAD

period	Unit1	Unit2	Unit3	Unit4	Unit5	Unit6	Unit7	Unit8	Unit9	Unit10	storage1	storage2	storage3	storage4	load
1	off	off	on	on	on	on	on	on	on	on	on	off	off	off	on
2	off	off	on	on	on	on	on	on	on	on	on	off	off	on	on
3	off	off	on	on	on	on	on	on	on	on	off	off	off	on	on
4	off	off	off	on	on	on	on	on	on	on	off	off	off	off	on
5	off	off	on	on	on	on	on	on	on	on	off	off	on	on	on
6	off	off	on	on	on	on	on	on	on	on	off	off	off	off	on
7	off	off	on	on	on	on	on	on	on	on	on	off	off	off	on
8	off	off	on	on	on	on	on	off	on	on	on	off	off	off	on
9	off	off	on	on	on	on	on	off	on	on	off	off	off	off	on
10	off	off	on	on	on	on	on	off	on	on	off	off	off	off	on
11	on	off	on	on	on	on	on	off	on	on	on	off	off	off	on
12	off	off	on	on	on	on	on	off	on	on	on	off	on	off	on
13	off	off	on	on	on	on	on	off	on	on	on	off	on	off	on
14	off	off	on	on	on	on	on	on	on	on	on	off	on	off	on
15	off	off	on	on	on	on	on	on	on	on	on	off	on	off	on
16	off	off	on	on	on	on	on	on	on	on	on	off	on	off	on
17	off	off	on	on	on	on	on	on	on	on	off	off	off	off	on
18	off	off	on	on	on	on	on	on	on	on	off	off	off	off	on
19	off	off	on	on	on	on	on	on	on	on	off	off	off	off	on
20	off	off	on	on	on	on	on	on	on	on	off	off	off	off	on
21	off	off	on	on	on	on	on	on	on	on	off	off	off	off	on
22	off	off	on	on	on	on	on	on	on	on	on	off	on	off	on
23	off	off	on	on	on	on	on	on	on	on	off	off	on	off	on
24	on	on	on	on	on	on	on	on	on	on	off	off	off	off	on

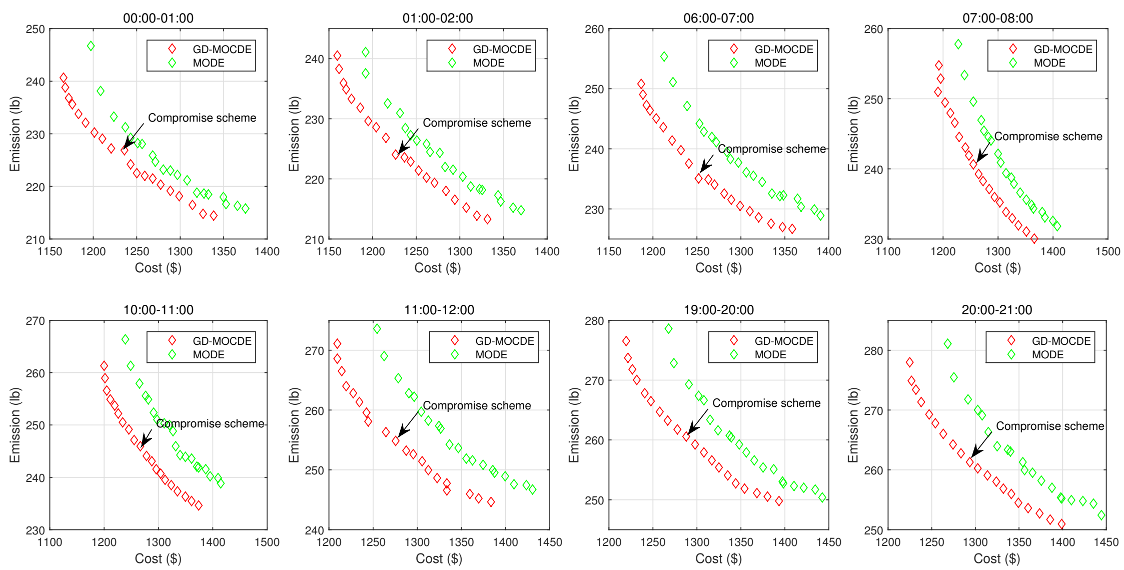

Fig. 5. Pareto optimal schemes by GD-MOCDE and MODE in some typical periods

TABLE V
THE ECONOMIC COST AND EMISSION OF SOME TYPICAL PERIODS

Periods	RO		Two stage approach	
	Cost	Emission	Cost	Emission
00:00-01:00	1780.168	223.142	1535.836	226.8745
01:00-02:00	1776.541	224.348	1526.278	224.077
06:00-07:00	1796.878	237.766	1651.548	235.0249
07:00-08:00	1903.875	239.416	1795.792	240.6667
10:00-11:00	2026.398	248.735	1966.264	245.9567
11:00-12:00	2036.938	254.179	1975.633	254.7754
19:00-20:00	2047.687	259.274	1987.835	260.6285
20:00-21:00	2054.649	261.367	1993.399	261.2676
Total	45733.04	5756.712	43130.62	5766.276

TABLE VI
THE COMPARISON OF TOTAL ECONOMIC COST ($), EMISSION RATE (LB) AND TRANSMISSION LOSS (MW) WITH RO

	RO	Two stage approach
Fuel cost	31623.432	30134.26
On/off cost of thermal unit	5571.96	4812.65
Charging/discharging cost	8537.652	8183.712
Cut-off load cost	0	0
Total cost	45733.044	43130.622
Total emission	5756.712	5766.276
Average confidence degree	0.852	0.915
Average transmission loss	78	66

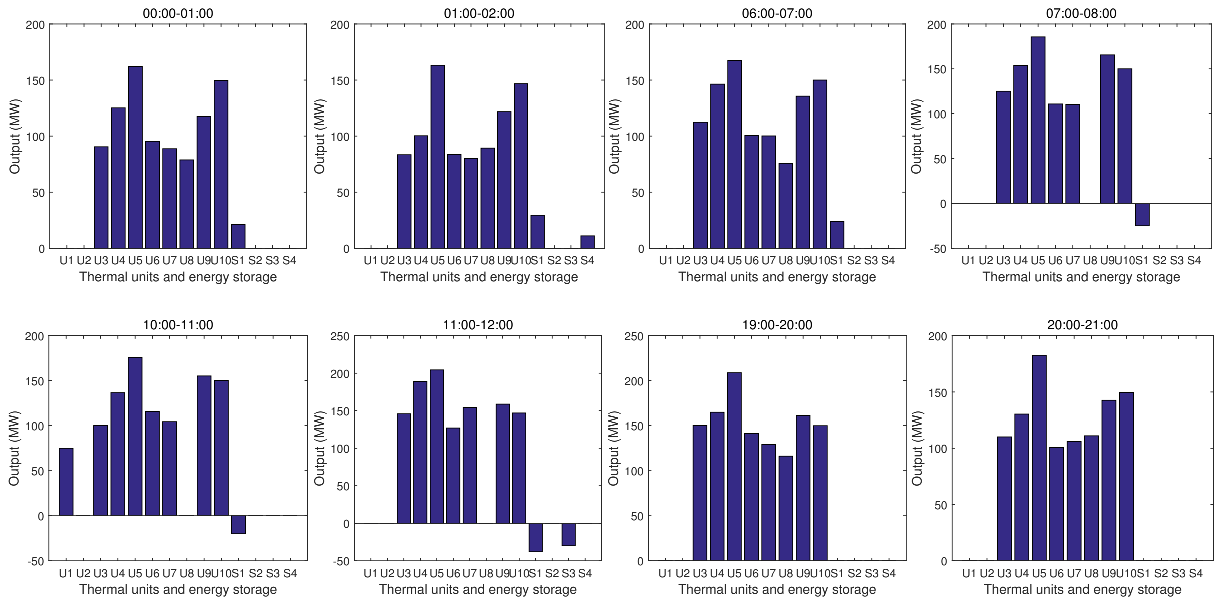

Fig. 6. The output of thermal units and energy storage in some typical periods

is utilized to optimize the economic cost and emission rate simultaneously. It searches the optimal scheme with gradient descent directions, which improves the convergence ability in comparison to MODE. With the GD-MOCDE algorithm, 20 Pareto optimal schemes are produced.

These simulation results verifies that the proposed two-stage optimization strategy with a TSK identification of supply-security can be a viable and promising approach for the optimal operation of isolated power system.

Acknowledgment

This work is supported in part by the National Natural Science key fund Under Grant 61533010 and 61833008, in part by the National Natural fund under Grant 61503199.

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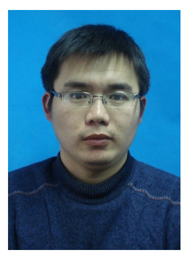

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