Lecture Series on

Intelligent Control

Lecture 27
Particle Swarm Optimization:
Multi-objective Optimization

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Multiobjective Optimal Power Plant Operation using Particle Swarm Optimization Techniques

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IEEE TRANSACTIONS ON ENERGY CONVERSION, VOL. 21, NO. 2, JUNE 2006

Contents

Introduction

- **Motivation**
  - Tighter load following requirement
  - Environmental impacts
  - Fuel consumption
  - Life extension of equipment
- **Multiobjective optimization of power plant**
  - Minimization of load tracking error
  - Minimization of pollutant emissions
  - Minimization of fuel consumption
  - Maximization of duty life

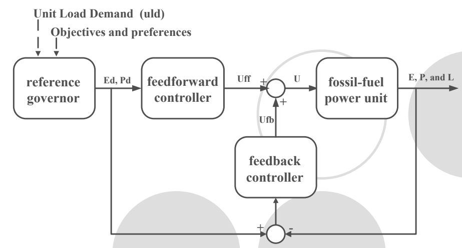
Optimal power plant operation

- Accomplishes through the optimal mapping between unit load demand and pressure set-point using the multiobjective optimization solution.

Goal of this study

- In order to realize the optimal mapping, PSO techniques are implemented in FFPU.

Control System



Ed : demand power set-point (MW)
Pd : demand pressure set-point (kg/cm^2)
Uff : feedforward control action
Ufb : feedback control action
E : power (MW)
P : pressure (kg/cm^2)
L : drum water level deviation (m)

Control structure: Coordinated Control Scheme (CCS)

- synthesize the advantages of boiler-following control and turbine-following control
- more stable and faster response

Power Unit Model

- The FFPU is 160 MW oil fired drum-type boiler-turbine generator unit.

- Third order MIMO nonlinear model with three state equations, three input $(u_1, u_2, \text{ and } u_3)$ **, three output** $(E, P, \text{ and } L)$

$$\frac{dP}{dt} = 0.9u_1 - 0.0018u_2 P^{9/8} - 0.15u_3$$

$$\frac{dE}{dt} = [(0.73u_2 - 0.16)P^{9/8} - E]/10$$

$$\frac{d\rho_f}{dt} = (141u_3 - (1.1u_2 - 0.19)P)/85$$

$$q_e = (0.85u_2 - 0.14)P + 45.59u_1 - 2.51u_3 - 2.09$$

$$\alpha_s = (1/\rho_f - 0.0015)/(1/(0.8P - 25.6) - 0.0015)$$

$$L = 50(0.13\rho_f + 60\alpha_s + 0.11q_e - 65.5)$$

- Position of valve actuators are constrained to [0,1] and their rates of change (pu/sec) are limited to :

$$-0.007 \le du_1/dt \le 0.007$$

$$-2.0 \le du_2/dt \le 0.02$$

$$-0.05 \le du_3/dt \le 0.05$$

Operating Windows

- Static equation in matrix form

$$\begin{bmatrix} 0.9 & -0.0018P^{9/8} & -0.15 \\ 0 & 0.73P^{9/8} & 0 \\ 0 & -1.1P & 141 \end{bmatrix} \begin{bmatrix} u_1 \\ u_2 \\ u_3 \end{bmatrix} = \begin{bmatrix} 0 \\ 0.16P^{9/8} + E \\ -0.19 \end{bmatrix}$$

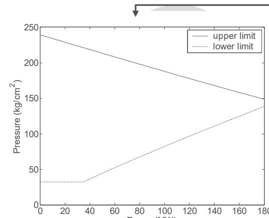
- Inverse static model

$$u_1 = (0.0018u_2 P^{9/8} + 0.15u_3)/0.9$$

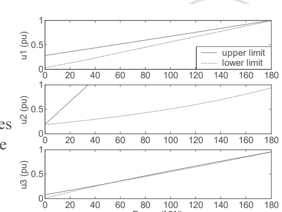
$$u_2 = (0.16P^{9/8} + E)/0.73P^{9/8}$$

$$u_3 = ((1.1u_2 - 0.19)P)/141$$

Obtain physically meaningful values of E and P



The upper and lower limit values are applied to the inverse static model.



Multiobjective Optimization

Formulation of Multiobjective Optimization Problem

- The objective functions can be described for minimization:

$J_1(u) = |E_{uld} - E_{ss}|$ ← load tracking error

$J_2(u) = u_1$ ← fuel consumption through the fuel valve actuator position

$J_3(u) = -u_2$ ← pressure control through the throttle valve actuator position

$J_4(u) = -u_3$ ← feedwater control through the feedwater valve actuator postion

E_{uld} : unit load demand

E_{ss} : the corresponding generation (MW) as provided by the steady-state equation:

$$E_{ss} = ((0.73u_2 - 0.16)/0.0018u_2)(0.9u_1 - 0.15u_3)$$

Note : In $J_3(u)$ and $J_4(u)$, maximizing u , or equivalently minimizing $-u$. Since the pressure drop increases as the valve closes, it is desired to keep it open as wide as possible. Similarly, pressure drop losses in the feedwater control valve.

1. Overview of the Basic PSO method ("IWA")

- Eberhart and Kenney developed particle swarm optimization based on the analogy of swarm of bird and school of fish.
- PSO is basically developed through simulation of bird flocking in two-dimensional space by Craig Reynolds.

- Predefine

The position of each agent : X-Y axis position

The velocity of each agent : v_x and v_y

Bird flocking optimizes a certain objective function

- Premise

Each agent knows its best value so far (Pbest) and its X-Y position

Each agent knows the best value so far in the group (gbest) among pbests

J. Kennedy and R. Eberhart, "Particle swarm optimization," *in Proc. 1955 IEEE international Conference on Neural Networks*, vol. IV, pp. 1942-1948.

- modification

Each agent tries to modify its position using the following information:

* the current position (x, y)
* the current velocities (v_x, v_y)
* the distance between the current position and pbest
* the distance between the current position and gbest

Velocity of each agent can be modified by the following equation:

$$v_i^{k+1} = wv_i^k + c_1 rand_1 \times (pbest_i - s_i^k) + c_2 rand_2 \times (gbest - s_i^k)$$

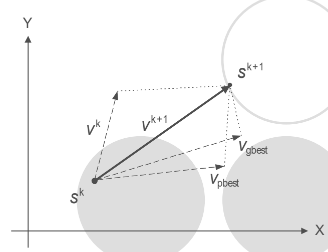
The following weighting function is usually utilized in the above equation:

$$w = w_{max} - ((w_{max} - w_{min})/(iter_{max})) \times iter$$ ← Inertia Weigt Approach (IWA)

The current position (search point in the solution space) is modified by the following equation:

$$s_i^{k+1} = s_i^k + v_i^{k+1}$$

- Concept of modification of a search point by PSO



s^k : current search point

s^{k+1} : modified search point

v^k : current velocity

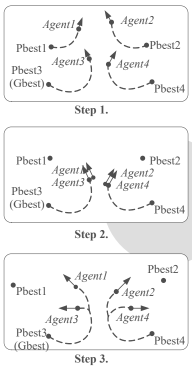
v^{k+1} : modified velocity

v_{pbest} : velocity based on pbest

v_{gbest} : velocity based on gbest

https://commons.wikimedia.org/wiki/File:ParticleSwarmArrowsAnimation.gif#/media/File:ParticleSwarmArrowsAnimation.gif

2. Hybrid PSO (HPSO): Natural selection mechanism such as "GA's"



Evaluations of Agents1 & 2 are low and those of Agents 3 & 4 are high

Search points of Agents 1 & 2 are changed to those of Agents 3 & 4 by the selection mechanism

New search is begun from the new search points

- The effect of pbest and gbest is gradually vanished by the selection, and broader area search can be realized
- pbest information of each agent is maintained
- Both intensive search in a current effective area and dependence on the past position with high evaluation are realized at the same time

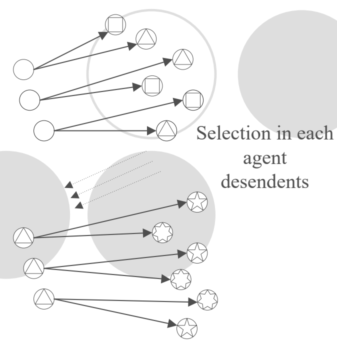
3. Evolutionary PSO (EPSO): $\sigma-$SA(Self Adapting) evolutionary stratagy

- Explicit selection procedure and self-adapting properties for its parameters

- The general scheme of EPSO is the following:

REPLICATION: each agent is replicated *r* times
MUTATION: each agent has its weights mutated
REPRODUCTION: each mutated agent generates an offspring according to the agent movement rule
EVLAUATION: each offspring has its fitness evaluated
SELECTION: by stochastic tournament the best agents survive to form a new generation

- Mutation and Selection by elitism



-The movement rule for EPSO is the following:

$$v_i^{new} = w_{i0}^* v_i + w_{i1}^* (pbest_i - s_i) + w_{i2}^* (gbest^* - s_i)$$
$$w_{ik}^* = w_{ik} + \tau \cdot N(0,1)$$
$$gbest^* = gbest + \tau' \cdot N(0,1)$$
$$s_i^{new} = s_i + v_i^{new}$$

w : the weights which undergo mutation.
$gbest$: the group best distributed randomly.
τ, τ' : the learning parameters (either fixed or treated also as strategic parameters, and therefore also subject to mutation).
$N(0,1)$: a random variable with Gaussian distribution, 0 mean and variance 1.

4. Constriction Factor Approach (CFA)

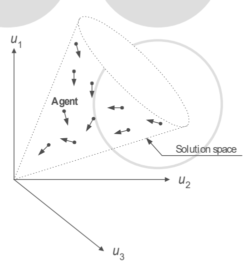
- Totally different from IWA
- The main algorism is similar to damping in control system
- Using the velocity equation with factor K

$$v_i^{k+1} = K\left[v_i^k + c_1 \times rand(\ ) \times \left(pbest_i - s_i^k\right) + c_2 \times rand(\ ) \times \left(gbest - s_i^k\right)\right]$$
$$K = \frac{2}{\left|2 - \varphi - \sqrt{\varphi^2 - 4\varphi}\right|}, \quad where\ \varphi = c_1 + c_2,\ \varphi > 4$$

PSO method for Multiobjective Optimal Power Plant Operation

Step 1. initialization

- select values of the factors (number of agent = 40, number of iteration = 130, $c=2$, w_{max} = 0.9 , w_{min} = 0.3, and random generation of *rand*)
- random generation of the initial agents (=positions) in the solution space (the position vectors are expressed by u_1, u_2, and u_3)
- random generation of the initial velocities in the same solution space



Step 2. Evaluation

- The evaluation for search point: use the deviation of multi-objective function which is weighted with preference value
- The maximum deviation of multiobjective function is as following:

$$\delta_m = \max_{i=1,\dots,k} \delta_{pi} \qquad \delta_{pi} \ge 0$$
$$\delta_{pi} = \beta(J_i(u) - J_i(u)^*) \qquad i = 1, 2, \dots, k \quad u \in \Omega$$
$$J_i^* = \min\{J_i(u); u \in \Omega\} \qquad i = 1, 2, \dots, k$$

δ_m : maximum deviation of multiobjective function
δ_{pi} : each weighed deviation
β : preference value
J_i : each objective function
J_i^*: each optimal cost value of objective function
Ω : the solution space

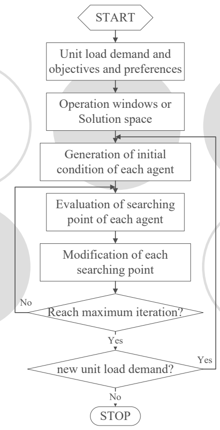
Step 3. Modification

- Using Basic PSO method: $v_i^{k+1} = wv_i^k + c_1 rand_1 \times (pbest_i - s_i^k) + c_2 rand_2 \times (gbest - s_i^k)$
- first term: corresponding to diversification in the search procedure
- second and third terms: corresponding to intensification in the search procedure
- using weigh function: $w = w_{\max} - ((w_{\max} - w_{\min})/(iter_{\max})) \times iter$
- updating current position: $s_i^{k+1} = s_i^k + v_i^{k+1}$

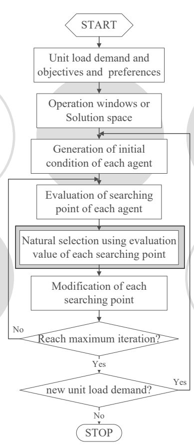
Step 4. Checking the Exit Condition

- If the current iteration number reaches $iter_{max}$, then exit
- If the unit load demand is changed, it starts again from the initialization.

- Total flow chart of **PSO** in the FFPU

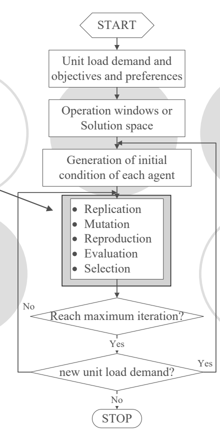


- Total flow chart of **HPSO** in the FFPU



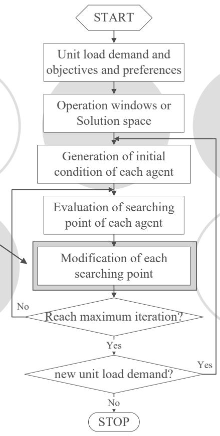
- Total flow chart of **EPSO** in the FFPU

Change the equations from the conventional PSO's.



- Total flow chart of **CFA** in the FFPU

Change the equations from the conventional PSO's.



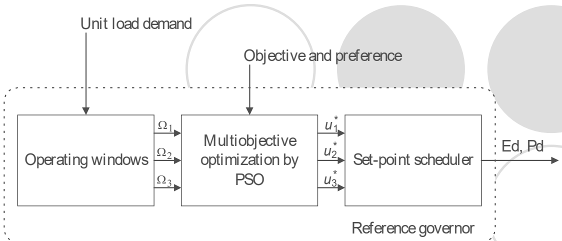
Set-point Scheduler

- The obtained optimal solutions are mapped into demand set-points through the set-point scheduler
- Set-point scheduling equation:

$$Ed = ((0.73u_2^* - 0.16)/(0.0018u_2^*))(0.9u_1^* - 0.15u_3^*)$$
$$Pd = 141u_3^*/(1.1u_2^* - 0.19)$$

Reference Governor

Configuration of reference governor



Ω : solution space , u : optimal solution in the solution space
Ed : demand power set-point , Pd : demand pressure set-point

Simulation Results

Simulations deal with three different cases

case 1 : "1-objective" → $J_1(u) = |E_{uld} - E_{ss}|$ $\beta = [1]$

case 2 : "2-objective" → $J_1(u) = |E_{uld} - E_{ss}|$, $J_2(u) = u_1$ $\beta = [1 \quad 0.5]$

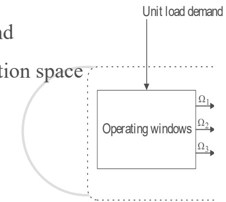
case 3 : "4-objective" → $J_1(u) = |E_{uld} - E_{ss}|$, $J_2(u) = u_1$, $J_3(u) = -u_2$, $J_4(u) = -u_3$ $\beta = [1 \quad 0.5 \quad 1 \quad 0]$

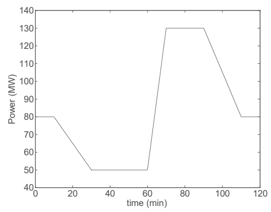
Note : the preference values mean 1 is the highest and 0 is the lowest

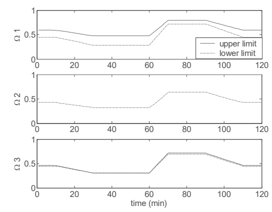
- The simulation process is similar to the procedure of reference governor!

Basic PSO method

- Given Unit load demand
- the corresponding solution space Ω_1, Ω_2, and Ω_3







Basic PSO method

Objective functions

$J_1(u) = |E_{uld} - E_{ss}|$

$J_2(u) = u_1$

$J_3(u) = -u_2$

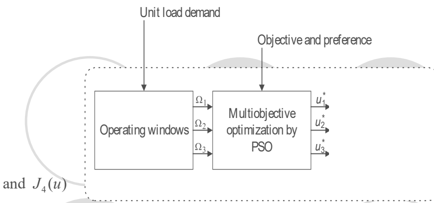
$J_4(u) = -u_3$

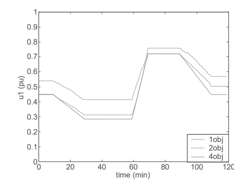
1-objective : $J_1(u)$

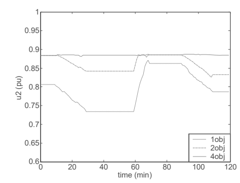
2-objective : $J_1(u)$ and $J_2(u)$

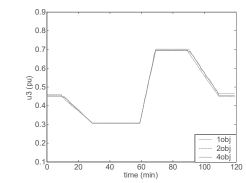
4-objective : $J_1(u)$, $J_2(u)$, $J_3(u)$, and $J_4(u)$

$\beta = [1 \quad 0.5 \quad 1 \quad 0]$



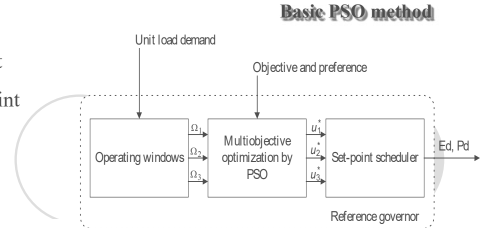


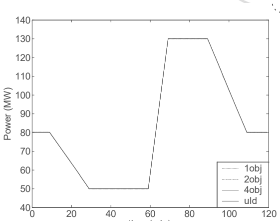


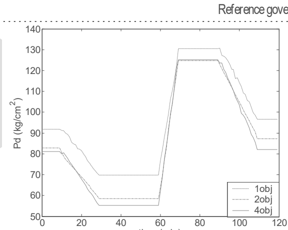


Basic PSO method

- demand power set-point
- demand pressure set-point

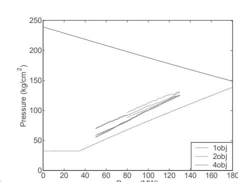


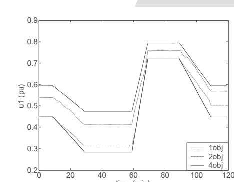


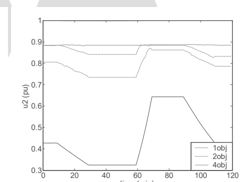


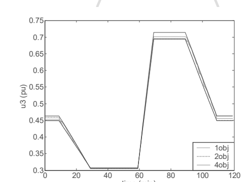
Basic PSO method

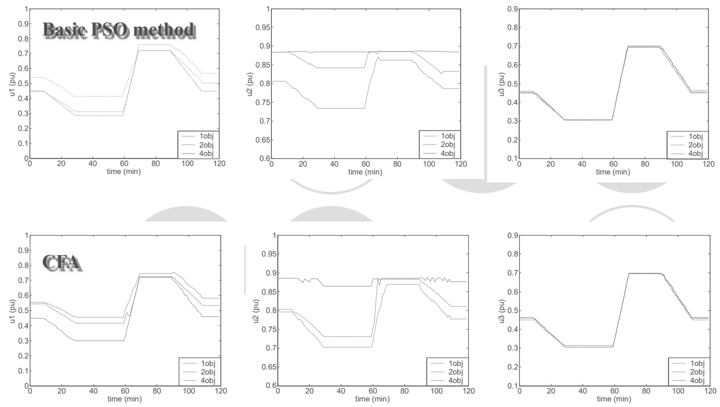
- Confirm the set-points by the power-pressure operating window

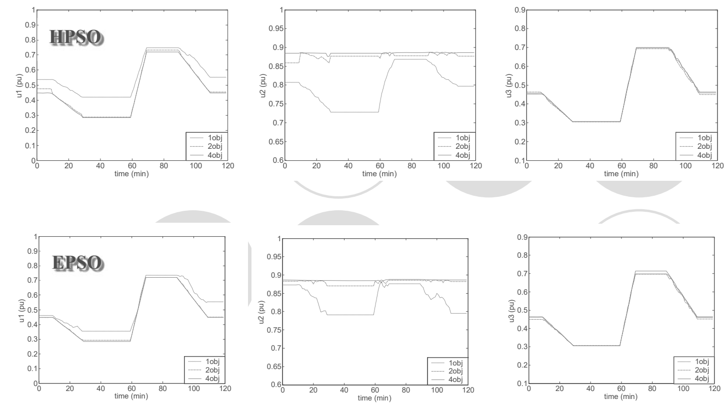




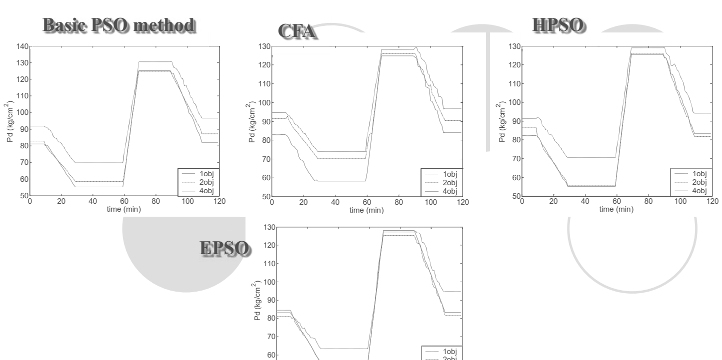




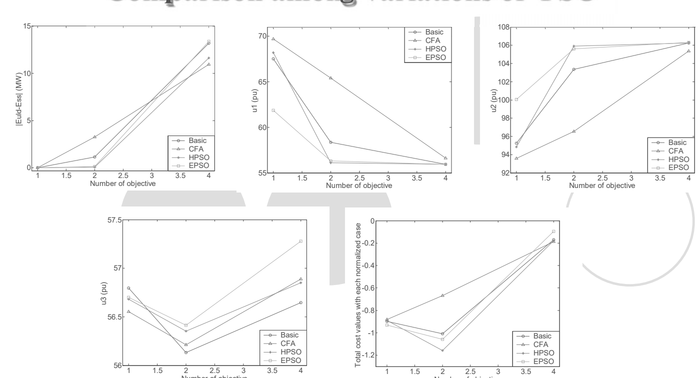




Demand pressure set-point



Comparison among variations of PSO



Conclusion

- The multi-objective optimization is performed through the basic PSO technique.
- The optimal mapping between unit load demand and pressure set-point is realized with a variable time.
- Variations of the PSO technique improve the performance of the basic PSO method.
- Hybrid PSO and EPSO techniques are shown to perform better compared to the basic PSO and the CFA techniques.
- Real-time operation is feasible by using the mappings generated by the PSO techniques.

Q & A