Application of adaptive genetic-simplex algorithm in parameter optimization of nuclear power components

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Abstract: An adaptive genetic-simplex algorithm for parameter optimization in nuclear power plant is proposed by using adaptive crossover and mutation techniques and integrating genetic algorithm with simplex algorithm. The modified algorithm enables the handing of nonlinear constrained optimization problem because of dramatically improved search capability. Performance comparison between the proposed algorithm and original ones is performed by solving the optimization test problem. To implement parameter optimization in nuclear power plant, the mathematical models of electric heating pressurizer and natural circulation steam generator are established. Finally, by using the modified algorithm, the optimization of steam generator and pressurizer aiming at minimizing weight and volume is implemented respectively. It has been found that the modified algorithm finds global optimal solution effectively in all algorithm tests while the original algorithms only make it in some of the tests. For parameter optimization, the weight and volume of steam generator decreases by 18.56% and 18.39% respectively, and the decrements are 16.54% and 18.97% for that of pressurizer. It is demonstrated that the adaptive genetic-simplex algorithm is capable of dealing with the optimization of nuclear power components. The optimization in this study may provide effective guide for engineering design.

Keyword: parameter optimization; steam generator; pressurizer; adaptive genetic-simplex algorithm

1 Introduction

Optimization methodology has been widely applied to the design of nuclear power plant, such as core design[1][2], fuel loading and management[3][4], system surveillance tests[5], *etc.* In recent years, the capacity of new designed nuclear power units has reached a high level (*i.e.*, 1750MW for EPR unit), which enlarges the size of nuclear power components. This is a concern not only because of difficult in manufacture, transportation and layout of large equipment but also because of increasing cost. The situation makes the researchers use optimization methodology to control or decrease the size and weight of nuclear power components. LIU *et al.* [6] minimized the weight and volume of a condenser using a modified genetic algorithm, and the reduction of the weight and volume was 6.926% and 12.587%. By using a complex algorithm to determine optimal set-points of primary loop pressure, inlet and outlet temp erature of core, U-tube outer diameter, tube pitch and coolant flow velocity, QIN[7] *et al.* minimize the weight of a steam generator(SG), and 17.16% off was achieved. LIU[8] *et al.* minimized the weight of a pressurizer by redesigning the system pressure, inlet and outlet temperatures of the core, inner diameter of the pressurizer, and the optimized volume was 15.3% of the original design.

Parameter optimization of nuclear power components is an approach that determines an optimal set of design parameters to minimize/maximize the objective in the presence of thermal-hydraulic and safety restrictions, which belongs to complex nonlinear constrained optimization problem. In order to solve the problem effectively, an optimization algorithm with strong search capability is indispensable. Simple genetic algorithm (SGA) is intuitionistic and easy to operate, but its convergence rate is slow and premature convergence often appears.

Using finite homogeneous Markov chain theory, Rudolph[9] proved SGA can't ensure that optimization converges to the global optimum. Srinvivas[10] *et al.* developed an adaptive technique that adapts the crossover probability and mutation probability according to individual fitness, group maximum

Received date: April 1, 2016
(Revised date: June 2, 2016)

fitness and average fitness. It ensures the group diversity and has been used in many studies[11][12]. Simplex algorithm (SA) is widely used in nonlinear function optimization because no differential is needed. It has strong search ability in local region but the global search ability is limited[13].

In fact the algorithm can't promise an optimal design if the search ability isn't strong enough. Hence, adaptive genetic-simplex algorithm (AGSA) is proposed in this work. The AGSA takes advantage of different algorithms by integrating adaptive techniques, genetic algorithm and simplex algorithm, which extremely enhances algorithm's search ability. The works conducted by QIN[7] *et al.* and LIU[8] *et al.* only concentrated on weight minimization, in this work component volume is also taken into account.

The paper is structured as follows, Section 2 presents the adaptive genetic-simplex algorithm and algorithm tests are also conducted. Section 3 presents the mathematical models of steam generator and pressurizer and the validation of the models is also presented. Section 4 presents the optimization of steam generator and pressurizer and the results are analyzed. Finally, concluding remarks and a discussion of future work are provided in section 5.

Nomenclature

Variables		ρ_3	density of SG U-tube, kg/m^3
D_{lho}	outer diameter of SG lower head, m	C_0	coefficient decided by SG critical heat load
D_{lhi}	inner diameter of SG lower head, m	υ'	specific volume of SG saturation steam, m^3/kg
D_l	inner diameter of SG lower shell, m	υ''	specific volume of SG saturation water, m^3/kg
D_u	inner diameter of SG upper shell, m	σ'	surface tension of SG saturation water, N/m
D_{ts}	diameter of SG tube sheet, m	μ'	viscosity coefficient of SG saturation water, Pa•s
d	diameter of tube hole on the tube sheet, m	D_{pi}	inner diameter of pressurizer, m
d_o	outer diameter of U-tube, m	h_{sp}	height of pressurizer shell, m
d_i	inner diameter of U-tube, m	h_{up}	height of pressurizer upper head, m
H_u	height of SG upper shell, m	h_{lp}	height of pressurizer lower head, m
H_l	height of SG lower shell, m	h_{st}	straight flange height of pressurizer head, m
L	length of U-tube, m	t_{up}	thickness of pressurizer upper head, m
N	number of U-tube	t_{lp}	thickness of pressurizer lower head, m
t_{ts}	thickness of tube sheet, m	t_{sp}	thickness of pressurizer shell, m
t_u	thickness of SG upper shell, m	S	allowable stress of pressurizer material, MPa
t_l	thickness of SG lower shell, m	E	lowest efficiency of any joint in pressurizer head
t_{uh}	thickness of SG upper head, m	c_1, c_2, c_3	additional thickness of pressurizer material, m
L	liquid level meter range, m	ρ_P	the density of pressurizer materials, m^3/kg
ρ_1	density of SG shell, kg/m^3	W_e	weight of one electric heater in pressurizer, kg
ρ_2	density of SG tube sheet, kg/m^3	N_e	the number of electric heater in pressurizer

2 Adaptive genetic-simplex algorithm

Genetic algorithm searches the optimal solution by simulating the biological evolution of Darwin Evolution Theory. Every individual in the evolution group represents a solution. The key operations are crossover, mutation and selection. By implementing these operations cyclically, good solutions are generated and protected and thus the group approximate to the optimal solution little by little.

Simplex algorithm is a deterministic search method based on geometry polyhedron. A N-dimensional convex polyhedron called simplex transforms its shape continuously in N-dimensional search space using reflection, expansion, contraction and reconstruction operation. Every vertex of the simplex represents a solution and thus the search space represents the solution space. By implementing the search, the inferior solutions are replaced by new ones and the simplex approximates to the optimal solution gradually.

2.1 Adaptive techniques

In genetic algorithm, crossover probability P_c and mutation probability P_m is manually set as fixed value. The two parameters have significant effect on algorithm's performance, such as search ability and convergence rate. Crossover probability determines the generation rate of new individuals. The larger the crossover probability is, the faster the generation of new individuals is. Too large a crossover probability may destroy good individual structure, while too small a crossover probability may slow down the search process and lead to prematurity. Mutation probability is the key factor to help algorithm jump out of local optimum. An excessively small mutation probability makes it difficult to generate new individual structures, but the GA will become a random search algorithm if the mutation probability is too large. In the evolution (search process) we hope that the good individual structures be protected and the bad individual structures be replaced by new ones. Obviously it's impossible if all the individuals are assigned with same crossover and mutation probability, because all the individuals have the same probability to be inherited/replaced. To overcome the defects, Srinvivas proposes an adaptive genetic algorithm that adaptively adjusts the crossover and mutation probability according to individual fitness (Fitness measures the individual quality). The adaptive crossover and mutation probability is calculated by formula (1) and formula (2).

$$P_c = \begin{cases} P_{c1} - \dfrac{(P_{c1} - P_{c2})(f' - f_{avg})}{f_{max} - f_{avg}}, & f' \geq f_{avg} \\ P_{c1}, & f' < f_{avg} \end{cases} \tag{1}$$

$$P_m = \begin{cases} P_{m1} - \dfrac{(P_{m1} - P_{m2})(f - f_{avg})}{f_{max} - f_{avg}}, & f \geq f_{avg} \\ P_{m1}, & f < f_{avg} \end{cases} \tag{2}$$

Where f_{max} is the largest fitness value in group, f_{avg} is the average fitness value of group, f' is the larger fitness value of the two crossover individuals, f is the fitness value of the mutation individual, P_{c1} is the maximum of crossover probability, P_{c2} is the minimum of crossover probability, P_{m1} is the maximum of mutation probability, P_{m2} is the minimum of mutation probability. Crossover probability generally ranges from 0.4 to 0.9, mutation probability generally ranges from 0.001 to 0.1.

The individual whose fitness is larger than the average value will be automatically assigned with small crossover and mutation probability to protect its individual structure. And the individual whose fitness is smaller than the average value would be distributed with large crossover and mutation probability so as to eliminate the poor individual structure. The adaptive crossover and mutation probability techniques can not only maintain the group diversity but also ensure the convergence of algorithm, which can effectively improve the algorithm's search ability.

2.2 Algorithms integration

GA is a heuristic and global optimization algorithm while SA is a deterministic and local one. They are complementary in search capacity: GA has strong global search ability but weak local search ability, SA, in contrast, has strong local search ability but weak global search ability. The proposed AGSA integrates GA, SA and adaptive techniques. The algorithm process is specified in Fig.1. It enhances search capacity by complementary mechanism. In initial and middle stage of search, AGSA has strong global search ability by performing genetic operations, which enables the group evolve in large range to find out the neighborhood space of global optimum. In late stage of search, simplex operations bring AGSA strong local search ability, which enables the group evolve in small range to find out the global optimum. Adaptive crossover and mutation probability are introduced in genetic operation to further improve AGSA's global search ability at initial and middle stage.

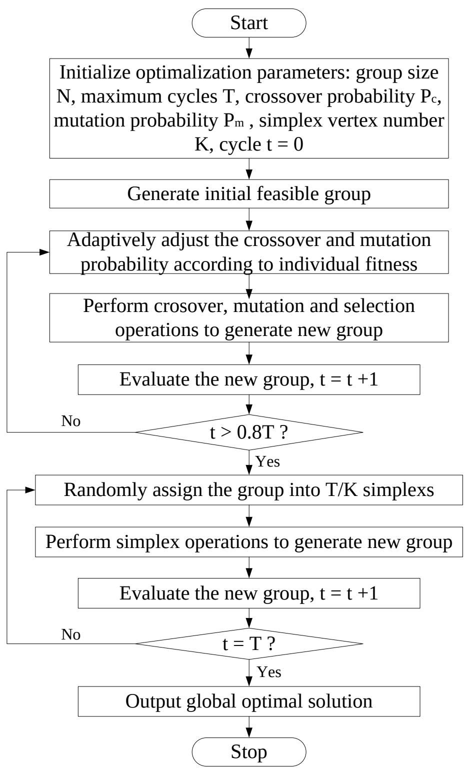

Fig.1 Flow chart of GSA.

2.3 Algorithms test

Two representative standard test problems proposed by Runarsson T. P. *et al.* for optimization algorithm are cited in this work[14]. They are nonlinear optimization problems with complex constraints, which can effectively determine algorithm's performance. The details of the test functions are given by formula (3) and (4).

Standard test function g06:

$$\begin{cases} \min f(\mathbf{X}) = (x_1-10)^3 + (x_2-20)^3, \\ g_1(\mathbf{X}) = -(x_1-5)^2 - (x_2-5)^2 + 100 \le 0, \\ g_2(\mathbf{X}) = (x_1-6)^2 + (x_2-5)^2 - 82.81 \le 0. \end{cases} \tag{3}$$

Standard test function g09:

$$\begin{cases} \min f(\mathbf{X}) = (x_1-10)^2 + 5(x_2-12)^2 + {x_3}^4 + 10{x_5}^6 \\ \quad +3(x_4-11)^2 + 7{x_6}^2 + {x_7}^4 + 4x_6x_7 - 10x_6 - 8x_7, \\ g_1(\mathbf{X}) = -127 + 2{x_1}^2 + 3{x_2}^4 + x_3 + 4{x_4}^2 + 5x_5 \le 0, \\ g_2(\mathbf{X}) = -282 + 7x_1 + 3x_2 + 10{x_3}^2 + x_4 - x_5 \le 0, \\ g_3(\mathbf{X}) = -196 + 23x_1 + {x_2}^2 + 6{x_6}^2 - 8x_7 \le 0, \\ g_4(\mathbf{X}) = 4{x_1}^2 + {x_2}^2 - x_1x_2 + 2{x_3}^2 + 5x_6 - 11x_7 \le 0. \end{cases} \tag{4}$$

For g06: $13 \le x_1 \le 100$ and $0 \le x_2 \le 100$. The optimum solution is $\mathbf{X} = (14.095, 0.84296)$, $f(\mathbf{X}) = -6961.81388$. Both inequality constraints are active and its feasibility ratio is only 0.0057%. For g09: $-10 \le x_i \le 10$, where $i = 1,\ldots,7$. The optimum solution is $\mathbf{X} = (2.330499, 1.951372, -0.4775414, 4.365726, -0.6244870, 1.038131, 1.594227)$, where $f(\mathbf{X}) = 680.6300573$. Two inequality constraints are active (g1 and g4) and its feasibility ratio is 0.5199%. Both g06 and g09 are multimodal function. Problem g09 has higher complexity because it has more variables and inequality constraints, though its feasibility ratio is much larger than that of g06.

The tests of the AGSA, GA and SA are carried out by optimization experiments of problem g06 and g09. The involved algorithm parameters are listed as follows: for all algorithms, group size $N = 120$, maximum cycle $T = 200$. For AGSA, $P_{c1} = 0.9$, $P_{c2} = 0.4$, $P_{m1} = 0.1$, $P_{m2} = 0.001$. For GA, $P_{c1} = 0.6$, $P_{m1} = 0.01$. For SA, K is 3 for g06 and 8 for g09.

Figure 2 and 3 present the performance comparison of the AGSA, GA and SA for g06 and g09 problem. In the experiment of g06 problem, AGSA found global optimum at 87th cycle and GA made it at 188th cycle, while SA was not able to found the global optimal solution. In the experiment of g09 problem, AGSA found the global optimum at 191th cycle, while both GA and SA fell into local optimums. In the optimization experiments of nonlinear constrained problems, AGSA performed significantly better than GA and SA. Even though GA found the global optimum of g06 problem, it achieved the goal at the late stage of search, which was much inefficient when compared with AGSA.

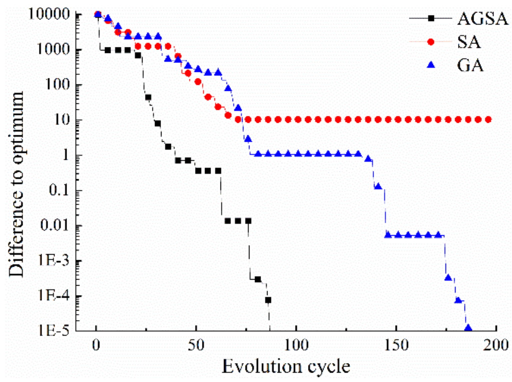

Fig.2 Experimental results for problem g06.

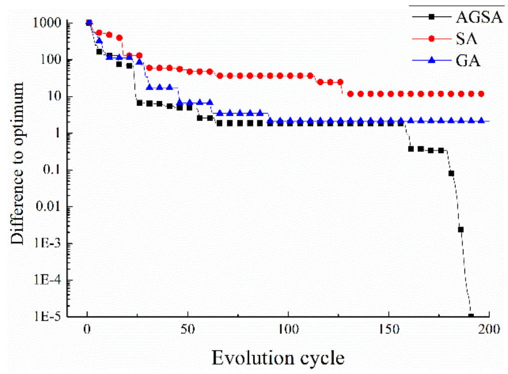

Fig.3 Experimental results for problem g09.

3 Mathematical models

In this section mathematical models of vertical natural-circulation steam generator and vertical electric-heating pressurizer are presented for determining the weight and volume of the equipment according to input parameters.

3.1 Mathematical model of steam generator

The vertical natural-circulation steam generator used in NPP provides means of transferring heat from the primary loop to the secondary loop. As shown in Fig.4, coolant of primary loop enters the steam generator inlet chamber via inlet nozzle, flows up through the tube sheet and U-bend tube, where the heat is transferred to the working fluid of secondary loop, then the coolant returns through the tube sheet to the steam generator outlet chamber and exits via outlet nozzle. In secondary loop section, the feedwater enters steam generator via the feedwater nozzle, mixes with the water removed by the moisture separators, and flows into the evaporation region (tube bundle region) through an annular downcomer formed by the pressure shell and tube wrapper. In the evaporation region, the feedwater is heated and boil happens, the steam-water mixture flows up through the moisture separator and steam dryer, where the steam is separated and flows out via the steam outlet nozzle.

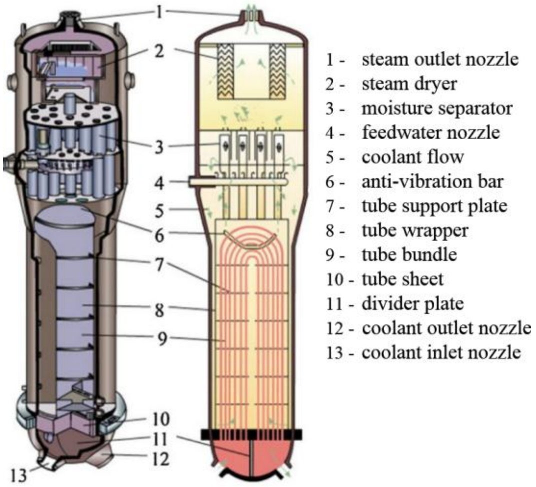

Fig.4 structure diagram of vertical natural circulation SG.

The mathematical model of vertical natural-circulation steam generator includes preliminary design and weight and volume calculation. Figure 5 presents the whole procedure of the model.

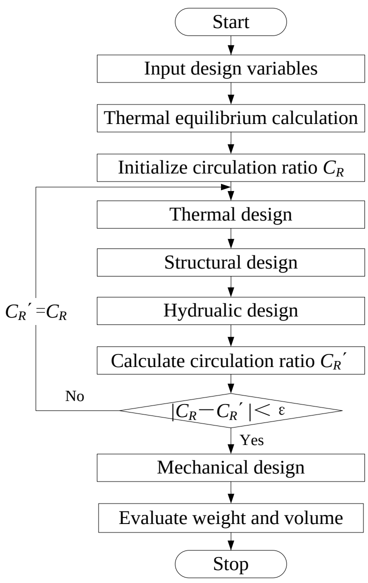

Fig.5 Flow chart of SG mathematical model.

3.1.2 Weight and volume calculation

1. Weight calculation

The steam generator mainly consists of lower head, tube sheet, tube bundle, lower shell, conical shell, upper shell, upper head, moisture separator and accessories. The formulas for weight and volume of these components are given as below.

The weight of lower head

$$W_1 = \frac{\pi}{12}\left({D_{lho}}^3 - {D_{lhi}}^3\right)\rho_1 \tag{5}$$

The weight of tube sheet

$$W_2 = \frac{\pi}{4}\left({D_{ts}}^2 - 2Nd^2\right)t_{ts}\rho_2 \tag{6}$$

The weight of tube bundle

$$W_3 = \frac{\pi}{4}\left({d_o}^2 - {d_i}^2\right)L\rho_3 \tag{7}$$

The weight of lower shell

$$W_4 = \frac{\pi}{4}\left[(D_l + 2t_l)^2 - {D_l}^2\right]H_l\rho_1 \tag{8}$$

The weight of conical shell

$$W_5 = \frac{\pi}{24}\cot\alpha\left[(D_u + 2t_u)^3 - (D_l + 2t_l)^3 - {D_u}^3 + {D_l}^3\right]\rho_1 \tag{9}$$

The weight of upper head

$$W_7 = \frac{\pi}{24}\left\{(D_u + 2t_{uh})^3 - {D_u}^3 + 6\left[(D_u + 2t_{uh})^2 - {D_u}^2\right]h\right\}\rho_1 \tag{10}$$

The weight of moisture separator can be estimated using formula proposed in Ref. [9].

$$W_8 = C_o B M_g C_R \sqrt{\frac{v''}{\sigma'}}\sqrt[3]{\mu' v'} \tag{11}$$

The weight of upper shell

$$W_6 = \frac{\pi}{4}\left[(D_u + 2t_u)^2 - {D_u}^2\right]H_u\rho_1 \tag{12}$$

The total weight of steam generator

$$W_{SG} = W_1 + W_2 + W_3 + W_5 + W_6 + W_7 + W_8 + W_9 \tag{13}$$

Where W_9 is the weight of accessories.

2. Volume calculation

The volume of lower head

$$V_1 = \frac{\pi}{12}{D_{lho}}^3 \tag{14}$$

The volume of lower shell

$$V_2 = \frac{\pi}{4}(D_l + 2t_l)^2 H_l \tag{15}$$

The volume of conical shell

$$V_3 = \frac{\pi}{24}\cot\alpha\left[(D_u + 2t_u)^3 - (D_l + 2t_l)^3\right] \tag{16}$$

The volume of upper shell

$$V_4 = \frac{\pi}{4}(D_u + 2t_u)^2 H_u \tag{17}$$

The volume of upper head

$$V_5 = \frac{\pi}{24}\left[(D_u + 2t_{uh})^3 + 6(D_u + 2t_{uh})^2 h\right] \tag{18}$$

The total weight of steam generator

$$V_{SG} = V_1 + V_2 + V_3 + V_4 + V_5 \quad (19)$$

3.1.3 Model validation

Table 1 presents the comparison between the model evaluation results and actual parameter values of Qinshan I steam generator[15]. One can see that the evaluation results are reasonably accurate as all the relative errors are within 4% when compared with actual values, which means the mathematical model can be applied for optimization design.

Table 1 Model evaluation results of Qinshan I SG

Parameters	Actual value	Evaluate value	Error (%)
U-tube number	2975	2975	0
Heat transfer area/m^2	3072.9	3067.31	-0.18
U-tube height/m	8.282	8.322	0.48
SG height/m	17.278	17.196	-0.47
SG volume/m^3	151.24	154.77	2.33
SG weight/t	208.6	206.32	-1.09

3.2 Mathematical model of pressurizer

The vertical electric-heating pressurizer in NPP plays a key role in controlling and stabilizing the pressure of primary loop. The mathematical model of pressurizer includes volume design, mechanical design, and weight and volume calculation. The volume design determines the volume of different parts; the mechanical design gives the dimensions of pressurizer and material thickness. Based on the pressurizer dimensions and material density, the pressurizer weight and volume are derived finally.

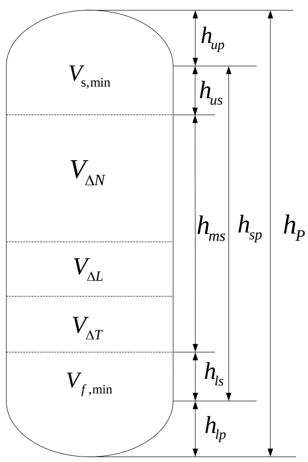

Fig.6 Volume constituent and dimension of pressurizer.

3.2.1 Volume design

Pressurizer volume design follows strict design criterion so as to fulfill pressure control requirement of primary loop under all working conditions. Transient analysis of pressurizer typical operation modes is indispensable in volume design. As shown in Fig. 6, the pressurizer volume is divided into steady-state minimum steam volume $V_{s,min}$, steady-state liquid-level change volume $V_{l,c}$ and steady-state minimum water volume $V_{w,min}$. The steady-state liquid-level change volume consists of three parts: steady-state power change volume $V_{\Delta N}$, liquid level meter deviation volume $V_{\Delta L}$, volume of temperature measurement deviation and control dead zone $V_{\Delta T}$. For transient analysis and volume derivation see Refs. [16] [17].

3.2.2 Mechanical design

For mechanical design, the inner diameter of pressurizer D_{pi} is taken as design variable. As the upper and lower head are standard ellipsoidal shape, the heights presented in Fig.6 can be derived directly.

$$h_{us} = \left(V_{s.min} - \frac{\pi}{24} D_{Pi}{}^3\right) / \left(\frac{\pi}{4} D_{Pi}{}^2\right) \quad (20)$$

$$h_{ls} = \left(V_{w.min} - \frac{\pi}{24} D_{Pi}{}^3\right) / \left(\frac{\pi}{4} D_{Pi}{}^2\right) \quad (21)$$

$$h_{ms} = (V_{\Delta N} + V_{\Delta L} + V_{\Delta T}) / \left(\frac{\pi}{4} D_{Pi}{}^2\right) \quad (22)$$

$$h_{sp} = h_{us} + h_{ls} + h_{ms} \quad (23)$$

$$h_{up} = h_{lp} = D_{Pi}/4 + h_{st} \quad (24)$$

$$h_P = h_{sp} + h_{up} + h_{lp} \quad (25)$$

The material thickness of pressurizer is calculated according to the norms of ASME boiler and Pressure Vessel Code.

Thickness of upper head

$$t_{up} = \frac{P_1 D_{Pi}}{2SE - 0.2P_1} + c_1 \quad (26)$$

Thickness of lower head

$$t_{lp} = \frac{P_1 D_{Pi}}{2SE - 0.2P_1} + c_2 \quad (27)$$

Thickness of cylindrical shell

$$t_{sp} = \frac{0.5 P_1 D_{Pi}}{2SE - 0.6P_1} + c_3 \quad (28)$$

3.2.3 Weight and volume calculation

The pressurizer consists of upper and lower head, cylindrical shell, electric heater and accessories (*e.g.* spray lines, foundation support and manhole cover). The formulas for weight and volume of these components are listed as below.

1. Weight calculation

The weight of upper head

$$W_{uh} = \frac{\pi}{24}\{\left(D_{Pi} + 2t_{up}\right)^3 - {D_{Pi}}^3 + 6\left[\left(D_{Pi} + 2t_{up}\right)^2 - {D_{Pi}}^2\right]h_{st}\}\rho_P \tag{29}$$

The weight of lower head

$$W_{lh} = \frac{\pi}{24}\{\left(D_{Pi} + 2t_{lp}\right)^3 - {D_{Pi}}^3 + 6\left[\left(D_{Pi} + 2t_{lp}\right)^2 - {D_{Pi}}^2\right]h_{st}\}\rho_P \tag{30}$$

The weight of cylindrical shell

$$W_s = \frac{\pi}{4}\left[\left(D_{Pi} + 2t_{sp}\right)^2 - {D_{Pi}}^2\right]h_{sp}\rho_P \tag{31}$$

The weight of electric heating elements

$$W_h = W_e N_e \tag{32}$$

The total weight of pressurizer

$$W_P = W_{uh} + W_{lh} + W_s + W_h + W_a \tag{33}$$

Where W_a is the weight of accessories.

2. Volume calculation

The volume of upper head

$$V_{uh} = \frac{\pi}{24}\left(D_{Pi} + 2t_{up}\right)^3 + \frac{\pi}{4}\left(D_{Pi} + 2t_{up}\right)^2 h_{st} \tag{34}$$

The volume of lower head

$$V_{lh} = \frac{\pi}{24}\left(D_{Pi} + 2t_{lp}\right)^3 + \frac{\pi}{4}\left(D_{Pi} + 2t_{lp}\right)^2 h_{st} \tag{35}$$

The volume of cylindrical shell

$$V_s = \frac{\pi}{4}\left(D_{Pi} + 2t_{sp}\right)^2 h_{sp} \tag{36}$$

The total volume of pressurizer

$$V_P = V_{uh} + V_{lh} + V_s \tag{37}$$

3.2.4 Model validation

Table 2 presents the comparison between the model evaluation results and actual values of Qinshan I pressurizer[15]. One can see that all the relative errors are within 2% when compared with actual values. It indicates that the mathematical model is accurately enough to be applied for optimization design.

Table 2 Evaluation results of Qinshan I pressurizer

Parameters	Actual value	Evaluation value	Error (%)
Pressurizer height/m	7.74	7.61	-1.68
Pressurizer diameter/m	2.6	2.6	0
Pressurizer volume/m^3	35	34.6	-1.14
Pressurizer weight/t	89	89.8	0.9

4 Optimization design

Based on the modified optimization algorithm proposed in section 2 and the mathematical models established in section 3, the weight and volume optimization of Qinshan I steam generator and pressurizer are implemented in this section.

4.1 Optimization of steam generator

4.1.1 Design variables and objective function

For parameter optimization, design variables are the parameters that influences objective value remarkably and independently. For the weight and volume optimization of steam generator, the flowing parameters are design variables: primary loop pressure P_1, reactor inlet coolant temperature T_{in}, reactor outlet coolant temperature T_{out}, average flow velocity in U-tube u_f, secondary loop pressure P_2, feedwater temperature T_{fw}, U-tube outer diameter d_o, ratio of U-tube pitch to U-tube outer diameter s/d_o. Therefore the vector of design variables can be expressed as

$$\begin{aligned}\mathbf{X} &= (x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8)^T \\ &= \left(P_1, T_{in}, T_{out}, u_f, P_2, T_{fw}, d_o, s/d_o\right)^T\end{aligned} \tag{38}$$

As the weight and volume minimization of steam generator are objective, the objective functions are written in form as

$$W_{SG} = \min_{\varphi_i(\mathbf{X})\le 0} f\left(P_1, T_{in}, T_{out}, u_f, P_2, T_{fw}, d_o, s/d_o\right) \tag{39}$$

$$V_{SG} = \min_{\varphi_i(\mathbf{X})\le 0} f\left(P_1, T_{in}, T_{out}, u_f, P_2, T_{fw}, d_o, s/d_o\right) \tag{40}$$

Where $\varphi_i(\mathbf{X}) \le 0$ presents the ensemble of constraint functions, i is the number of constraint functions.

4.1.2 Constraint conditions

The parameter optimization of steam generator is subject to many constraints and requirements. Considering the thermal-hydraulic and suitability, the following constraints should be satisfied.

1. The design variables are bounded with upper and lower limits. For details, see table 3.
2. The circulation ratio (C_R) of steam generator should be within specified boundaries.
3. The secondary loop flow velocity (u_o) should be larger than certain value to alleviate or avoid stagnant area.
4. The height of steam generator, number of U-tubes, tube buddle diameter and tube thickness should be restricted.

4.1.3 Optimization results

The optimization results are given in Table 3.The optimum weight is 169.88 t, it is 18.56% less than original value. Because of the powerful search capability of AGSA, the weight optimization result is superior to QIN's work whose optimum value is 17.16% less than original. As the models for steam generator weight optimization are the same in both works. For volume optimization of steam generator, an 18.39% reduction is obtained.

Table 3 also presents the variation of design variables and main parameters due to optimization. It indicates that the variable variation trends in weight and volume optimization are similar. The primary loop pressure P_1 determines the material thickness of steam generator shell. It decreases in the optimization, which reduces the weight and volume directly. The reactor inlet/outlet coolant temperature (T_{in} and T_{out}) and secondary loop pressure P_2 influence the objectives in synergetic mechanism. On the one hand, the average temperature of primary loop water increases with the value of T_{in} and T_{out}, on the other hand, the temperature of secondary loop water decreases with the reduction of secondary loop pressure P_2 . These factors leads to a larger temperature difference of heat transfer, which means smaller heat transfer area is needed, finally the reduction of weight and volume. With the increasing of u_f and u_o, the heat transfer coefficient increases, which reduces the heat transfer area in another way. Meanwhile, a larger u_o help to alleviate stagnant area in heat transfer region. As for U-tube outer diameter d_o and tube pitch coefficient s/d_o , they both decrease because the dimension of U-tube buddle is directly proportional to their values. Note that the variation of d_o and s/d_o might cause the circulation ratio C_R out of range. In the weight and volume optimization, the values of circulation ratio are 4.06 and 4.13 respectively, and they are in reasonable range.

4.2 Optimization of pressurizer

4.2.1 Design variables and objective function

For the weight and volume optimization of pressurizer, the flowing parameters are design variables: pressurizer inner diameter D_i , primary loop pressure P_1 , reactor inlet coolant temperature T_{in} , reactor outlet coolant temperature T_{out} , and spray coefficient α_{sp} . Therefore the vector of design variables can be expressed as

$$\begin{aligned}\mathbf{X} &= (x_1,\ x_2,\ x_3,\ x_4,\ x_5)^T \\ &= \left(D_i,\ P_1,\ T_{in},\ T_{out},\ \alpha_{sp}\right)^T\end{aligned} \tag{41}$$

As the weight and volume minimization of pressurizer are objective, the objective functions are written in form as

$$W_P = \min_{\varphi_i(\mathbf{X})\le 0} f\left(D_i,\ P_1,\ T_{in},\ T_{out},\ \alpha_{sp}\right) \tag{42}$$

$$V_P = \min_{\varphi_i(\mathbf{X})\le 0} f\left(D_i,\ P_1,\ T_{in},\ T_{out},\ \alpha_{sp}\right) \tag{43}$$

Where $\varphi_i(\mathbf{X}) \le 0$ presents the ensemble of constraint functions, i is the number of constraint functions.

4.2.2 Constraint conditions

Taking thermal-hydraulic performance into consideration, the following constraints should be satisfied.

1. The design variables are bounded with upper and lower limits. For details, see table 4.
2. The height of pressurizer isn't arbitrary, and it should not exceed an upper limit.
3. The difference between reactor inlet coolant temperature and outlet coolant temperature is constant.
4. The steam volume and the water volume should be in a reasonable range at full power state.

The minimum steam volume must be larger than a lower limit.

4.2.3 Optimization results

The optimization results of pressurizer are given in Table 4. The optimum weight is 74.28 t and it is 16.54% less than the original value. This optimization result is superior to LIU's work whose optimum weight is 75.38 t. As the models for pressurizer weight optimization are the same in both works. For volume optimization of pressurizer, an 18.97% reduction is obtained.

The variation of design variables are also presented in Table 4. It indicates that the variable variation trends in weight and volume optimization are similar. The primary loop pressure P_1, reactor inlet/outlet coolant temperature (T_{in} and T_{out}) and pressurizer inner diameter D_i decrease in different degree, and spray coefficient α_{sp} is the only design variable that increases in the optimization. A relatively large α_{sp}

leads to a smaller steady-state minimum steam volume, which means smaller pressurizer volume is obtained.

5 Conclusion

An adaptive genetic-simplex algorithm (AGSA) is proposed for parameter optimization of nuclear power components. The AGSA integrates adaptive techniques, genetic algorithm and simplex algorithm and its strong search ability is validated.

The optimization results of steam generator and pressurizer shows that the minimized weight and volume can vary in the range of 80-85% of the original values. It indicates that an optimization algorithm with outstanding search ability is indispensable in dealing with nonlinear constrained optimization problem. The optimization results indicate that there is much space to reduce the weight and volume of existing nuclear power components by parameter optimization. And the optimization method and result can provide reference for engineering design of such kind components. Note that the optimization results of weight and volume may be amplified because the target models and optimization constraints have been simplified.

Table 3 Constraints and optimization results of steam generator

Parameter	Unit	Qinshan I value	Lower bound	Upper bound	Volume optimization	Relative deviation	Weight optimization	Relative deviation
P_1	MPa	15.2	14.5	15.5	14.78	-2.76%	14.61	-3.88%
T_{in}	℃	288.8	278.8	293.8	291.9	1.07%	292.1	1.14%
T_{out}	℃	315.2	305	320	316.4	0.38%	316.2	0.32%
u_f	m/s	5.2	4.0	6.0	5.5	5.77%	5.6	7.69%
P_2	MPa	5.54	4.0	7.0	5.14	-7.22%	5.22	-5.77%
T_{fw}	℃	220	210	230	223.7	1.68%	225.8	2.64%
d_o	m	0.022	0.015	0.03	0.021	-4.55%	0.02	-9.09%
s/d_o	—	1.41	1.2	1.6	1.31	-7.09%	1.29	-8.51%
C_R	—	4.45	3.0	5.5	4.13	-7.19%	4.06	-8.76%
u_o	m/s	0.4	0.3	0.5	0.41	2.5%	0.42	5.0%
H_{SG}	m	17.28	14.0	20.0	16.31	-5.61%	15.93	-7.81%
V_{SG}	m^3	151.2	—	—	123.39	-18.39%	—	—
W_{SG}	t	208.6	—	—	—	—	169.88	-18.56%

Table 4 Constraints and optimization results of pressurizer

Parameter	Unit	Qinshan I value	Lower bound	Upper bound	Volume optimization	Relative deviation	Weight optimization	Relative deviation
P_1	MPa	15.2	14.5	15.5	14.66	-3.55%	14.72	-3.16%
T_{in}	℃	288.8	278.8	293.8	279.1	-3.36%	282.5	-2.18%
T_{out}	℃	315.2	305	320	305.9	-2.95%	308.8	-2.03%
α_{sp}	—	0.5	0.4	0.6	0.53	6.0%	0.55	10.0%
D_i	m	2.6	2.2	3.0	2.41	-7.31%	2.48	-4.61%
V_p	m^3	35	—	—	28.36	-18.97%	—	—
W_p	t	89	—	—	—	—	74.28	-16.54%

Acknowledgments

The author acknowledges the discussion with associate professor Jian-jun WANG.

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