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Design of A Cyclone Separator Using Approximation Method

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Abstract. A Separator is a device installed in industrial applications to separate mixed objects. The separator of interest in this research is a cyclone type, which is used to separate a steam-brine mixture in a geothermal plant. The most important performance of the cyclone separator is the collection efficiency. The collection efficiency in this study is predicted by performing the CFD (Computational Fluid Dynamics) analysis. This research defines six shape design variables to maximize the collection efficiency. Thus, the collection efficiency is set up as the objective function in optimization process. Since the CFD analysis requires a lot of calculation time, it is impossible to obtain the optimal solution by linking the gradient-based optimization algorithm. Thus, two approximation methods are introduced to obtain an optimum design. In this process, an L_{18} orthogonal array is adopted as a DOE method, and kriging interpolation method is adopted to generate the metamodel for the collection efficiency. Based on the 18 analysis results, the relative importance of each variable to the collection efficiency is obtained through the ANOVA (analysis of variance). The final design is suggested considering the results obtained from two optimization methods. The fluid flow analysis of the cyclone separator is conducted by using the commercial CFD software, ANSYS-CFX.

1. Introduction

A cyclone separator is a device that makes mixture flow into the inlet, generates a cyclone, and separates particulates from a gas, air or liquid stream by the use of centrifugal force. Usually, the cyclone separator has a simple structure, thus it is easy to manufacture the product. The cyclone separator is widely used in various industries, such as those involved with removing dusts, collecting microparticles, cleaning equipment, biosensors, and air purification systems. The cyclone separator investigated in the present study is a device that removes brine particulates from the mixed brine and steam. This cyclone separator is used as a unit of the geothermal power plant [1].

The previous studies [2-7] have focused on the numerical analysis and design to improve the separator performance. Most researches have investigated the effect of the shape and process conditions such as the dimensions of each part of the cyclone, the shape of the inlet, flow rate, and/or temperature, on the performance of the cyclone separator. Starimand [2] has expressed the size of the cyclone separator, maximizing its efficiency. However, the research was based on the trial and error method. Robert [3] and Grane [4] tried to improve the collection efficiency of the cyclone by designing a multiport shaking device and parallel cyclone. Weddin [5] predicted the efficiency of the cyclone separator through theoretical model. Suh [6, 7] suggested the working formula for the channel design of a decanter-type centrifuge.

Most researches have relied on the empirical method or the simplified mathematical model to predict the performance of the cyclone separator. Thus, there are limits to finding an optimum design.

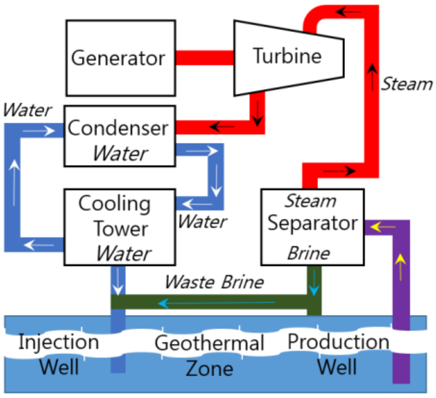

Figure 1. Geothermal power plant

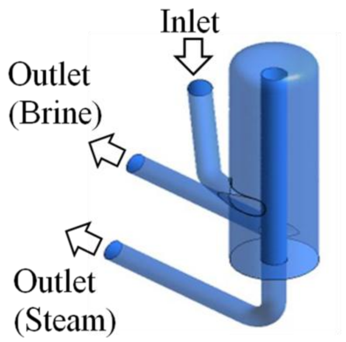

Figure 2. Initial CAD model of cyclone separator

In this study, six design variables related to its shape and the presence of filter are defined as the design variables to find an optimum design, maximizing the collection efficiency. The six design variables are selected by assuming that they are significant factors with respect to the collection efficiency. The collection efficiency in this cyclone separator is calculated by dividing a mass flow of the discharged brine at the outlet by the mass flow that entered at the inlet. The collection efficiency can be regarded as an index to measure the separation amount [1]. Thus, the collection efficiency is set up as the objective function in the optimization process.

This research adopts the DOE and the meatmodel based optimization technique to determine an optimum design of the cyclone separator. The L_{18} orthogonal array [8, 9] is introduced to perform the DOE. The effects of interactions in the orthogonal array are evenly distributed among the columns with exception of the relationship between columns 1 and 2 [9]. The effect on the collection efficiency by each design variable is evaluated, following 18 CFD analyses. The sensitivity information of each design variable to the collection efficiency is calculated quantitatively in an ANOVA table. After that, the optimum level that maximizes the collection efficiency of the cyclone separator is statistically predicted. However, the optimum is selected in the discrete values. Thus, the metamodel based optimization using the kriging is performed to overcome the difficulty. Finally, the optimum design considering the results obtained from two methods is suggested as the final design. All the CFD analyses in this research are performed by using ANSYS-CFX [10].

2. Initial Design and Numerical Analysis

2.1. Geothermal energy and initial design
In this study, we are interested in the types of geothermal power generation as shown in Figure 1. The schematic plot of the cyclone separator is shown as Figure 2. The initial design is determined on the basis of the shape which is widely and experientially used. When a steam-brine mixture flows into the main body through the inlet, a swirling motion down through the inner wall of the cyclone separator is formed. This swirling motion pushes the brine towards the wall by a centrifugal force, and the brine accumulates at the bottom of the system. In contrast, separated steam moves up from the bottom and discharges through the outlet resulting the brine to be separated from a steam-brine mixture.

An initial model is made by utilizing CATIA followed by a numerical analysis model using an ANSYS-workbench. The numerical model for CFD analysis is made of 27,003 grids and 131,169 meshes. To predict the collection efficiency of initial design, a commercial software ANSYS-CFX [10] is utilized. The velocity of fluid flow to the inlet is set at 33m/s and the mass ratio of the brine to steam is 1:9. The boundary condition at the outlet is set as an atmospheric pressure.

2.2 Analysis results of the initial design
The collection efficiency is defined as:

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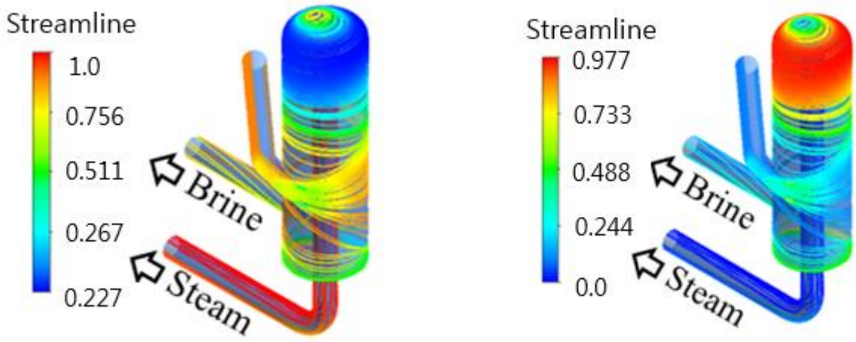


(a) Volume fraction of steam (b) Volume fraction of brine

Figure 3. Volume fraction result of initial design

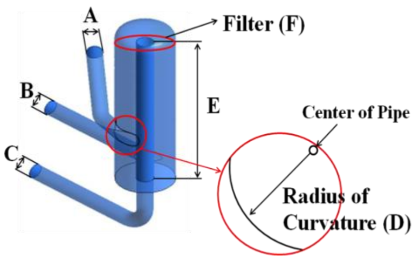


Figure 4. Six design variables

$$\eta = \frac{\dot{m}_{out}}{\dot{m}_{in}} \quad (1)$$

where $\dot{m}_{out}$ is the mass flow rate of the discharged brine at the outlet, and $\dot{m}_{in}$ is the mass flow rate that entered at the inlet. That is, it can be said that the larger the collection efficiency is, the better the performance of the cyclone separator is. The fluid flow inside the separator is investigated through CFD analysis.

The volume fractions and stream lines of steam and brine are represented in Figure 3. From Figure 3(b), it can be seen that the cyclone makes particulates of the brine gather on the top of cyclone body. Then, they are dropped to its bottom, and leave the cyclone body through the outlet. The collection efficiency of the initial design is calculated as 57.3% by the CFD analysis. The value is slightly larger than the usual collection efficiency of around 55.0% used in the plant.

3. Optimization Using DOE and Kriging Metamodel

3.1. Definition of design variables

The six design variables are defined to find a design that maximizes the collection efficiency. They are diameter of the inlet(A), diameter of the brine outlet(B), diameter of the steam outlet(C), radius of curvature of the nozzle which is inserted into the body from the inlet(D), length of the pipe extended to the steam outlet inside the body(E), and the presence of a filter helping the separation process inside the body(G). The design variables are represented in Figure 4. The objective in this study is to find an optimum value of each design variable for maximizing the collection efficiency.

3.2. Optimization using OA

The design of experiments using orthogonal array is adopted to select an optimum settings of the design variables to maximize the collection efficiency. For five design variables, a number of levels is set to three. The second level is set up as the initial value. The first and third levels are fixed by the lower and upper ones around the initial value, respectively. The levels of design variables for an orthogonal array are determined as shown in Table 1. Then, an appropriate orthogonal array is selected by considering the number of design variables and levels.

Table 1. Levels of design variables

level	*A*(mm)	*B*(mm)	*C*(mm)	*D*(mm)	*E*(mm)	*G*
1	637	637	637	2700	7758	O
2	708	708	708	3000	8167	X
3	778	778	778	3300	8575	

Table 2. Experiments using orthogonal array $L_{18}(2^1 \times 3^7)$

Exp. No	*G*	*A*	*B*	*C*	*D*	*E*	*error*	*error*	η
1	1	1	1	1	1	1	1	1	57.3
2	1	1	2	2	2	2	2	2	58.3
3	1	1	3	3	3	3	3	3	50.8
4	1	2	1	1	2	2	3	3	54.1
5	1	2	2	2	3	3	1	1	50.9
6	1	2	3	3	1	1	2	2	58.6
7	1	3	1	2	1	3	2	3	55.3
8	1	3	2	3	2	1	3	1	57.8
9	1	3	3	1	3	2	1	2	57.6
10	2	1	1	3	3	2	2	1	49.6
11	2	1	2	1	1	3	3	2	55.0
12	2	1	3	2	2	1	1	3	58.6
13	2	2	1	2	3	1	3	2	60.6
14	2	2	2	3	1	2	1	3	56.5
15	2	2	3	1	2	3	2	1	57.6
16	2	3	1	3	2	3	1	2	54.0
17	2	3	2	1	3	1	2	3	54.0
18	2	3	3	2	1	2	3	1	57.9

Table 3. ANOVA for collection efficiency

Factor	*S*	*Ø*	*V*	F_0
G	0.50	1	0.50	0.06
A	7.09	2	3.54	0.44
B	9.93	2	4.96	0.62
	17.41	2	8.71	1.09
D	32.28	2	16.14	2.01
E	45.13	2	22.57	2.82
error	48.10	6	8.02	

Table 4. Pooled ANOVA for collection efficiency

Factor	*S*	*Ø*	*V*	F_0	*F*(0.05)	*F*(0.1)
C	17.41	2	8.71	1.99	3.98	2.86
D	32.28	2	16.14	3.69	3.98	2.86
E	45.13	2	22.57	5.16	3.98	2.86
error	48.10	11	4.37			

The $L_{18}(2^1 \times 3^7)$ orthogonal array is selected for the DOE. The orthogonal array has an advantage that the interaction are distributed evenly across from third column to eighth column except first two columns [8, 9]. The variables, *A*, *B*, *C*, *D* and *E* are assigned to the second-sixth columns. The last two columns are filled with errors. The collection efficiencies obtained from each experiment are shown in Table 2. Based on the analyses results, the relative importance of each variable to the collection efficiency can be obtained through an ANOVA. Tables 3 and 4 show ANOVA results at 0.05 and 0.1 significance levels. For 0.05 significance level, it can be seen from the Tables 3 and 4 that the most sensitive variable is *E*, and the variables, *G*, *A*, *B* and *C* are insignificant. On the contrary, for 0.1 significance level, the variables, *E* and *D* are significant. From the ANOVA tables, the effect on the collection efficiency of each design variable can be found. Based on the ANOM (analysis of mean), the optimum design is selected as $A_2B_3C_2D_1E_1G_2$. The predicted collection efficiency at the optimum design is calculated as:

$$\eta_{pred} = \mu_f + a_i + b_j + c_k + d_l + e_m + g_n \tag{2}$$

where η_{pred} is a predicted value of the collection efficiency, μ_f is the overall mean, a_i, b_j, c_k, d_l, e_m and g_n are the main effects of *A*, *B*, *C*, *D*, *E* and *G* at *i*, *j*, *k*, *l*, *m* and *n* level, respectively. The predicted collection efficiency 61.7% is obtained by Eq. (2), which is the point estimator. The collection efficiency of 55.1~68.2% is obtained with the confidence interval 95%. The true value of the collection efficiency at the optimum levels determined from the ANSYS-CFX is 60.4%.

3.3. Optimization using Kriging model

Kriging model is one of metamodel utilized in complex design problem. Kriging is an interpolation method named after a South African mining engineer named D. G. Krige. In general, the response function $\eta(\mathbf{x})$ is represented as[11-14]

$$\eta(\mathbf{x}) = \beta + z(\mathbf{x}), \tag{3}$$

where $\mathbf{x}=[x_1\ x_2\ x_3\ x_4\ x_5]=[A\ B\ C\ D\ E]$, β is a constant, and $z(\mathbf{x})$ has a zero mean and variance σ^2 following the Gaussian distribution. For the presence and absence of filter(design variable G), each kriging model of $\eta(\mathbf{x})$ is built.

Let $\hat{\eta}(\mathbf{x})$ be an approximation model of the collection efficiency. When the mean squared error between $\eta(\mathbf{x})$ and $\hat{\eta}(\mathbf{x})$ is minimized, $\hat{\eta}(\mathbf{x})$ becomes:

$$\hat{\eta}(\mathbf{x}) = \hat{\beta} + \mathbf{r}^T(\mathbf{x})\mathbf{R}^{-1}(\boldsymbol{\eta} - \hat{\beta}\mathbf{i}). \tag{4}$$

where $\mathbf{R}$ is the correlation matrix, $\mathbf{r}$ is the correlation vector, $\boldsymbol{\eta}$ is the collection efficiency vector obtained from Table 2, and $\mathbf{i}$ is the unit vector.

Correlation matrix and correlation vector are defined as

$$R(\mathbf{x}^j, \mathbf{x}^k) = Exp\left[-\sum_{i=1}^{5} \theta_i \left|x_i^{\,j} - x_i^{\,k}\right|^2\right], \quad (j = 1,\ldots,18,\ k = 1,\ldots,18) \tag{5}$$

$$\mathbf{r}(\mathbf{x})=[R(\mathbf{x},\mathbf{x}^{(1)}),\ R(\mathbf{x},\mathbf{x}^{(2)}),\ \ldots\ ,\ R(\mathbf{x},\mathbf{x}^{(18)})]^{T} \tag{6}$$

where superscript of $\mathbf{x}$ is the row number in Table 2.

The unknown parameters θ_1, θ_2,…, θ_n are obtained from the following equation.

$$maximize \quad -\frac{[18 ln(\hat{\sigma}^2) + ln|\mathbf{R}|]}{2}, \tag{7}$$

where θ_i (i=1,2,3,4,5) > 0.

The optimization process suggested in this section is summarized in Figure 5. At the first step, the sample points are defined, which are the same as Table 2. From 18 analysis results, the kriging metamodel of the collection efficiency represented as Eq. (4) is built. As the final step, the sequential quadratic programming built in VisualDOC [15] is adopted to calculate an optimum design. For the presence case of filter, the predicted collection efficiency is calculated as 58.6%. On the contrary, for the absence case of the filter, the predicted collection efficiency is calculated as 60.6%, which is the 13th response of 18 responses in Table 2. Because the Kinging is an interpolation method, a prediction at the *i*-th sample point, the estimator gives the *i*-th response. The optimum parameters of the kriging model and the optimum design variables are summarized in Table 5. The volume fraction at the optimum design are represented as Figure 6.

4. Conclusions

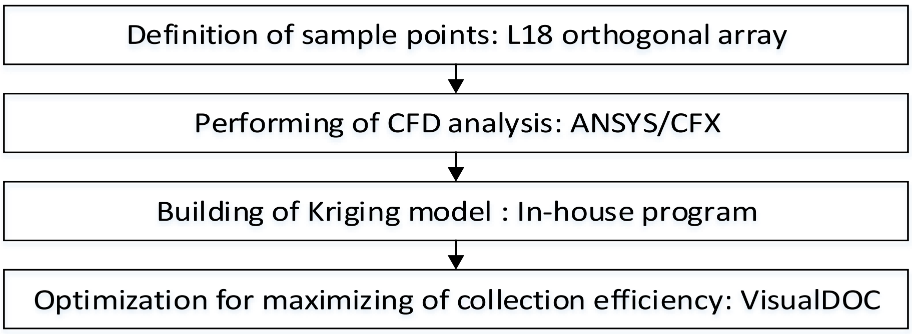
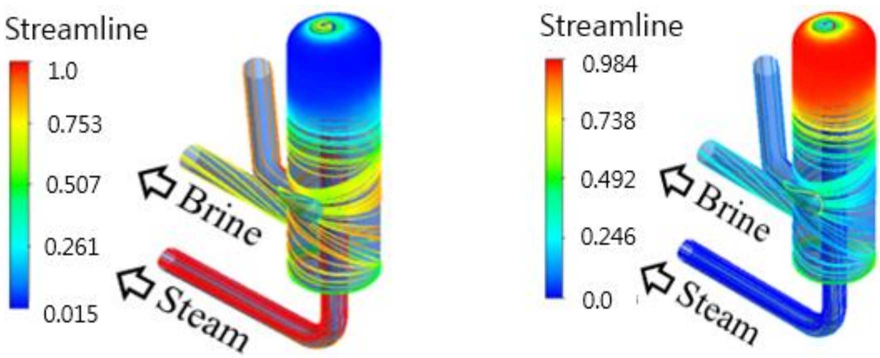


Figure 5. Design process using metamodel



(a) Volume fraction of steam (b) Volume fraction of brine

Figure 6. Volume fraction result of optimum design

Table 5. Optimum parameters and optimum design values (absence of filter)

	A	*B*	*C*	*D*	*E*
Optimum parameters(θ_i in Eq. (5))	32.8	6.7	18.1	0.1	8.2
Optimum design variables(mm)	708	637	708	3300	7758

In this study, the collection efficiency of the cyclone separator for the plant is calculated through the numerical analysis. Furthermore, the optimum design for maximizing the collection efficiency is suggested by defining the design variables and introducing the DOE scheme and the Kriging interpolation method. Based on the ANOVA, the relative importance of each variable to the collection efficiency is investigated. From the ANOVA, it can be seen that the most sensitive variables are *E* and *D*, and the variables, *A, B, C* and *G* are relatively insensitive. Finally, the optimum design is determined based on the results obtained from two optimization methods. The collection efficiency of the suggested optimal design is increased up to 60.6%, comparing with the 57.3% of the initial design.

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