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Investigation on the real-time control of the optimal discharge pressure in a transcritical CO_2 system with data-handling and neural network method

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Abstract

In order to develop an acceptable real-time control approach in terms of accuracy and computation time in industrial and commercial applications, the based Back Propagation Neural Network (BPNN) approach was introduced into the discharge pressure optimization process of the transcritical CO_2 heat pump systems. The relevant characteristic variables concerning to the discharge pressure was minimized by the Group Method of Data Handling (GMDH) method, and the relevance of all the variables with the optimal rejection pressure were investigated one by one. Prediction error of different type neural network were compared with each other. Finally, the performance of neural network based transcritical CO_2 system was compared with that of conventional empirical correlations-based systems in terms of the optimal discharge pressure, which showed that the novel PSO-BP prediction model provides an innovative and appropriate idea for developers and manufacturers.

Keywords: CO_2 heat pump, Optimal dischagre pressure, real-time control, neural network; COP

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Nomenclature

A	training sample	Q	loss function
B	testing sample	T	temperature
b	estimated parameters	W	threshold value from input layer to hidden layer
C	prediction sample	w	threshold value from hidden layer to output layer
E	expected value	Y	output variables
f	function	y	output values
P	pressure		

1. Introduction

Transcritical CO_2 heat pump system has the characteristics of green environmental protection, high energy saving and wide application, which can provide 60 to 90 ˚C of hot water in a wide range of ambient temperatures [1, 2]. It combines the energy saving function of heat pump with the excellent environmental protection performance of CO_2.

For a better application, researchers have done many investigations to enhance the system performance, including improvement of the system COP [3], decrease of the power consumption [4] and so on. Lots of parameters affected the system COP. It was widely known that the system COP increased firstly but then decreased with the increasing discharge pressure, thus leading to the existence of an optimal rejection pressure [5].

Many researchers have investigated the optimal discharge pressure of the CO_2 heat pump, and put forward many empirical correlations [6-10]. However, Aprea and Maiorino [11] found that the mathematic correlations failed to predict the real rejection pressure in their experiment. Meanwhile, Cecchinato et al. [12] developed sets of mathematic models to simulate the optimal discharge pressure, and stated that results deviated from the one predicted by current correlations of other researchers. Actually, the optimal discharge pressure often varied with the different heat pump designs, different operation condition and even the aging problem. With a real-time controller through the comparison of the transient COP, the heat pump might work in the high system performance operations. Nevertheless, it will consume much time for a dynamic operation heat pump when a traditional real-time controller was used, resulting in a long time that the pump actually not run at the optimal condition.

In the present paper, a novel prediction model based on statistical data handing method was introduced for the optimal discharge pressure prediction. Thousands of original data were recorded from the traditional real time control CO_2 heat pump, and the PSO-BP neural network was developed to predict the optimal rejection pressure according to the original data sample. The group method of data handling-type (GMDH) method was applied to investigate the significance of different parameters on the optimal discharge pressure. Results showed the better prediction performance, and it could be used in the real-time control for better system performance.

2. Transcritical CO_2 heat pump and its system performance

2.1. Working principle of CO_2 heat pumps

A typical transcritical CO_2 heat pump heat pump is made up of four major components, which are a compressor, a gas cooler, a throttling valve and an evaporator. The vapor is firstly compressed in the compressor to the high-pressure vapor. Then, it flows into the gas cooler, where the gas is cooled to a low temperature gas. The gas cooler is the main component which provides heating capacity in a heat pump. After that, the low temperature gas is throttled in a throttling valve, and the working fluid turns into the liquid with a much lower temperature. Eventually, the low temperature liquid absorbs heat from the surroundings, and it evaporates into the saturated superheated vapor.

2.2. The optimal discharge pressures

Fig.2 depicts the *p-h* diagram of the transcritical CO_2 cycle. As shown in Fig.3, it could be obviously seen that the system COP increased firstly with the increasing discharge pressure and then decreased gradually.

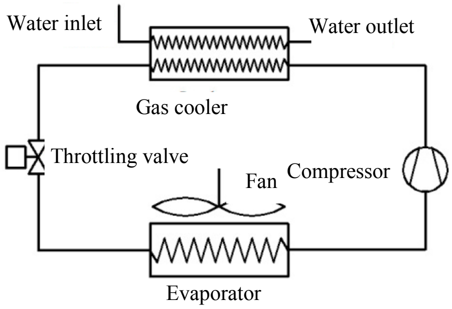

Fig.1. Typical schematic CO2 heat pump

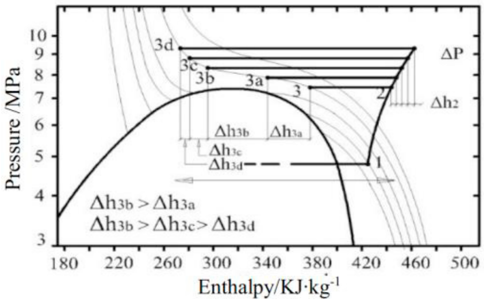

Fig.2. *p-h* diagram of a CO_2 heat pump

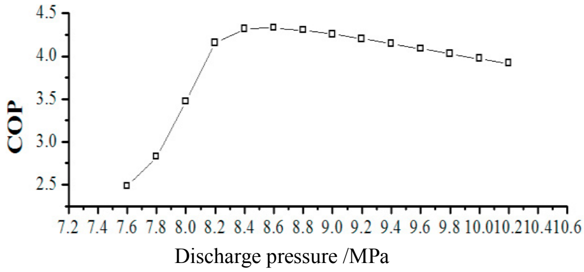

Fig.3. Relationship of COP with the increasing discharge pressure

3. Transcritical CO_2 heat pump and its system performance

3.1. GMDH method

In order to confirm the most important factor that heavily affected the optimal discharge pressure, the GMDH method was introduced in the presented paper. Fig.4 gives the data handing model of the GMDH method.

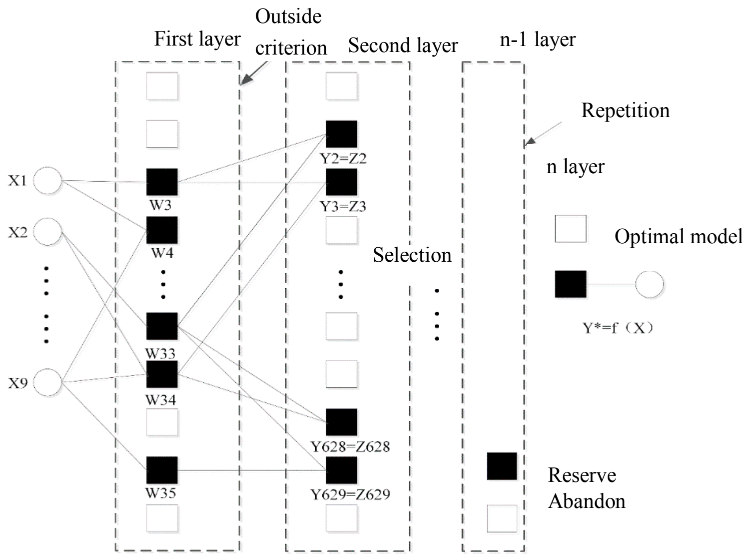

Fig.4. Data handing model of the GMDH method

3.2. Samples

The original data were obtained from three-separated CO_2 heat pump. Meanwhile, the heat pumps were all equipped with the transient pressure control based on the comparison of the system COP. As for the dynamic pressure control heat pump system, it needs a long time to get the stable condition, and all the data used for the data handing were selected from the stable condition. The data was collected every 5 minutes but only recorded the stable one. After a long practical operation, 8418 groups of the data were obtained, which were the original data.

3.3. Mathematic model of GMDH method

The Kolmogorov-Gabor Polynomial is used as the reference function.

$$f(x_1x_2...x_n) = a_0 + \sum_{i=1}^{n} a_i x_j + \sum_{j=1}^{j=n} a_{n+j} x_j^2 + \sum_{k=1}^{k=n-1} a_{2n+k} x_1 x_{k+1} + \sum_{k=1}^{k=n-2} a_{3n-1+k} x_2 x_{k+2} + ... + a_{2n+\frac{n(n-1)}{2}} x_{n-1} x_n \quad (1)$$

The intermediate model is established based on the training sample, and then the parameters are estimated. The outside criterion is depicted in the following.

$$J(C) = E\left\{Q(y^M, y, C)\right\} \quad (2)$$

$$i^2(A) = \sum_{i \in C} \left\{y_t - y_t^m(A)\right\}^2 \quad (3)$$

$$i^2(B) = \sum_{i \in C} \left\{y_t - y_t^m(B)\right\}^2 \quad (4)$$

The transfer function is:

$$y = b_1 x_1 + b_2 x_2 \quad (5)$$

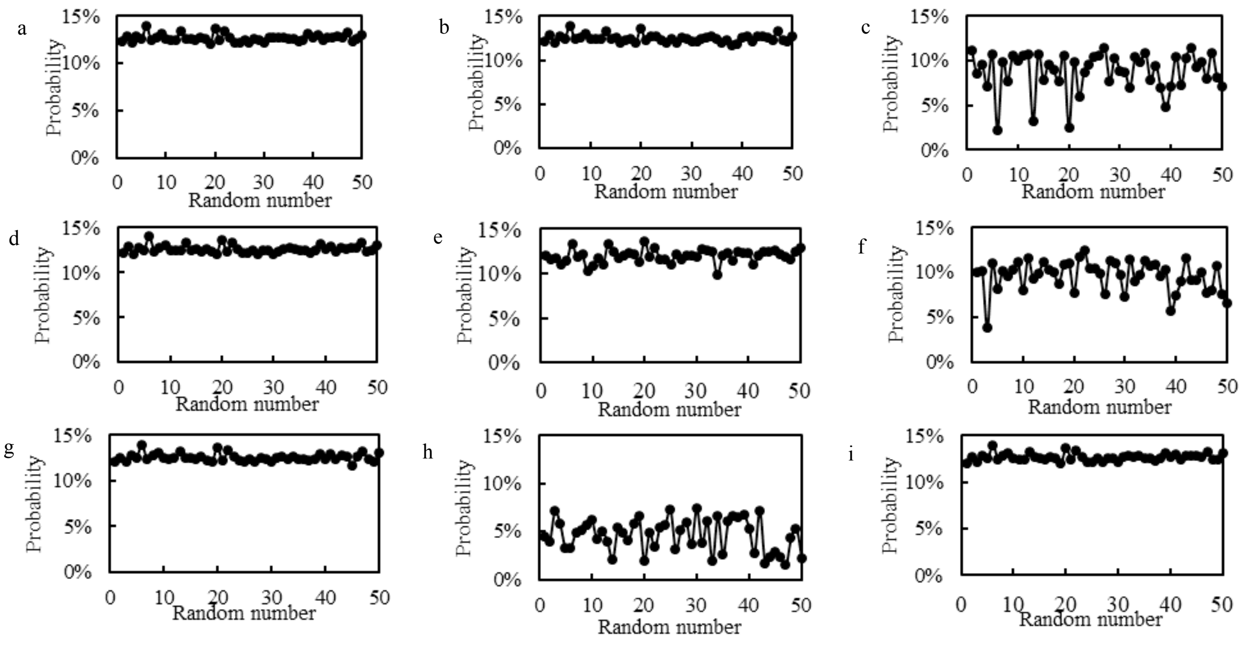

Fig. 5. (a) Probability of evaporative temperature; (b) Probability of ambient temperature; (c) evaporator outlet temperature; (d) Probability of gas cooler outlet temperature; (e) Probability of water outlet temperature; (f) Probability of water inlet temperature; (g) Probability of discharge temperature;(h) Probability of suction temperature; (i) Probability of suction pressure

3.4. Relevance of the variable with the optimal discharge pressure

The number of training sample increased from 2 to 8148, and the maximum random number of the random permutation for the training sample are 50. Here, the total number of the feature extraction were 407,350. The probability of the variable reflected the importance of the parameters. Fig.5 gives probabilities of selected variables. The discharge temperature, the suction temperature and pressure sometimes directly affected the discharge pressure, so they were not the appropriate variable due to none independence. Probabilities of the evaporative temperature are always higher than 10%, and the values are relative stable. It could be considered as the high relevance with the optimal discharge pressure. According to the similar principle, the four most relevant characteristic variables were the ambient temperature, the evaporative temperature, the gas cooler and water outlet temperature.

4. Transcritical CO_2 heat pump and its system performance

4.1. Model of neural network

There are six main type neural network. As the most mature technology and widely application neural network, the BP neural network is introduced in the present paper for the prediction of the optimal discharge pressure. Fig.6 shows the typical topological structure of the BP neural network. The input layer of the network is the variable of the heat pump. The output layer is the predicted optimal pressure. The transfer function is listed as below.

$$\begin{aligned} P_{best} &= w_1 \times \tan sig(W_{1,1} \times T_e + W_{2,1} \times Tair + W_{3,1} \times T_{gc,out} + W_{4,1} \times T_{water,out} + \theta_1) + \\ &w_2 \times \tan sig(W_{1,2} \times T_e + W_{2,2} \times Tair + W_{3,2} \times T_{gc,out} + W_{4,2} \times T_{water,out} + \theta_2) + ... + \\ &w_n \times \tan sig(W_{1,\ n} \times T_e + W_{2,\ n} \times Tair + W_{3,\ n} \times T_{gc,out} + W_{4,\ n} \times T_{water,out} + \theta_{\mathrm{n}}) + a_1 \end{aligned} \tag{6}$$

where w is the weight value, and the a is the threshold value.

Learning rules of the BP network is the changing of the weight value, and the supervised learning type is used.

The input of the node in the hidden layer is calculated as follows.

$$net_i = \sum_{j=1}^{M} \omega_{ij} x_j + \theta_i \tag{7}$$

The output of the node in the hidden layer is listed as below.

$$y_i = \phi(net_i) = \phi(\sum_{j=1}^{M} \omega_{ij} x_j + \theta_i) \tag{8}$$

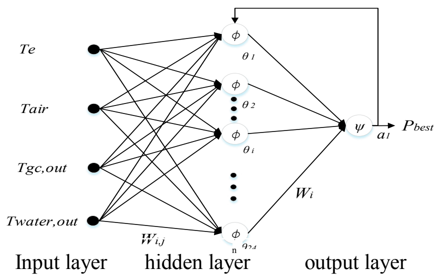

Fig.6. Prediction model of the optimal discharge pressure with PSO-BP method

The input of the node in the output layer is:

$$net_k = \sum_{i=1}^{q} \omega_{ki} y_i + a_k = \sum_{i=1}^{q} \omega_{ki} \phi(\sum_{j=1}^{M} \omega_{ij} x_j + \theta_i) + a_k \tag{9}$$

The output of the node in the output layer is:

$$y_k = \psi(net_k) = \psi(\sum_{i=1}^{q}\omega_{ki}y_i + a_k) = \psi\left[\sum_{i=1}^{q}\omega_{ki}\phi(\sum_{j=1}^{M}\omega_{ij}x_j + \theta_i) + a_k\right] \tag{10}$$

The error transferred from the output to the input, and the weight and threshold value were corrected every time due to the gradient descent method. The transfer function of the error is:

$$E_p = \frac{1}{2}\sum_{k=1}^{L}(T_k - y_k)^2 \tag{11}$$

In the BP neural network, the weight value was corrected during the error transfer time after time, so it had the strong ability of the parallel computing. However, it still had some disadvantages, including the deficiency of the saturation resistance, the low convergence efficiency and the long computing period. Therefore, the additional method was required to avoid the local optimum value efficiently in the prediction model.

To avoid the local optimization value and improve the prediction accuracy, different algorithms were combined with BP neural network for the optimization. Two different method, including GA-BP (Genetic Algorithms) and PSO-BP (Particle Swarm Optimization) were both introduced. GA-BP network utilized genetic algorithms to improve the BP neural network. In the PSO-BP network, the Particle Swarm Optimization was used for the optimization of the weight and threshold value. All the weight and threshold value were reserved in the particle. With the fitness calculation, the optimal value was obtained from the iterative calculations. There were four main steps in the PSO-BP network, including population initialization, particle fitness, particle optimization and BP network training.

4.2. Prediction performance of different type network

To compare the prediction performance of the three-type network, the regression analysis was introduced here, which could be used to analyze the relevance of different variables. The regression analysis was the prediction model in the Big Data Analysis, and the linear coefficient was often applied for the accuracy evaluation. The TR and V linear regression coefficient were the coefficient of predicted and expected value in the network-training, network-validation sample, network-testing and whole network samples. The value of MSE was the maximum iterations, and the higher value resulted in the more accurate prediction because of the larger iterations. As shown in Fig. 7, almost all the linear regression coefficient of the PSO-BP network were the largest. The PSO-BP network also had the largest iterations.

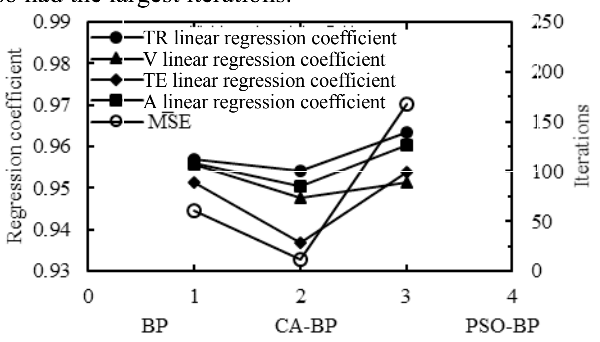

Fig.7. The prediction performance of the three-type neural network

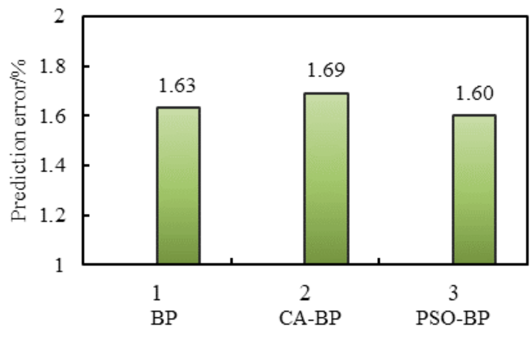

Fig.8. The prediction error of the three-type neural network

Fig. 8 illustrates the prediction error of the three-type network. Although there was no huge error difference among the three-type neural network, the error of the PSO-BP prediction model was the least one. The average prediction error was about 1.6%. Therefore, the PSO-BP neural network was selected in the present paper for the optimal discharge pressure prediction.

5. Transcritical CO_2 heat pump and its system performance

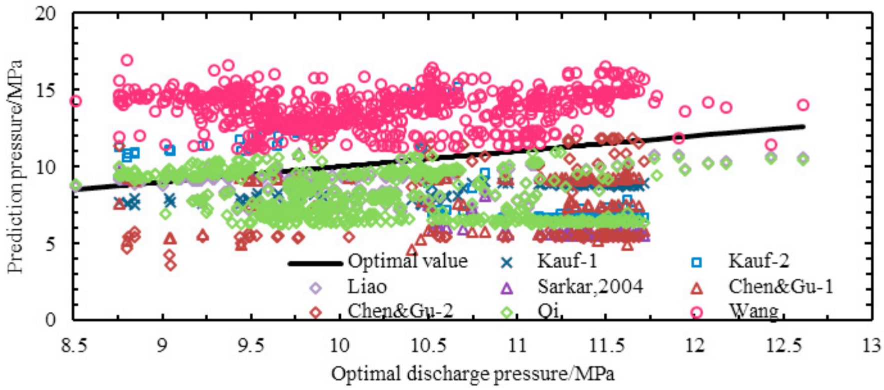

Fig.9 The optimal discharge pressure prediction of the current correlations

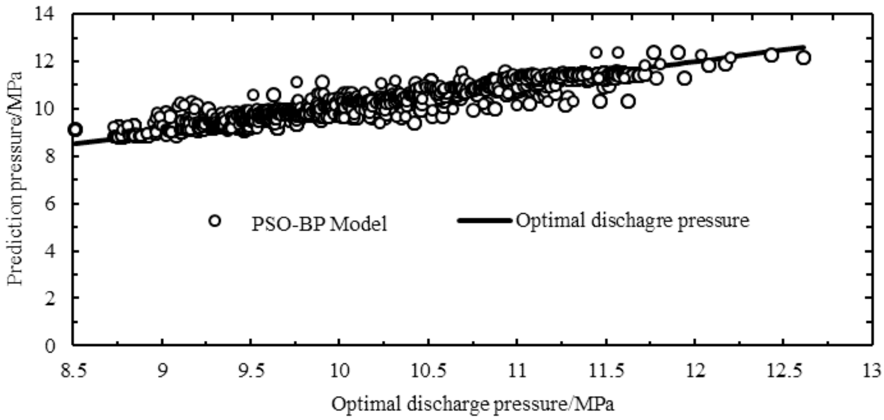

Fig. 10. The prediction of PSO-BP neural network

Table 1. Current empirical correlations of optimal discharge pressure

	Prediction correlations	Application range
Kauf [6]	$P_{opt,kauf} = 2.6t_{air} \approx 2.6t_{gc,out} + 7.54$	$30^{\circ}\mathrm{C} \le t_{air} \le 50^{\circ}\mathrm{C}$
Liao et al. [7]	$P_{opt,Liao} = (2.778 - 0.0157t_e)t_{gc,out} + 0.381t_e - 9.34$	$-10^{\circ}\mathrm{C} \le t_e \le 20^{\circ}\mathrm{C}$ $30^{\circ}\mathrm{C} \le t_{gc,out} \le 60^{\circ}\mathrm{C}$
Sarkar et al.2004[8]	$P_{opt,sarkar} = 4.9 + 2.256t_{gc,out} - 0.17t_e + 0.002t_{gc,out}^2$	$30^{\circ}\mathrm{C} \le t_{air} \le 50^{\circ}\mathrm{C}$ $-10^{\circ}\mathrm{C} \le t_e \le 10^{\circ}\mathrm{C}$
Sarkar et al.2006[13]	$P_{opt,sarkar} = 8.545 + 0.0774t_{w,in}$	$20^{\circ}\mathrm{C} \le t_{w,in} \le 40^{\circ}\mathrm{C}$
Chen and Gu[9]	$P_{opt,Chen} = 2.68t_{air} + 0.975 = 2.68t_{gc,out} - 6.797$	$30^{\circ}\mathrm{C} \le t_{air} \le 50^{\circ}\mathrm{C}$
Qi et al. [14]	$P_{opt,Qi} = 13.23 - 0.84t_{gc,out} + 0.03t_{gc,out}^2 - 2.77\times10^{-4}t_{gc,out}^3$	$20^{\circ}\mathrm{C} \le t_{gc,out} \le 45^{\circ}\mathrm{C}$
Wang et al. [10]	$P_{opt,Wang} = 1.09 + 0.106t_{w,out} + 0.101t_{air} - 0.001t_{air}^2$	$5^{\circ}\mathrm{C} \le t_{air} \le 35^{\circ}\mathrm{C}$
	$P_{opt,Wang} = 2.47 + 0.122t_{w,out} - 0.0004t_{w,out}^2 + 0.016t_{air}$	$-15^{\circ}\mathrm{C} \le t_{air} < 5^{\circ}\mathrm{C}$

For the better operation performance of the transcritical CO_2 heat pump, different empirical correlations had been proposed by different researchers, which are shown in table 1. However, the correlations had different application range. Fig.9 gives the prediction error of different correlations that satisfied the application range in the sample. The solid black line is the optimal discharge pressure that from the experimental sample. Although some of the points have good prediction performance, there are still a large number of the data deviating far from the optimal value. Current predictions failed to predict the optimal discharge pressure.

However, the PSO-BP prediction model always shows the good prediction performance, as depicted in Fig.10. The mathematic model of the CO_2 heat pump was not enough to evaluate the optimal rejection pressure, and the coupled factor mainly partly affect the results. Only one or two variables cannot be well used to predict the optimal discharge pressure. The network that was developed in the presented paper can be used for the real-time control during the CO_2 heat pump practical operation.

6. Conclusion

In this paper, a novel model based on the statistical method was introduced for the application of the real-time control of the optimal discharge pressure in a transcritical CO_2 heat pump. The original data were recorded from three heat pumps from the engineering operation case, and the group data handing method was utilized to distinguish the relevance between the parameters and the optimal discharge pressure. Four variables, including the ambient temperature, evaporative temperature, gas cooler and water outlet temperature, were selected as the input layer for the prediction of neural work. After comparison of the BP network, GA-BP and PSO-BP network, the PSO-BP neural network was finally chosen to predict the optimal discharge pressure due to the highest accuracy. Results showed that the prediction values were well agreement with the experimental ones, while the current empirical correlations often failed to evaluate the optimal rejection pressure.

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