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Optimization of regenerative cycle with open feed water heater using genetic algorithms and neural networks

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Abstract This article determines the operating conditions leading to maximum work in a regenerative cycle with an open feed water heater through a procedure that combines the use of artificial neural networks (ANNs) and genetic algorithms (GAs). Water is an active fluid in the thermodynamical cycle; an objective function is obtained by using vapor enthalpy (a nonlinear function of operating conditions). Utilizing classical methods for maximizing the objective function usually leads to suboptimal solutions. Therefore, this article uses ANNs to estimate the steam properties as a function of operating conditions and GAs to optimize the thermodynamical cycle. The operating conditions are chosen with the aim of gaining maximum work in a boiler for a specific heat. To estimate the thermodynamic properties, an ANN was used to provide the necessary data required in the GA calculation.

Keywords Genetic algorithm · Artificial neural network · Rankin cycle · Maximum work

Introduction

The Rankin cycle is a simplified powerhouse model with four steady state processes that consist of:

(1) isentropic pumping process;
(2) isobaric heat transfer process in a boiler;
(3) isentropic expansion in a turbine; and
(4) isobaric heat transfer process in a condenser.

Figure 1 illustrates a typical schematic of this type of cycle. In the analysis of the Rankin cycle, the efficiency of the cycle is considered according to an input temperature in a boiler and an output temperature in a condenser. An increase in the mean temperature of the input heat and a decrease in the mean temperature of the output heat cause an increase in the efficiency of the Rankin cycle. One important configuration of the Rankin cycle is the regenerative aspect. In such a cycle an open feed water heater is used. Due to the fact that in the regenerative cycle the mean input temperature is higher than the mean output temperature, the efficiency is improved [1].

After some steam expansion in the turbine, a part of the expanded steam enters into an open feed water heater, as shown by stream 6 in Fig. 1. The other part of the expanded steam is condensed in a condenser and pumped into the open feed water heater, where it is mixed with steam. Some of the steam is removed because saturated liquid (stream 3 in Fig. 1) is needed. In this cycle, this liquid is pumped into a boiler. By appropriately setting the operating conditions, the maximum work from the cycle can be obtained. To achieve this objective, a GA is used in the current research. Furthermore, in order to estimate the steam properties, an ANN model is utilized instead of using classical thermodynamics models [2, 3].

Artificial neural network

Defining the steam properties–operating conditions relationship requires a more accurate and easier-to-implement

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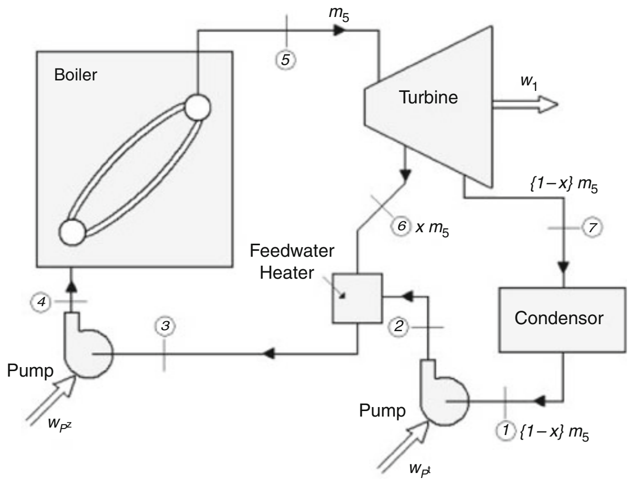

Fig. 1 Schematic of the Rankin Cycle considered in this article

method than traditional empirical methods. The ANN technique examines the input–output relationships to efficiently approximate any function with a finite number of discontinuities [4, 5]. Experiments can be used to identify these algorithms, which are also fault tolerant as they can handle noisy and incomplete data sets. Indeed, ANNs effectively deal with nonlinear problems; once trained, they can perform predictions and generalizations rapidly [6, 7].

ANNs are composed of many neurons interconnected by links to determine the empirical relationship between the inputs and outputs of a given system. Figure 2 depicts a multilayered arrangement of a typical interconnected neural network consisting of an input, an output, and one hidden layer. Each connecting line has an associated weight. ANNs are trained by adjusting these input weights (connection weights); accordingly the outputs calculated are approximated using the desired values. A transfer function applied to a weighted summation of neuron input to provide an output, as follows [8]:

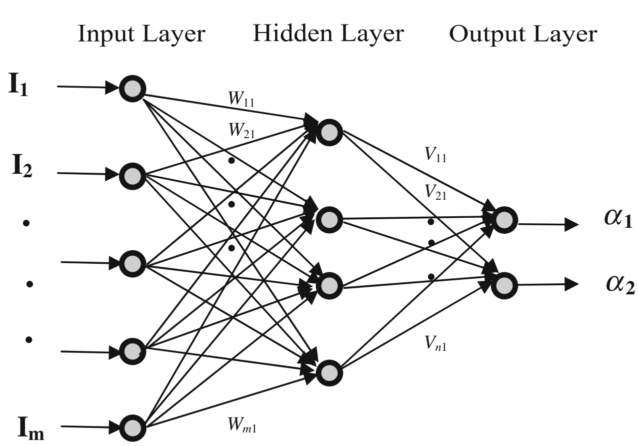

Fig. 2 Schematic of a typical multilayer neural network architecture

$$\alpha_{jk} = F_k\left(\sum_{i=1}^{N_{k-1}} w_{ijk}\alpha_{i(k-1)} + \beta_{jk}\right) \tag{1}$$

where α_{jk} is neuron j's output from k's layer and β_{jk} is the bias weight for neuron j in layer k. The model fitting parameters w_{ijk} are the connection weights. The nonlinear activation transfer functions F_k may have many different forms; classical forms are threshold, sigmoid, Gaussian, and linear function [9]. For more details of various activation functions, see Bulsari [10].

Throughout training process, the network performance functions are minimized by iteratively adjusting of the network weights and biases [11]. For training feed-forward neural networks, the typical performance function used is the network Mean Squares Error (MSE):

$$\mathrm{MSE} = \frac{1}{N}\sum_{i=1}^{N}(e_i)^2 = \frac{1}{N}\sum_{i=1}^{N}(t_i - \alpha_i)^2 \tag{2}$$

This article employs the back propagation learning algorithm [12]. The simplest implementation of this algorithm is the network weights and biases updated in the direction of the negative gradient, which result in the performance function decreasing most rapidly. An iteration of this algorithm can be written as follows [8]:

$$x_{k+1} = x_k - l_k g_k \tag{3}$$

A flowchart outlining the procedure for identifying the optimal model is provided in Fig. 3. There are many advanced versions of back propagation algorithms. Levenberg–Marquardt (LM) is the fastest training

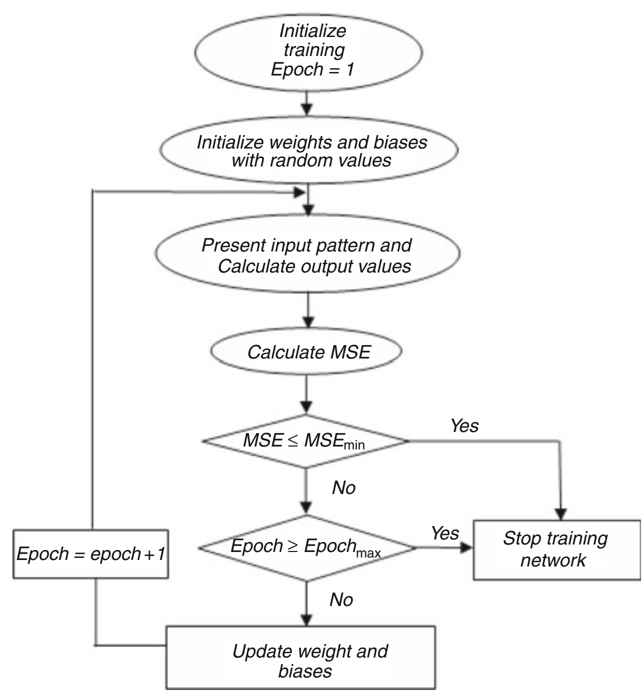

Fig. 3 Flowchart illustrating the training process

algorithm for networks of a moderate size. However, Scaled Conjugate Gradient (SCG) is considered as one of the most important all-purpose back propagation training algorithms [9, 11].

Comparing neural networks performance to the classical statistical modeling is at least the same as, and even better, in most cases [12]. The models built by neural networks are more reflective of the data structure and are significantly faster.

The best ANN models for the estimation of thermodynamic properties of water were developed using seven neurons in the hidden layer and SCG algorithm as the most suitable training algorithm, with the minimum Mean Square Error [2].

Genetic algorithm

The optimization of process operations leads to the production of the best product or to the best operating performance, with respect to a specific situation. Different method can be employed to carry out the optimization. As the result of the work depends on the method of the optimization, it is important to determine which method should be used to find the optimum outcome.

GAs are computational search methods based on an optimization algorithm, gene structure, and chromosomes. They are effective search techniques for expansive search space. In these algorithms, the design space must change according to the genetic space; as such, GAs work with some encoded variables. Three important steps are associated with the implementation of a GA [13]:

(1) Identification of the objective function or cost function;
(2) Identification and implementation of genetic space; and
(3) Identification and implementation of the GA operator.

Implementation of the genetic algorithm to the present problem

In the current study, by changing T, P, and the mass flow rate of stream 6 in Fig. 1, the maximum work from the cycle can be obtained. The following steps were taken to achieve this goal.

Step 1: Search space

The objective of the optimization is to obtain the pressure of stream 6 that leads to the maximum work from the cycle. The range of this pressure falls between condenser pressure and boiler pressure.

Step 2: Encoding values

Several methods can be used to indicate unit genes. In this research, genes were shown as bit strings. To solve the problem with GA, the unknown variables must be detected as bit strings. The length of the string was defined *a priori* according to the desired accuracy, and binary encoding is employed to produce several chromosomes with minimum bits. In the use of GA, an important step is the interpretation of the problem variables on chromosomes. Using a chromosome that has n bits to indicate pressure results in 2^n codes. If we know the numerical value of the one code, we can obtain a pressure related to this code by using the following formula:

$$\begin{bmatrix}\text{Flow}\\ \text{pressure}\end{bmatrix} = \begin{bmatrix}\text{Minimum}\\ \text{pressure}\end{bmatrix} + \begin{bmatrix}\text{Maximum}\\ \text{pressure}\end{bmatrix} - \begin{bmatrix}\text{Minimum}\\ \text{pressure}\end{bmatrix} * \left[\frac{\text{A value of code}}{2^n - 1}\right] \tag{4}$$

Step 3: Objective function

The objective function employed in this research aims to maximize the network obtained from the cycle [1]—namely:

$$\dot{w}_{tur} = (\dot{m}_5 \times h_5) - (x \times \dot{m}_5 \times h_6) - ((1 - x) \times \dot{m}_5 \times h_7) \tag{5}$$

$$\begin{aligned}\dot{w}_{p1} &= \dot{m}_5 \times (1-x) \times (h_2 - h_1) = \dot{m}_5 \times (1-x) \times v_1 \times (p_2 - p_1)\\ \dot{w}_{p2} &= \dot{m}_5 \times (h_4 - h_3) = \dot{m}_5 \times v_3 \times (p_4 - p_3)\end{aligned} \tag{6}$$

$$x = \frac{h_3 - h_7}{h_6 - h_7} \tag{7}$$

Objective function:

$$\dot{w}_{net} = \dot{w}_{tur} - \dot{w}_{p1} - \dot{w}_{p2} \tag{8}$$

Step 4: Reproduction

Reproduction is a first action applied to a population. In this method, certain chromosomes are chosen as producers. Using crossover and mutation actions, children are produced. Several methods can be used to choose chromosomes. This article used a competition method, in which the best chromosomes are chosen as producers to produce the next generation [14].

Step 5: Mutation action

Mutation, which is used to produce new chromosomes in the search space, includes different operators:

(1) AND operator: In this operator, if both bits are equal to one, the operator will return one; otherwise, it will return zero.

(2) OR operator: In this operator, if one of the bits is equal to one, the operator will return one; otherwise, it will return zero.
(3) XOR operator: In this operator, if one of the bits is one and another one is zero, the operator will return one; otherwise, it will return zero.
(4) One complement operator: This operator can convert one to zero and zero to one [14].

Case study

In one open feed water heater, the pressure of the condenser is 20 kPa, and the maximum pressure is 5 MPa. Input heat in a boiler is $4 \times 10^3\,\mathrm{kJ/kg}$. The output water coming from an open feed water heater is a saturated liquid that enters a second pump. This study seeks to calculate the condition of the steam in stream 6 (see Fig. 1) in order to achieve a maximum network from the cycle. Turbines are assumed to operate isentropically. Pressure drops in the tubes are ignored as it is assumed that giving and taking heat is a constant pressure process. The steps in the solution process are described below:

(1) For this problem, the search space should span all possible values of pressure; therefore, the pressure falls between 20 kPa and 5 MPa:

$$20\,\mathrm{kPa} \le p_6 \le 5,000\,\mathrm{kPa}$$

(2) In this problem, a string is used with 13 bits to indicate flow pressure. As a result, the length of each chromosome is equal to 13 bits. Thus, $2^{13} = 8,192$ values for pressure must be considered. Each code has a specific numerical value that can be obtained from the formula given below:

$$p_6 = 20 + \frac{5,000 - 20}{2^{13} - 1} \times A$$

where A represents a numerical value of code in base 10.

For example, given the following code:

0	0	0	0	0	0	1	1	0	0	1	0	0

$(1100100)_2 = 100$

Then:

$$p_6 = 20 + \frac{5,000 - 20}{8,191} \times 100 \rightarrow p_6 = 506.804 \approx 507\,\mathrm{kPa}$$

Thus, the above code indicates a pressure equal to 507 kPa.

(3) The current case study aims to maximize the network obtained from the cycle; as such, the objective function is $\dot{w}_{net}$. To evaluate this objective function, the enthalpy of the steam at a specific condition must be identified. The neural network model was used for this purpose.
(4) The population in which the search was conducted has $2^{13} = 8,192$ chromosomes. Five chromosomes were randomly chosen from this population while the algorithm continued generating candidate solutions as described in Fig. 4.

A rate of mutation equal to one was used throughout the algorithm, meaning that the total population changed in each step. Overall, using the five initial chromosomes and the application of the GA operator, 36 new chromosomes were generated. Five chromosomes were subsequently chosen to give a maximum objective function; using these new values, the algorithm was continued. If the number of

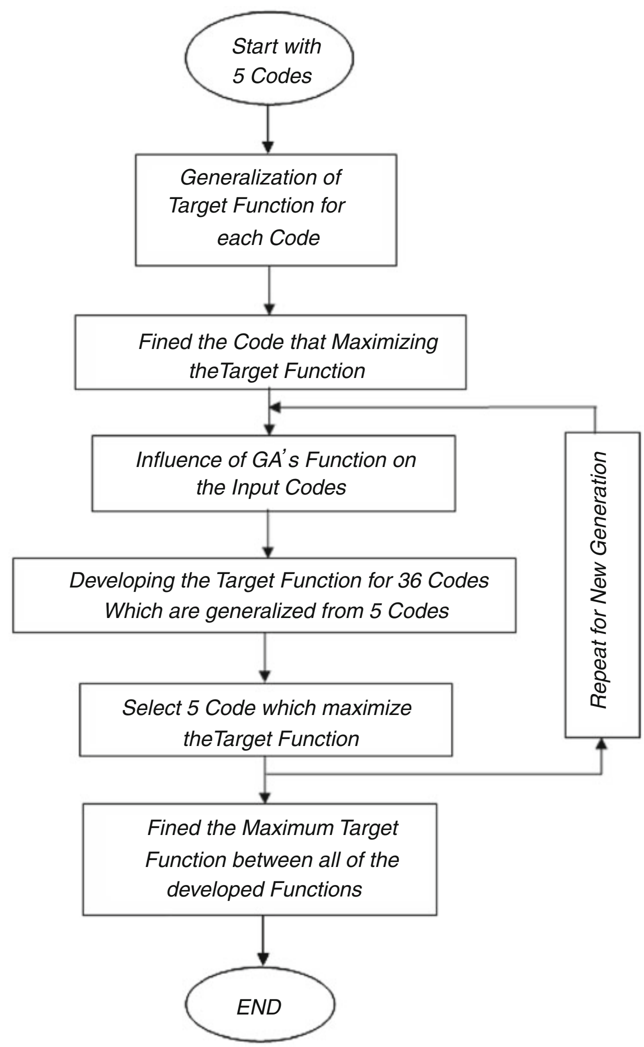

Fig. 4 Flowchart illustrating the procedure undertaken to obtain a best answer by means of the genetic algorithm for the case study considered

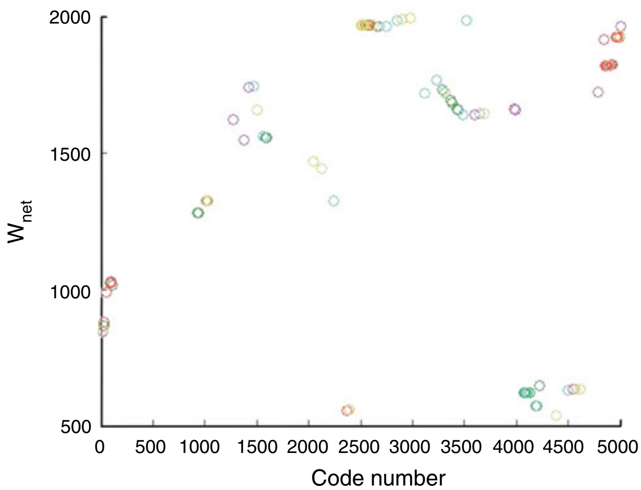

Fig. 5 The search ability of the genetic algorithm

the generation production is high, more data will be surveyed, meaning more accurate answers can be achieved. The current case study obtained an answer equal to 4,901. Thus, if P is equal to 2,999.73 kPa, maximum output is achieved. This work is equal to 1,993.75 kJ/kg.

Figure 5 illustrates the search potential of the algorithm. As evident in this figure, to produce five generations, many points are surveyed; if the production of the generations increases, more points will be surveyed. Indeed, 200 generations were used to solve the current problem. As Fig. 5 indicates, for the production of the five generations, nearly 180 points were surveyed, which demonstrates the high ability of the algorithm to achieve an optimum answer.

Conclusions

GAs represent a promising method available for the optimization of thermodynamical systems. In this article, an ANN model was first prepared based on experimental measurements in order to obtain thermal properties of water. This model was then integrated within a general optimization model for the optimization of a regenerative cycle with an open feed water heater. The neural network model was employed in the prediction of the thermodynamical properties of the water, thereby avoiding the requirement to obtain such properties from steam tables, which is not practical in an optimization setting. This allowed for the formulation of the optimization problem using an equation-based approach.

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