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MULTI-CRITERION OPTIMIZATION OF CONTROL PROCESS BASED ON DPCA AND ANN

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Abstract. Dynamic principal component analysis is an extension of Principal component analysis and DPCA helps to capture the auto correlative behaviour of the parameters in industrial system. The proposed ANN model using DPCA method and NSGA-II algorithm allow us to find more efficient solution to the multicriteria optimization of any industrial system. The main design aspect of DPCA includes the selection of lags and components for final model.

Keywords: neural network model, principal component analysis, multicriteria optimization, genetic algorithm for non-dominated sorting, dynamic principal component analysis.

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МНОГОКРИТЕРИАЛЬНАЯ ОПТИМИЗАЦИЯ ПРОЦЕССА УПРАВЛЕНИЯ С ИСПОЛЬЗОВАНИЕМ DPCA И ANN

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Аннотация. Динамический анализ основных компонентов является расширением анализа основных компонентов, а DPCA помогает фиксировать автокорреляционное поведение параметров в промышленной системе. Предложенная модель ANN, использующая метод DPCA и алгоритм NSGA-II, позволяют нам найти более эффективное решение для многокритериальной оптимизации промышленной системы. Основным аспектом проектирования DPCA является выбор лагов и компонентов для окончательной модели.

Ключевые слова: нейросетевая модель, метод главных компонент, многокритериальная оптимизация, генетический алгоритм недоминируемой сортировки, динамический метод главных компонент.

Introduction

The numerous updates happening in the industrial control systems make the optimization problem more complex and difficult. We know that multi criteria optimization is always deals with a trade-off between the objectives. But the revolution in the industrial 4.0 is using the application of machine learning and Artificial neural network. Industrial revolution also uses many sensors and control parameters. When a control object has many control parameters then it makes the process of optimization more complex. A general description of different optimization methods used in the field of optimization having more than one objective to solve is described here [1]. One of the best methods to solve multicriteria optimization is pareto optimization method [2]. In pareto optimization method it is providing a set of pareto solution set rather a solution. Thus, the decision maker can select the solution according to his or her choices. When we considering a control object having many parameters, then it is difficult to control. Principal component analysis used to reduce the dimensionality of a large dataset of a control object. But here the case study devoted to applying Dynamic Principal Component Analysis (DPCA) to capture the dynamic nature of a control object [3]. In DPCA it uses the repetitive observation to the original matrix and form an extended matrix to perform the PCA operation. This will help us to learn more about the underlying structure and pattern of the values inside the dataset. To model the characterise of the control object, we can use

Artificial Neural Network (ANN). ANN provide wide range of possibilities to perform the characterises of industrial steam boiler and here the dataset is like time series data. So recurrent ANN is suitable for capturing the pattern inside the dataset [4].

The case study in the paper devoted to multicriteria optimization of steam boiler system using DPCA and ANN mythology. Non-dominated Sorting Genetic Algorithm (NSGA-II) used to solve the multicriteria optimization problem. Here we are trying to improve the efficiency and productivity of a steam boiler based on its control parameters.

1. Multicriteria optimization

In simple terms it includes more than one objective function to solve to find a solution for an optimization problem. Generally, the decision makers try to combine the multiple objectives to a single objective and solve it using single optimization problem. But this method is not much efficient, and the decision maker must put some weights on the objective to select to perform the optimization algorithm.

Optimization has a lot of variety of categories, constrained and unconstrained, linear and nonlinear, deterministic and stochastic etc [5].

$$\begin{gathered} Max\ or\ Min\ f(x), \rightarrow Objective\ function \\ s.t. \rightarrow h(x) = 0, \rightarrow Equality\ constraints \\ g(x) \leq or \geq 0, \rightarrow Inequality\ constraints \\ xmin \leq x \leq xmax \rightarrow variable\ bounds \end{gathered}$$

This equation is an example of single objective problem. In multiobjective problems it requires to optimize the multiple objective functions simultaneously. In multiobjective problems we can't find single solution generally, so we try to find a set of solutions is called Pareto optimal solutions [6]. Pareto optimization methodology comes under the posterior method, in this method the decision made after calculating a set of pareto solutions. It is difficult to optimize a complex industrial system having many correlated parameters that change over time. The definition of the boiler system is described mathematically.

The steam boiler system can be represented as nonlinear dynamic system with $\boldsymbol{x}(t)$ denote the state of the system at t and control parameter is represented by $u(t)$ and the output is represented as $y(t)$.

The state-space representation of the system is described below:

$$\begin{gathered} \dot{x} = f\big(x(t), u(t)\big), \\ y(t) = g\big(x(t), u(t)\big), \end{gathered}$$

where $\dot{x}$ – represents the rate of change of the system state, $f(\,)$ – represents the dynamics of the system, $g(\,)$ – represents the output function.

The optimal control parameters are obtained from the below multicriteria optimization problem solution.

$$Max\, J = y(t);$$

Constraints over the control parameters $u(t)$ and state variables $x(t)$ need to be satisfied. The flowchart describes the flow of methodology of multicrtieria optimization using DPCA and ANN.

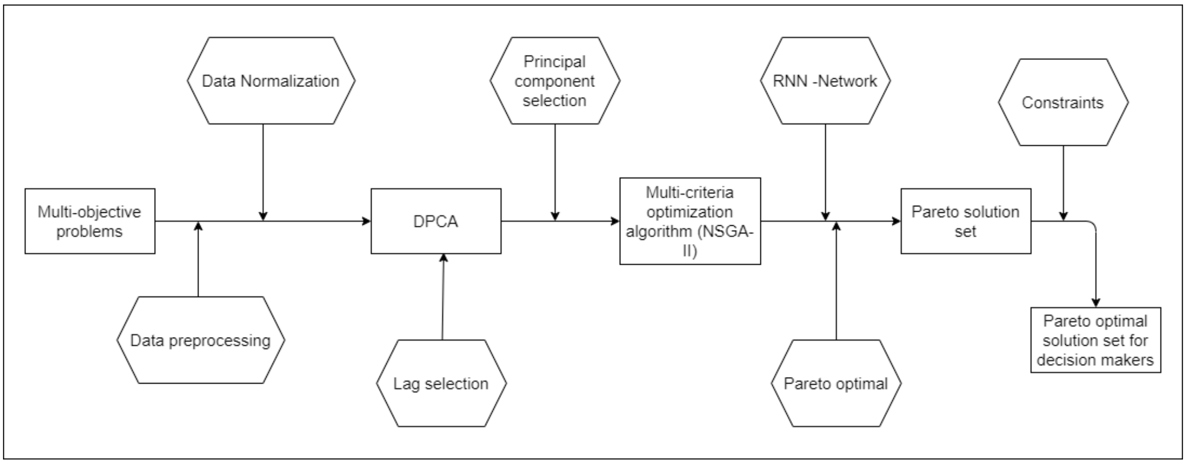

Fig. 1. Flowchart DPCA-ANN formulation

2. Principal Component Analysis

It is a well-known method used to reduce the dimensionality of a large dataset into a small dimension. It helps to remove the correlation between the parameters of the steam boiler system to an independent value which help us to change according to our needs [7]. The algorithm for PCA is explained in algorithm:

1) standardization of the original dataset X (zero mean and single standard deviation);
2) calculation the covariance matrix $\mathbf{C} = \mathbf{X}^T \mathbf{X}$;
3) calculation of eigenvalues $\boldsymbol{\lambda}$: $|\mathbf{C} - \boldsymbol{\lambda}\mathbf{I}| = 0$, $\mathbf{I}$ is the unit matrix;
4) calculation of corresponding eigenvectors: $\mathbf{CX} = \boldsymbol{\lambda}\mathbf{X}$;
5) the eigenvector with the largest eigenvalue is the principal component of the dataset **X**.

Principal component analysis helps to remove the correlation between the parameters and give us an independent Principal component. This method widely uses when there are many control parameters to control at the same time. The PCA method try to find the correlation between the parameters and form the Eigen values and vectors. These properties of matrix are used to solve the curse of higher dimensionality of any dataset. It is necessary to normalize the dataset before performing PCA operation.

3. DPCA

Dynamic principal component analysis is an extended version of Principal component analysis. One of the adaptations in dpca is that it will help to add the ability to find the autocorrelation behaviour in every process. The key feature of DPCA is its structure, which means that the number of times shifted (lags) replicates of each feature and include the decision to choose how many numbers of components to retain after performing DPCA [8, 9]. In this method I used same lag for every feature in the model. The lagged version of the feature set will help to form the extended matrix and then perform the same operation as PCA do. DPCA will help to capture the static relationship and dynamic structure together. Backbone of this method is the selection of the number of lags. This can be done through different methods present while performing the Autoregressive Model (AR) or Autoregressive Moving Average (ARMA) model. The selection of principal component is done by using the Fig. 2.

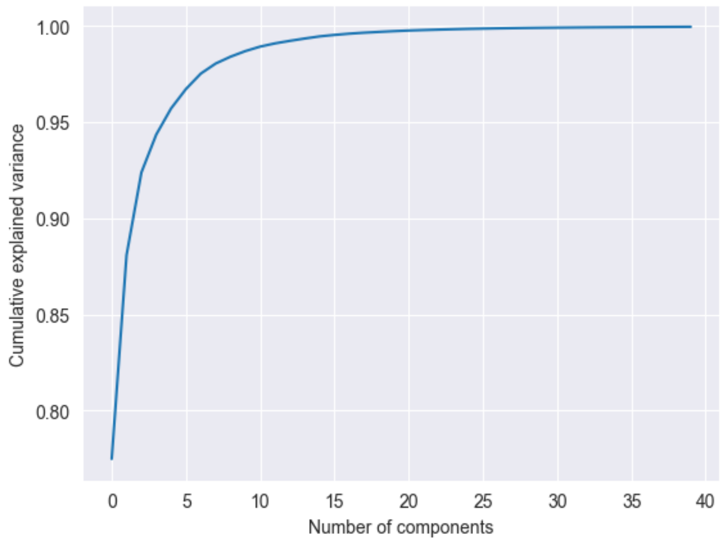

Fig. 2. Selection of Principal components

DPCA uses an extended matrix $\widehat{\mathbf{X}}$, which is the matrix $\mathbf{X}$ augmented with the time-shifted repeat values of all variables. The number of lags can be selected from the order of an AR model.

$$\hat{y} = \alpha_1 y_{t-1}, \dots \alpha_p y_{t-p}$$

AR models assumes that the current value is dependent on previous values, $y_{t-1}, y_{t-2}, \dots y_{t-p}$, where p is the order of AR.

Partial autocorrelation can be used to find the order of AR models. The same number of lags are selected for each parameter in this method.

$$\mathrm{X} = [X_t, X_{t-1}, X_{t-2}, X_{t-3}].$$

4. Artificial Neural network formation

The number principal component determines the input to the neural network. So, the neural network contains 5 inputs, it is determined by the help of Fig. 1. and it covers 97 % variance of original dataset. Here we used the recurrent ANN with 3 hidden layers having 64, 64 and 32 neurons in each layer. The output layer is used to predict the efficiency and productivity of the steam boiler. The data set is divided into a training, validation, and testing in the percentage of 80 %, 10 % and 10 %. And for tuning the hyper parameters of the neural network, I used 25 as the batch size, 100 epochs, dropout is 20 % and l2 regularization for not obtaining the overfitting problem. The neural network has the explained variance sore is r^2 is 0.91.

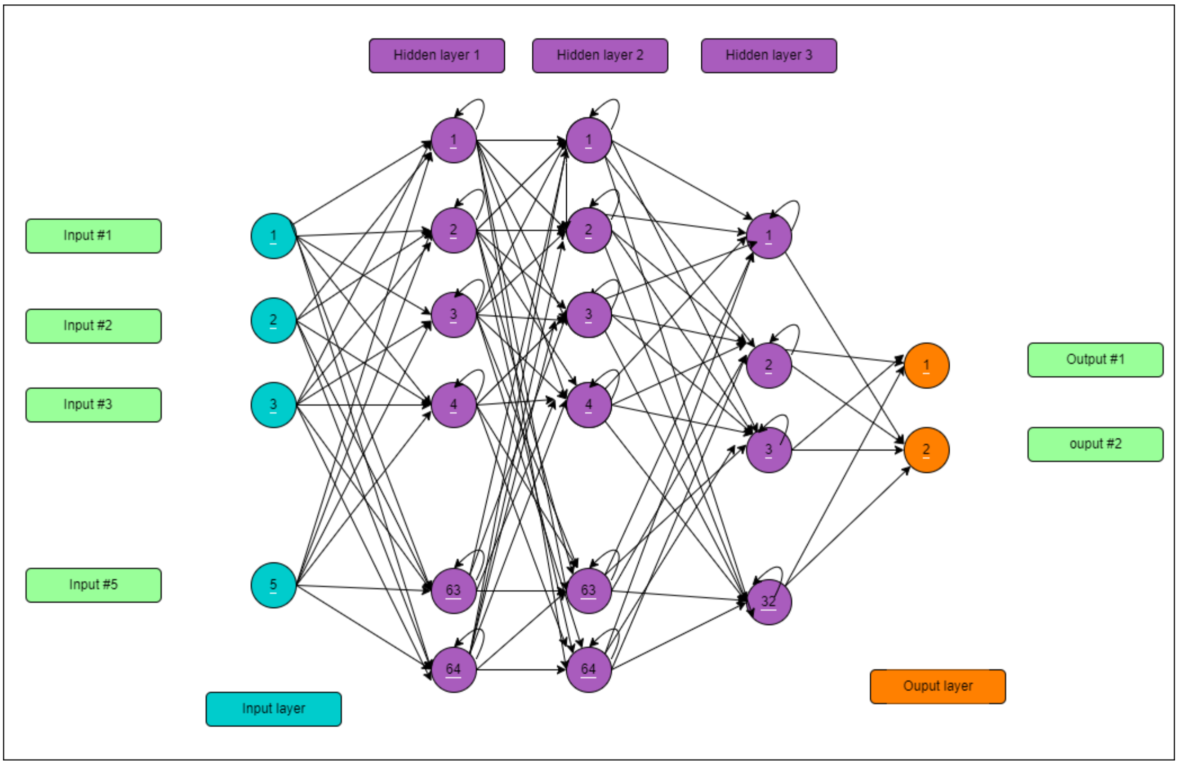

Fig. 3. RNN structure

Mathematical representation of the RNN structure can be expressed here.

$$\mathbf{h}_t^{(1)} = \boldsymbol{\phi}(\mathbf{W}^{(1)}\boldsymbol{x}_t + \mathbf{U}^{(1)}\mathbf{h}_{t-1}^{(1)} + \mathbf{b}^{(1)}),$$
$$\mathbf{h}_t^{(l)} = \boldsymbol{\phi}\left(\mathbf{W}^{(l)}\mathbf{h}_t^{(l-1)} + \mathbf{U}^{(l)}\mathbf{h}_{t-1}^{(l)} + \mathbf{b}^{(l)}\right),$$
$$\boldsymbol{y}_t = \boldsymbol{\varphi}(\mathbf{W}^4\mathbf{h}_t^3 + \boldsymbol{b}^4),$$

where $\mathbf{x}_t$ – input vector, $\mathbf{W}^{(l)}$ – weight matrix connecting layer l to $l+1$, $\mathbf{U}^{(l)}$ – weight matrix connecting previous hidden state to the current hidden state of layer $l = 2{,}3$), $\mathbf{b}^{(l)}$ – bias vector of layer l, $\mathbf{h}_t^{(l)}$ – hidden state vector of layer l at time step t, $\boldsymbol{\phi}(\,)$ and $\boldsymbol{\varphi}(\,)$ – nonlinear and linear activation functions in hidden and output layer respectively.

5. Results

After modelling the neural network, we perform the Non dominated sorting algorithm on the objective function of the steam boiler with the constraints defined over the min and max of the principal component analysis. The population size used in the algorithm is 200, cross over probability is 0.9 and mutation rate is 1/5. We keep 50 populations in each iteration to generate a new solution.

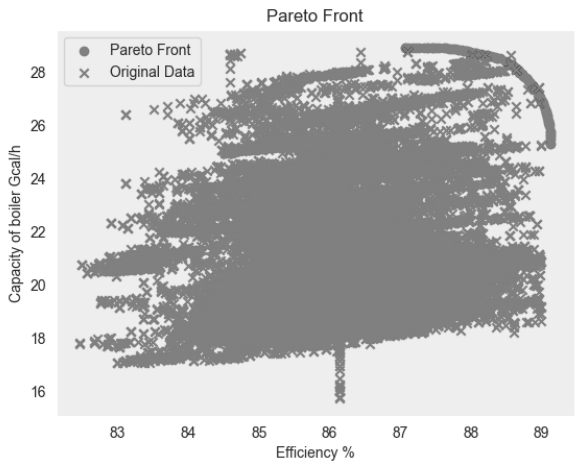

Fig. 4. Pareto optimal solution

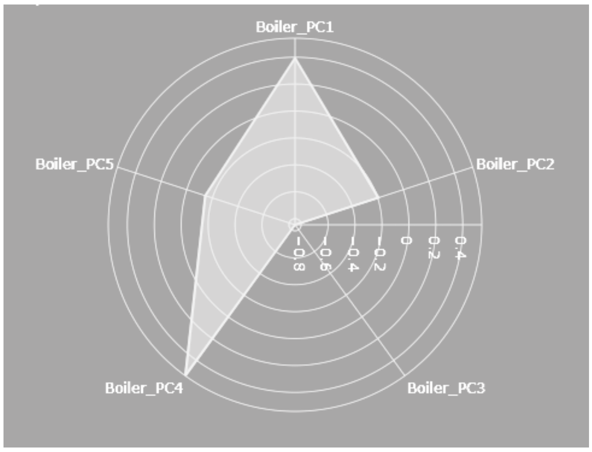

Fig. 5. Principal component values of a solution in pareto solutions

Using an evolutionary algorithm, we could be able to solve an multi objective optimization problem with help of dimensionality reduction method and Artificial neural network.

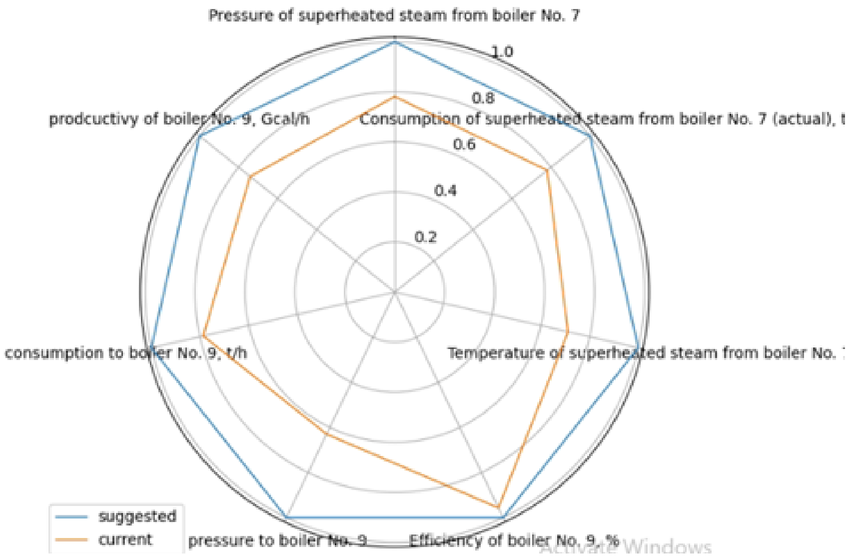

Fig. 6. Comparison of current and suggested control parameters

The final phase of the study consists of obtaining the original values from the PCA parameters. Perform this operation, it is necessary to use the inverse function defined in the Python language. Restore the original parameters from PCA, it is necessary to save the mean values of the training set. The necessary information is stored in an object of the PCA. After performing those operations, which will give the original physical parameters, this approach helps the decision-makers see the original values after performing the PCA operation and NSGA2 optimization algorithm. The result of an optimal solution can be visualized in a spider graph Fig. 4. The realization of the original parameters from the Pareto solutions will help to automate the steam boilers' working in an optimized way. The decision maker can choose any solution from the Pareto optimal solution and operate the steam boiler. The diversity in the optimal solutions makes the Pareto optimal methodology more suitable for solving multiobjective problems in real-time.

Conclusion

The ANN model is developed based on real-time data, which can make sure that it will take care of every physical character of the steam boiler. The model gives the optimal mean square error for the training and validation data. The conclusion of the above information leads to the conclusion that the Ann model is highly suitable for performing the multiobjective optimization problem of a steam boiler. The Pareto optimal solution contains many Pareto solutions, which give the decision-makers a diverse range of options to choose the best steam boiler parameters to maximize efficiency and productivity. Also, the hierarchical pareto optimization help us to optimize each individual subsystem separately. After this optimization process, we can receive the optimized solution set. This solution set help to find the optimized the control parameters of the steam boilers. As the last step, we can find the optimal solution set of boiler units. This process works forward and backward, that is lower and higher-level connection. If we use the optimal solution set to operate the steam boiler units, we could improve the efficiency and productivity at the same time. We can improve it till 88 % from 86 % as normal working efficiency.

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