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Static and dynamic neural networks for simulation and optimization of cogeneration systems

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ABSTRACT

In this paper, the application of neural networks for simulation and optimization of the cogeneration systems has been presented. CGAM problem, a benchmark in cogeneration systems, is chosen as a case study. Thermodynamic model includes precise modeling of the whole plant. For simulation of the steady sate behavior, the static neural network is applied. Then using dynamic neural network, plant is optimized thermodynamically. Multi- layer feed forward neural networks is chosen as static net and recurrent neural networks as dynamic net. The steady state behavior of Excellent CGAM problem is simulated by MFNN. Subsequently, it is optimized by dynamic net. Results of static net have excellent agreement with simulator data. Dynamic net shows that in thermodynamic optimization condition, σ and pinch point temperature difference have the lowest value, while CPR reaches a high value. Sensitivity study shows turbomachinery efficiencies have the highest effect on the performance of the system in optimum condition.

Keywords

Neural network, simulation, optimization, cogeneration system

1.Introduction

Neural network theory is one of the principalmembers ofthe soft computing union that includes, in addition, fuzzy logic,evolutionary computing and probabilistic computing. Withinthis union, the principal contribution of neural network theoryis the machinery for learning, adaptation and modeling of bothstatic and dynamic system and real time optimization.

First step in optimization is that the behavior of systemshould be known. In fact, behavior of system is the relationbetween independent variables and dependent outputs. Sincethe transient time is short, especially for cogeneration systemsbased on gas turbine, the optimization is done for steady stateof system. The nature of energy systems is nonlinear so, systemis assumed as black box and the relation between decisionvariables and outputs is determined using the multi-layer feedforward neural networks. In fact, by means of this method (theapplication of static net), the behavior of system is identifiedand at the following dynamic network is applied foroptimization.

In the optimization of complex energy systems (i.e., powerplants), the thermodynamic optimization aims to minimize thethermodynamic inefficiencies: exergy destruction and exergylosses that it obtains by fuel mass flow minimization. TheCGAM problem refers
to a cogeneration plant, which generates30MW electricity power and 14 kg/sec of saturated steam at 20bars. The structure of the plant is shown in fig (1). The plantconsists of a gas tur-

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bine adopted by a recuperator that uses partof the thermal energy of exhaust gases and a HRSG forproducing steam. It is be notable that assumed environment isin ISO condition; subsequently gas turbine works in designcondition. The fuel is natural gas with a lower heating value(LHV) equal to 50000 kJ/kg.

The application of soft computing to model and optimization of systems is sharply increasing. Shouraki [1] proposed a method for fuzzy modeling; which is called as active learning method (A.L.M). The basic idea behind A.L.M is looking for single input single output subsystems whose fuzzy Combination, in a parallel structure, will result in the model of multi input single input system. It is shown that A.L.M is a universal approximator [2] and the ability of this method for curve fitting, interpolation and extrapolation presented for a two dimensional nonlinear mapping [3]. Assadi [4] used a static neural network to model the performance of the simple gas turbine and generate the engine performance map, which covered a wide range of operational and environmental conditions.
Tsatsaronis and Cziesla [5] used fuzzy logic inference system as an optimizer engine for iterative exergoeconomic optimization of CGAM problem. The iterative exergoeconomic analysis is illustrated elaborative in [6], [7].

In this paper, the steady state behavior of CGAM problem is modeled by MFNN. For this reason, we code the training algorithm of MFNN

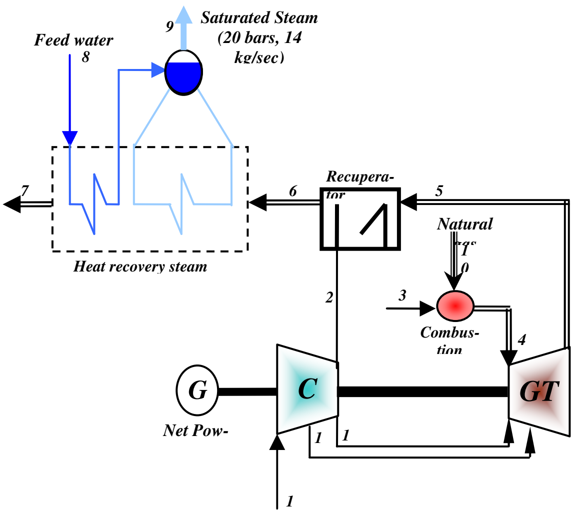

Fig.1: Flow diagram of the CGAM problem

using FORTRAN programming language. using this approach, an explicit functional relation for fuel mass flow, net power, steam mass and stack temperature obtains and optimization procedure is done using recurrent neural network, which is modeled in MATLAB.

2. Artifical Neural Networks

An ANN is an information-processing system that has certain performance characteristics in common with biological neural networks. ANNs have been developed as generalization of mathematical models of human cognition or neural biology, based on the assumptions that:

1. Information processing occurs at many simple elements called neurons.
2. Signals are passed between neurons over connection links.
3. Each connection link has an associated weight, which, in a typical neural net, multiplies the signal transmitted.
4. Each neuron applies an activation function (usually nonlinear) to its net input (sum of weighted input signals) to determine its output signal.

An ANN is characterized by (1) its pattern of connectionsbetween the neurons (called its architecture), (2) its method ofdetermining the weights on the connections (called its trainingor learning algorithm) and (3) its activation function [8].

2.1. Static ANN to Find Functional Relation

In general, static system is a system that its outputs are a function of only the current inputs. It is suitable to use MFNN as a static net to simulate the steady behavior of system. Applications using such nets can be found in many fields that involve mapping a given set of inputs to specified set of target outputs (so learning is supervised). Backpropagation algorithm, which is the optimization technique based gradient descent, is applied for training of MFNNs.

The training of MFNNs by Backpropagation algorithm involves three stages: feed forward of the input training patterns, the calculation and Backpropagation of associated error and the adjustment of the weights by means of adaptive algorithm. Because of implementation of BP, for training of MFNN the activation function should have several important characteristics. It should be continuous, differentiable and monotonically increasing. Here bipolar sigmoid activation function is considered which has range of (-1, 1) and is defined as

$$Sig(x) = \frac{2}{1+\exp(-x)} - 1 \qquad (1)$$

In order to explain the BP algorithm in its basic form, thelearning of single neuron, which is located in the output layerof MFNN, has be shown in fig (2).Although a single layer net is severely limited in themapping, a MFNN (with one or more hidden layers) can learnany continues mapping to any arbitrary accuracy. In fact,MFNNs are universal approximators. This theorem is namedkolmogrov theorem which states that a feed forward neuralnetwork with three layers of neurons (input units, hidden unitsand output units) can represent any continuous function exactly.More than one hidden layer may be beneficial for someapplications, but one hidden layer is sufficient.

After training, application of the net involves only the computations of the feed forward phase. This means that after training the MFNN is a nonlinear mapping from input space to out put space. This mapping can be written as:

$$f: R^n \rightarrow R^m\, ; (y_1, y_2, \dots, y_m) = f(x_1, x_2, \dots, x_n) \qquad (2)$$

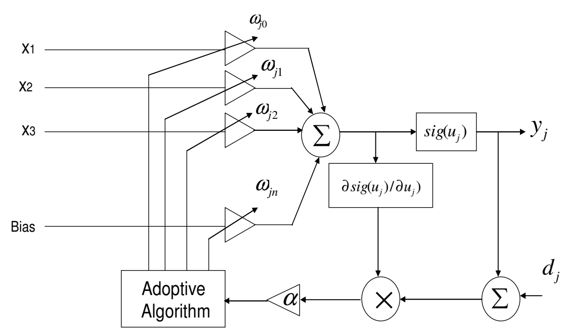

Fig.2: Implementation of BP algorithm for the single neuron located in the output layer

y_k, which present functional relation between input vector and k'th output, can be given as:

$$y_k = Sig\left(w_{0k} + \sum_{j=1}^{P}\left(Sig\left(v_{0j} + \sum_{i=1}^{n} x_i v_{ij}\right)\right) w_{jk}\right) \qquad (3)$$

2.2. Dynamic ANN for Optimization

In general, extra to the depending on current inputs, thecurrent output of the system, in dynamic systems, depends onprevious outputs. The degree of dependency of current outputto the previous outputs determines the order of system.Dynamic neural units, the basic elements of dynamic neuralnetworks, receive not only external inputs but also statefeedback signals from other dynamic neural units in thenetwork. From the aspect of dynamic systems, a dynamicneural unit forms a nonlinear dynamic subsystem that isdescribed by a single-variable nonlinear dynamic equation. Figure (3) illustrates schematic representation of the individualdynamic neural unit. According to this figure, a generalmathematical model of the i_{th} DNU that is connected to other(n-1) DNUs in an n-neuron dynamic network structure isdescribed as

$$\frac{dx_i(t)}{dt} = -a_i x_i(t) + f_i(\omega_{ai}, x_a) \qquad (4)$$

$$y_i(t) = g\big(x_i(t)\big) \qquad (5)$$

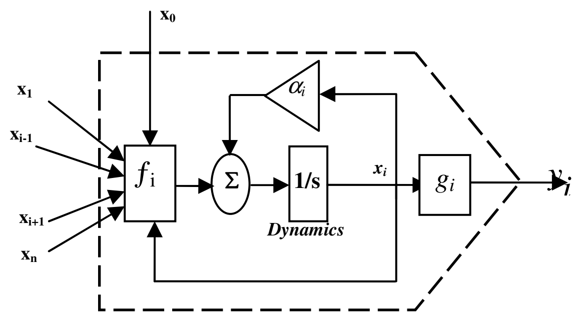

Fig.3: Schematic representation of the ith DNU

It is notable that due to different choices of the nonlinear function fi in the general DNU model given in (4), (5) and different types of synaptic connection that possibly exist among the DNUs, different dynamic neural models can be considered [9].

One of the most promising applications of dynamic neural networks is in the area different classes of optimization problems. The ability of analog neuron-like network process simultaneously a large number of variables makes it possible to find solutions for complex optimization problems in almost real time. Different classes of optimization problems are discussed comprehensively in [10]. Here, regarding our case study we consider continuous nonlinear optimization with equality constraints, which can be state as

Find $X = [x_1, x_2, \dots, x_n]^T \in R^n$ which minimizes the scalar function$f(x_1, x_2, \dots, x_n)$

Subject to

$$h_i(x) = 0 \tag{6}$$

Where x is an n-dimensional vector called the decision variables vector, f(x) is objective function and $h_i(x)$ represent equality constraints.

To formulate the optimization problem to fit for ANNs the key step is to derive a computational energy function (Lyapanov function) so that the lowest energy state will correspond to the optimum point. In fact, the stable state for dynamic systems corresponds to the minimum surface of relevant Lyapanov function of the system.

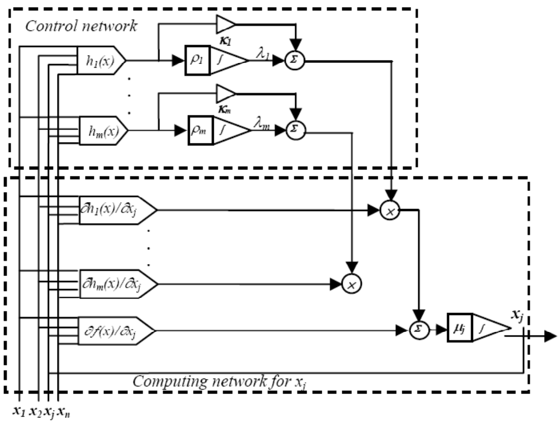

Fig.4: Block diagram of a network for nonlinear optimization problems with equality constraints based on augmented Lagrange multiplier method

Suitable Lyapanov function can be derive regarding objective function and constraints by means of different methods.

At the following suitable recurrent neural net is made which has equivalent energy function. Now the stable state for this net is equivalent the optimum condition for main problem.

The augmented Lagrange multiplier method is a new class of optimization method, which known simply as the multiplier method or as primal-dual methods, is proposed by Hestenes and Powell [11], [12]. Via this method, the relevant Lyapanov function for optimization problem, which stated in (6), can be written as

$$E(x, y, k) = f(x) + \sum_{i=1}^{m} \lambda_i h_i(x) + \sum_{i=1}^{m} k_i P_{ih}(x) \tag{7}$$

Where $\lambda = [\lambda_1, \lambda_2, \dots, \lambda_m]^T$ is the Lagrange multipliers and $k = [k_1, k_2, \dots, k_m]^T$ is the penalty parameters with $k_i > 0$. If the classical quadratic penalty functions are used, we obtained the Lyapanov function

$$E(x, y, k) = f(x) + \sum_{i=1}^{m} \left(\lambda_i h_i(x) + \frac{1}{2} k_i h_i^2(x) \right) \tag{8}$$

Therefore, the multiplier method replaces the equality constraint optimization problem by the unconstraint minimization of the penalized Lagrangian. Now this problem can be converted into the problem to solve the system of differential equations consist of

$$\begin{aligned} \frac{dx}{dt} &= -\mu \nabla_x E(x, \lambda, k) \\ \frac{dy}{dt} &= \rho \nabla_\lambda E(x, \lambda, k) \end{aligned} \tag{9}$$

With the initial conditions $x(0) = x^{(0)}$and $\lambda(0) = \lambda^{(0)}$, where μand ρ are positive scalar variables. Based on the above set ofdifferential equations we can construct an appropriate ANN asshown in fig (5). Note that Lagrange multipliers $\lambda_i(t)$ are usedhere as adaptive control parameters during the minimizationprocess.

3. Case Study

As mentioned above we choose the CGAM cycle as a case study for simulation and optimization procedure. The structure of the CGAM cycle has been shown in fig (1).

In this model, compressor pressure ration CPR, compressor polytropic efficiency $\eta_{\infty,c}$, compressor inlet mass flow m_{air}, turbine inlet temperature T_4, turbine polytropic efficiency $\eta_{\infty,t}$, the turbine blade cooling parameter σ, pinch-point temperature in HRSG ΔT_{pp} and effectiveness coefficient of recuperator ε are considered as decision variables. Detail modeling of the system, parameters definition and other assumptions has been presented in [13].

It is notable that fuel mass flow, net power, steam mass flow and exhaust temperature functional relation, which are vital for optimization procedure, cannot be state versus decision variables.

In this problem, the input is an 8×1 vector whose elements are decision variables presented in table (1), Also output is a 4×1 vector consist of dependent variables which presented in table (3). Because of the sensitivity of activation function, both Input and output values are normalized between -1, 1 to train the network. As mentioned above, we have used bipolar activation function and chosen ten neurons for the hidden layer. It should be noted that the number of neurons of the hidden layer is chosen by trial and error. 4000 pairs of inputs and outputs are assumed for training the net. These 4000 patterns are obtained from thermodynamic simulator which explained in [13]. As proposed by Hetch-Nielsen [14] net is trained by 2800 patterns and tested by the rest. Training continues until the learning rate is less than 0.0000001. In addition, the initial weights of net have been chosen between 0.5 and -0.5 randomly. In this problem, the Backpropagation algorithm is adapted by "Search-Then-Converge" strategy [15], [10]. According to this strategy, the learning rate is gradually decreasing during the learning process. In the first phase of learning (search phase) learning rate is constant while it must be sufficiently large.

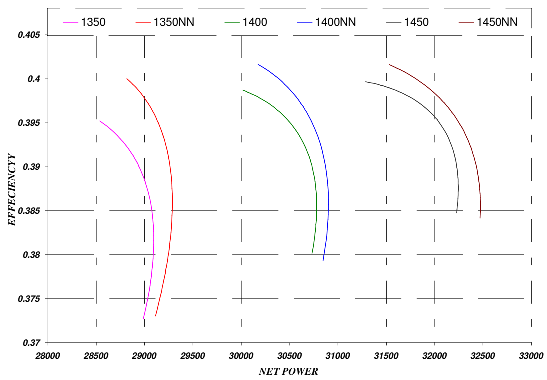

Fig.5: Variation of efficiency and power of CGAM with CPR for simulator and MFNN (NN) at σ =0.2

Table 1.Decision variables changes range

Variable	Minimum value	Maximum value
CPR	8	15
m_{air}	90	140
$\eta_{\infty,c}$	0.85	0.92
$\eta_{\infty,t}$	0.85	0.91
T_4	1233	1533
σ	0.2	0.5
ε	0.6	0.9
ΔT_{pp}	0	30

Table 2. Results for thermodynamic optimization

Variable	Value	Variable	Value
CPR	15	ε	0.6853
m_{air}	107.125	T_4	1362.1
$\eta_{\infty,c}$	0.8771	σ	0.2
$\eta_{\infty,t}$	0.91	ΔT_{pp}	0

Table 3. Values of dependent thermodynamic variables for optimum design

T_2	T_3	T_5	T_6	M_c/M_{air}
687.664	740.615	764.64	716.64	0.044286

In the second phase (convergence phase), the learning rate exponentially decreases to zero. After training, in fact, the nonlinear functional relation between decision variables and outputs has been determined and we are ready for optimization phase. As already stated, the objective function is fuel mass flow and there are three equality constraints. Our prospect from system and physical limitations impose the constraints that stated as

- For avoiding the acid droplet, the exhaust gas temperature of the HRSG Texh should not be below 120°C.
- Net electric power W& net generated is 30MW.
- 14 kg/sec saturated steamM&steam , as a utility, at 20 bars should be produced.

Although, it can be inferred from the first limitation, that exhaust temperature must be greater than or equal to 120°C, for minimizing the exergy losses it must be decreased as far as possible. This means that the exhaust temperature must be 120°C. therefore we have continuous nonlinear optimization problem with three equality constraints. The relevant energy function defines as

$$\begin{aligned} E(x,y,k) = \dot{m}_f(x) & \\ &+ \Big(\lambda_1(\dot{w}(x) - 30000) \\ &+ \frac{1}{2}k_1|\dot{w}(x) - 30000|^2\Big) \\ &+ \Big(\lambda_2(\dot{m}_{steam}(x) - 14) \\ &+ \frac{1}{2}k_2|\dot{m}_{steam}(x) - 14|^2\Big) \\ &+ \Big(\lambda_3(T_{exh}(x) - 393.3) \\ &+ \frac{1}{2}k_3|T_{exh}(x) - 393.3|^2\Big) \end{aligned} \tag{10}$$

Where κi are chosen by trial and error and λi are determined adaptively as shown in fig (4). Now according to (9), (10) we can construct the suitable dynamic network looks like fig (5) for optimization.

4. Result And Discussion

Based on the methodology described in the previous sections, at first, we present the results of estimate the steady state behavior of CGAM problem, which is done using static neural network and at the following, the optimization results have been shown. Finally, the sensitivity analysis is done to show the sensitivity of the Lyapanov function, which indicates sensitivity of system according to decision variables changes around the optimum points.

4.1. Thermodynamic Simulation Validation

In this section, the accuracy of static neural network as a CGAM simulator is presented. In order to test accuracy of gas turbine simulator, some of the gas turbine performance behavior graphs for CGAM simulator and static neural network will be compared here.

Figures (5) and (6) show that for all TITs, CPRs (9-14) and with different blade cooling technologies, MFNN can predict CGAM behavior with little error. Maximum error is less than 1 % for all cases.

As can be seen, with variation in blade cooling technology(σ), power and efficiency decrease significantly due to increasein coolant mass flow. Both simulator and MFNN predict thistrend with little differences.

In figure (7) effect of change in value of σ on coolant mass flow is presented for TIT=1400 K. both models show that with increase in σ coolant mass flow increase and this increase is higher for high CPR. Fig (8) show that decrease in σ increase gas turbine exhaust temperature and more energy will be transferred to recuperator and heat recovery boiler. These trends are predicted with two models simultaneously.

From the above results, we can conclude that the MFNN can predict behavior of CGAM with good accuracy. Therefore the functional relations, which are produced by static net, can be used in dynamic neural net for optimization.

4.2. Optimization

Using proper dynamic neural net for the CGAM problem, we can obtain optimum values for decision variables. As mentioned above the net is going to reach its minimum Lyapanov function

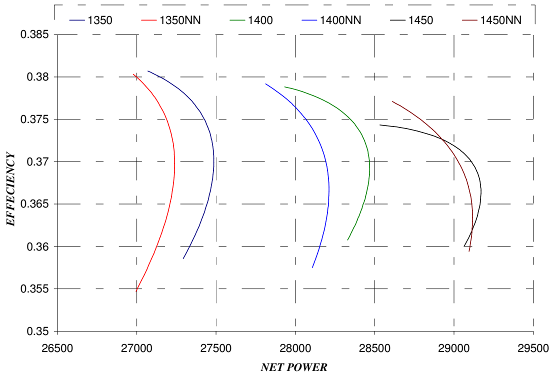

Fig.6: Variation of efficiency and power of CGAM with CPR for simulator and MFNN (NN) at σ =0.4

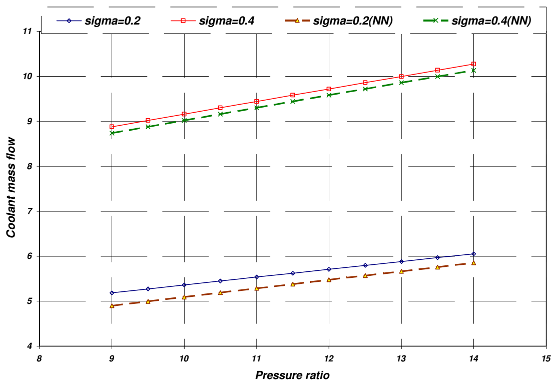

Fig.7: Variation of coolant mass flow versus CPR for simulator and MFNN (NN) at σ =0.4, 0.2

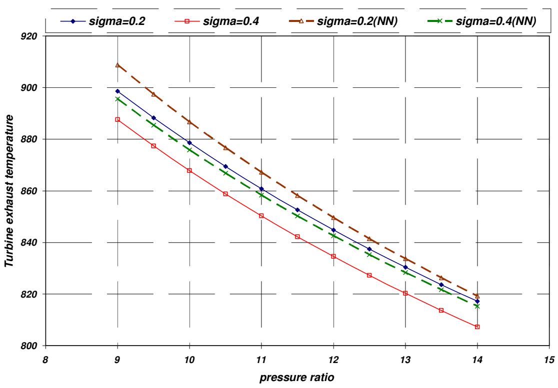

Fig.8: Variation of turbine exhaust temperature versus CPR for simulator and MFNN (NN) at σ =0.4, 0.2

value. This condition is equivalent with the optimum values for decision variables. The final values for decision variables are shown in table (2) and relevant trajectories are drowning at the following.

Table (3) shows the dependent thermodynamic variables values in optimum condition. In thermodynamic optimization, minimizing fuel mass flow is our object; therefore inlet air mass flow to compressor must decrease to minimize fuel consumption. Also, pinch point temperature difference must reach zero to minimize exergy destruction in HRSG. As described in [16] the stack temperature must reach its minimum value (fig (20)) to minimize exergy loss so it needs the inlet temperature of gas entering HRSG increase. More comprehensive discussions are presented in [16]. The results for thermodynamic optimization are reaching high CPR (to minimize fuel mass flow), low TIT, high compressor and turbine polytropic efficiency and high blade cooling technology (the lowest possible value for σ). The computer simulations of these variables are shown in figures (9)-(17). In addition figures (18), (19), (20) show the error of the outputs from their desired values. As be shown the steady state error for desired outputs is zero. As will be described in sensitivity analysis, compressor and turbine polytropic efficiency have the highest effect on gas turbine cycle performance.

4.3. Sensitivity Analysis

After the optimization procedure, in order to investigate the effective variables on optimum performance, 5 % change around the optimum point values in decision variables is done, and then using MFNN, the sensitivity analysis of Lyapanov function is plotted.

Lyapanov function consists of mass flow rate and desired outputs of plants, so its variation according to decision variables helps to understand general behavior of the plant around optimum condition. The sensitivity of Lyapanov function in thermodynamic optimum condition is shown in fig (21), (22). Fig (21) shows that the most important decision variable is compressor polytropic efficiency. This result is similar to results presented in [17]. As shown, reducing

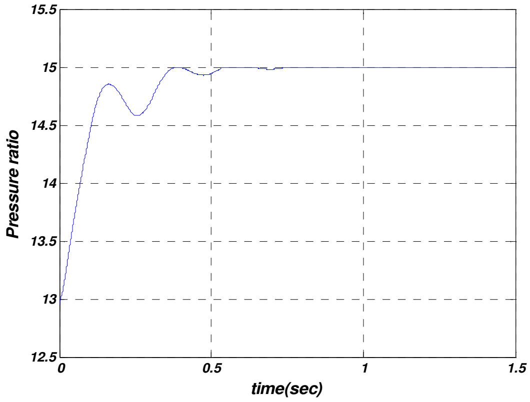

Fig.9: Computer simulated trajectory forpressure ratio

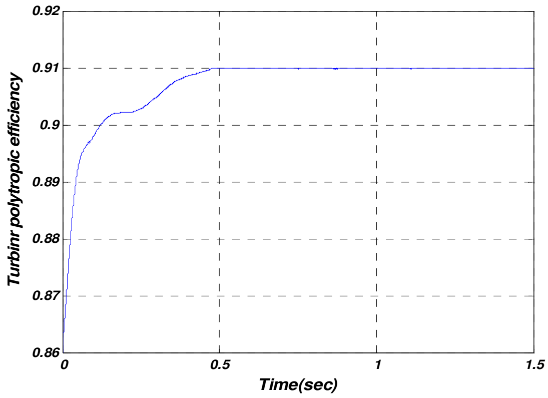

Fig.12: Computer simulated trajectory for turbine polytropic efficiency

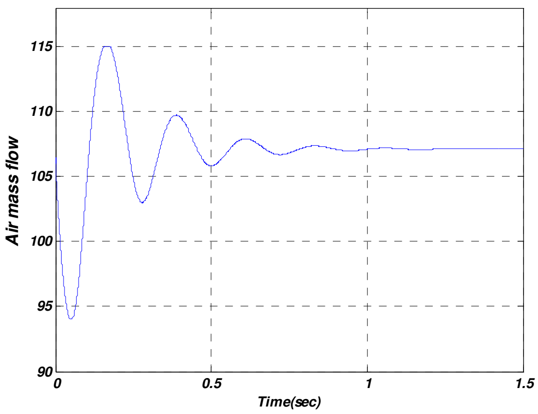

Fig.10: Computer simulated trajectory for air mass flow

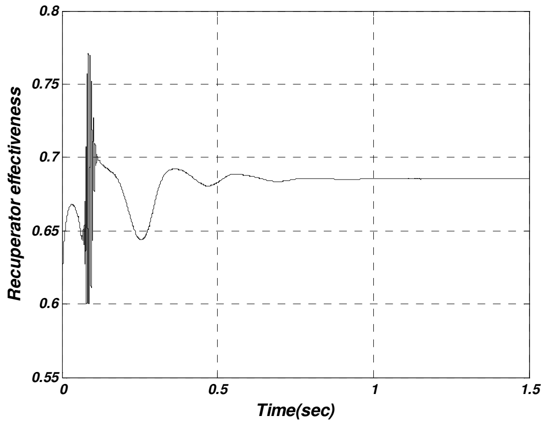

Fig.13: Computer simulated trajectory for Recuperator effectiveness

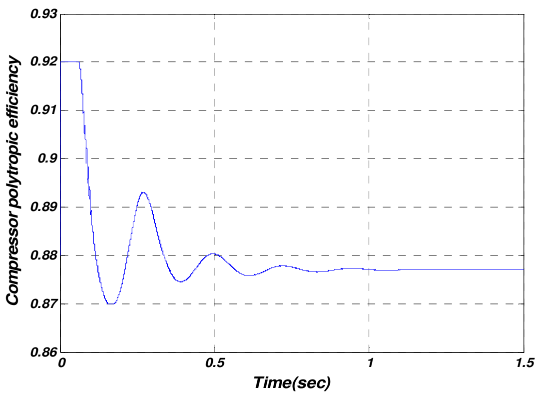

Fig.11: Computer simulated trajectory for compressor polytropic efficiency

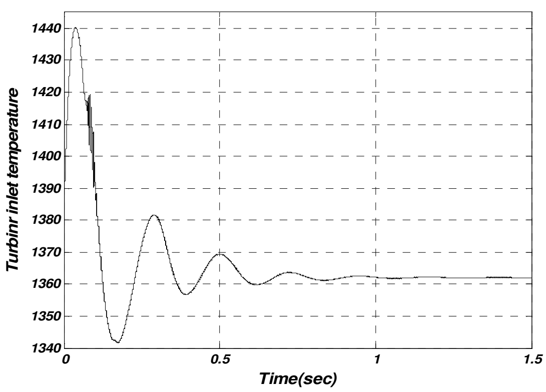

Fig.14: Computer simulated trajectory for turbine inlet temperature

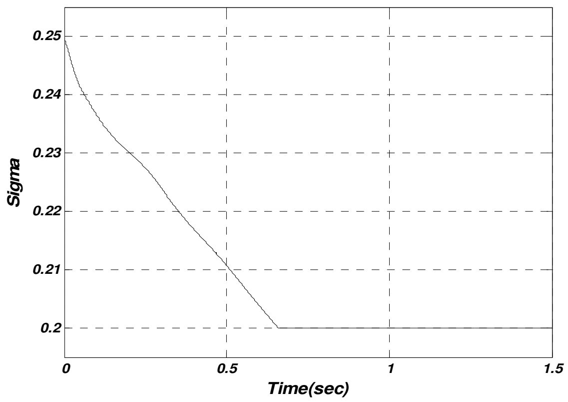

Fig.15: Computer simulated trajectory for blade cooling parameter

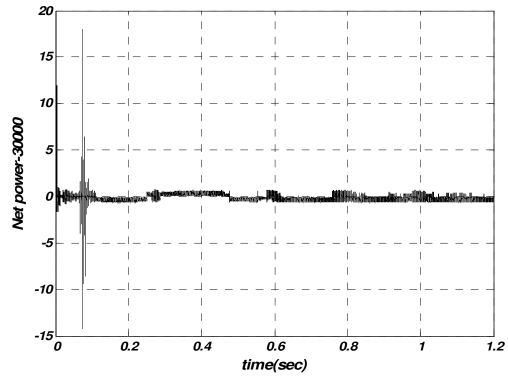

Fig.18: Computer simulated trajectory for error in desired power

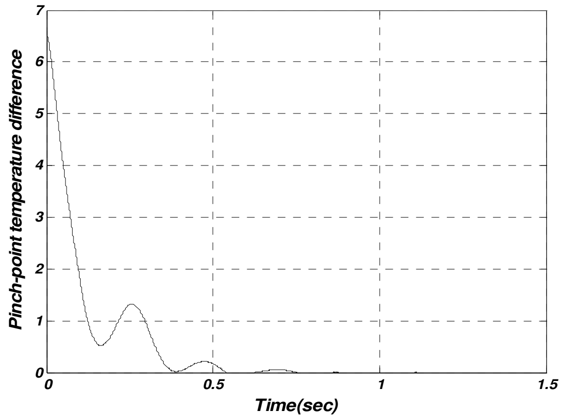

Fig.16: Computer simulated trajectory for pinch-point temperature difference

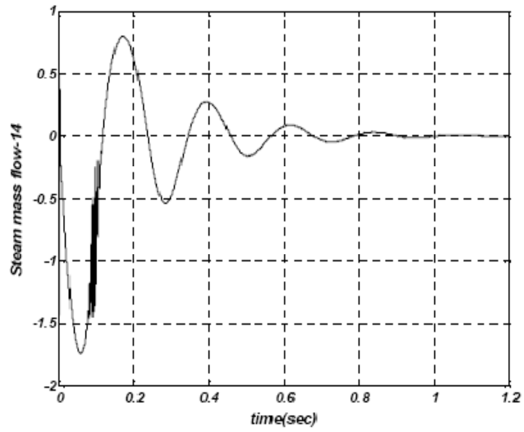

Fig.19: Computer simulated trajectory for error in desired steam mass flow

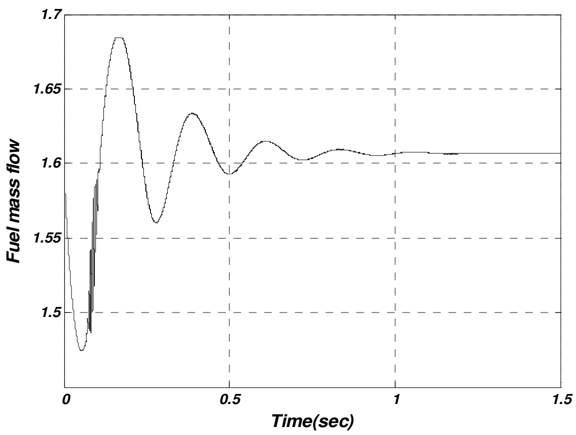

Fig.17: Computer simulated trajectory for fuel mass flow

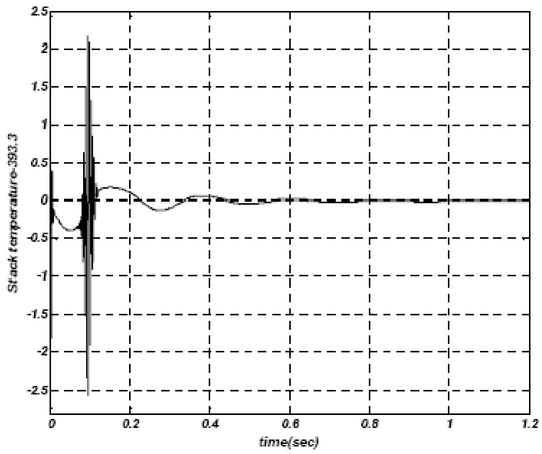

Fig.20: Computer simulated trajectory for error in stack temperature

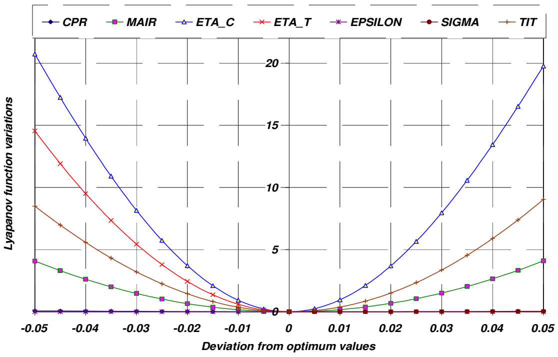

Fig.21: Effect of change in decision variables on Lyapanov function around the thermodynamic optimum condition

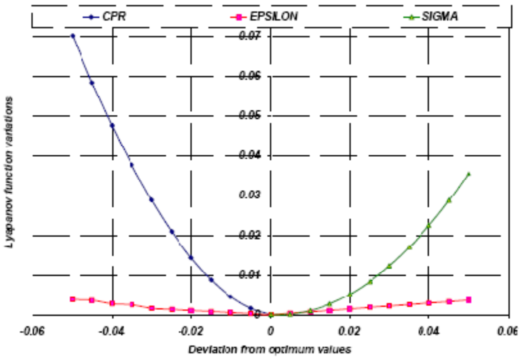

Fig.22: Effect of change in decision variables on Lyapanov function around the thermodynamic optimum condition

polytropic efficiency changes optimum condition more than increase its value. Turbine polytropic efficiency is the second effective variable on Lyapanov function. TIT and mair cause to similar trend and quantities. Other variables like ε, σ and CPR have similar effect. These behaviors are all in accordance with [16].

5. Conclusions

In this paper, we present the application of neural networks for simulation and optimization of cogeneration systems. At the following, the thermodynamic optimum design of CGAM problem is presented. Modifications in both of the thermodynamic model of the cycle and method of optimization are done. The main findings of the paper are:

- Results of MFNN shows that this type of neural networks are suitable tools for nonlinear and multi-dimensional modeling
- Dynamic neural network can be used effectively for solving engineering problems, which formulated as optimization problem. The basic idea behind of using dynamic neural network for optimization problem is that any natural dynamic system will go to its minimum values of energy (minimum value of Lyapanov function).
- In thermodynamic optimization, the object is to minimize fuel mass flow, which minimizes exergy losses and destructions. Therefore, CPR has high value; TIT, blade cooling technology and inlet air mass flow have low value. ΔTpp is zero and ε has a moderate value.
- Turbomachinary efficiency (especially compressor polytropic efficiency) is the most important variable that affects design condition of the whole plant. TIT and inlet air mass flow have lower influence.

6. Nomenclature

Sig	Bipolar activation function
f	Fuel air ratio (mass basis)
ISO	ISO condition (15°C, 1.01325 bar, 60% relative humidity)
Δ T	Temperature Difference
V	specific volume
g_i	activation function of i'th neuron
T_i	weight matrix of neuron

Abbreviations

GT	Gas Turbine
HRSG	Heat Recovery Steam Generator
MFFN	Multi layer feed forward neural network
ANN	Artificial Neural Network
LHV	Lower Heating Value (kJ/kg)
CGAM	**C**. Frangopoulos, **G**. Tsatsaronis, **A**. Valero, **M**.Spakovsky
BP	Back Propagation
DNU	Dynamic Neural Unit
m	mass flow rate (kg/s)

P	Pressure (bar)
T	Temperature (ºK)
CPR	pressure ratio
e	error signal
d	desired output

Greek symbols

η_{∞}	Polytropic Efficiency (c: compressor, t: turbine)
α	Learning rate
ε	Heat exchanger efficiency
σ	Non dimensional parameter (blade cooling)
x	Input training vector x=[x1,x2,...,xn]
ω_{0k}	Bias on output unit k
v_{0j}	Bias on hidden unit j

Subscribe

Exh	Exhaust
G	Gas
PP	Pinch Point

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