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Deriving to an Optimum Policy for Designing the Operating Parameters of Mahshahr Gas Turbine Power Plant Using a Self Learning Pareto Strategy

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Abstract
In the last decades, analyzing and optimizing the power plants based on thermodynamic laws and intelligent control techniques absorb an incremental interest of researchers. This is because deriving the efficient operating parameters for designing and optimizing the performance of power plants will lead to an acceptable investment and avoiding from discarding the energy. However, there are a few areas of application of mathematical optimization method. Optimizing the governing equations and designing parameters of power plants simultaneously leads to a multi-objective problem in industry. Some of these objectives are nonlinear, non-convex and multi-modal with different type of real life engineering constraints. In this paper a new method called Synchronous Parallel Shuffling Self Organized Pareto Strategy Algorithm (SPSSOPSA) is presented which synthesized evolutionary computing, swarm intelligence techniques and Time Adaptive Self Organizing Map(TASOM) simultaneously incorporating with a data shuffling behavior. Thereafter it will be applied to verifying the optimum decision making for parameter designing of Mahshahr power plant that produced about 117MW electricity, sited in Iran, as a multi-objective and multi-modal problem. The results show the deep relation of the unit cost on the change of the operating parameters.
Key words: Economic optimizing; Exergetic optimizing; Work output maximization; Evolutionary algorithm; Self organized map; Power plant

Parameters and Decision Variables

Decision Variables:

r_p	Compressor pressure ratio
η_c	Compressor isentropic efficiency
η_T	Turbine isentropic efficiency
T_3	Combustion chamber input temperature
T_5	Combustion product temperature
T_2	Compressor output temperature
T_1	Compressor input temperature
$\dot{m}_a$	Air mass flow rate
$\dot{m}_f$	Fuel mass flow rate

Model Parameters and Variables:

PWF	Present worth factor
CRF	capital recovery factor
PEC	Purchased equipment cost
CHE	Chemical properties
MEC	Mechanical properties
T	Thermal properties
SV	Salvage value
AC	Air compressor
GT	Gas turbine
AP	Air preheater
CC	Combustion chamber
$\dot{Z}_K$ (\$/s)	Capital investments rate for K_{th} component
φ_k	Maintenance cost rate for K_{th} component
$\dot{E}_k$	Exergy stream for K_{th} component
	Exergetic efficiency
η_I	First law of thermodynamic efficiency

$\dot{W}$	Power output
P_K	Pressure of K_{th} component
h_K	Enthalpy of K_{th} component
ΔT	Mean logarithmic temperature difference
T_{ref}	Standard state temperature
P_{ref}	Standard state pressure
n	Time period
C_P	Specific heat ratio
Q	Heat transfer rate
$\dot{S}$	Entropy flow rate
W	Work or electricity
$\dot{C}_K(\$/year)$	Component cost
m	Material

INTRODUCTION

The importance of developing and controlling thermal system such as power plants that effectively use energy resources such as natural gas is apparent. Designing efficient and cost effective systems, which also meet environmental conditions, is one of the foremost challenges that researchers almost meet[1]. In the world with finite natural resources and large energy demands, it becomes increasingly important to understand the mechanisms which degrade energy and resources and to develop systematic approaches for improving in order to improving the performance of systems like power plants and also reducing the impact of emission and pollution on environment. One of the common tools in analyzing and optimizing the thermal systems like power plants derived from combining exergetic and economic properties of the flow stream in such systems. Exergetic and microeconomics forms the basis of thermoeconomics, which is almost known as exergoeconomics[2]. Combining the second law of thermodynamic with economics (thermoeconomics) using availability of energy (exergy) is one of the major objects that an engineer should apply in optimizing the thermodynamic systems. Its goal is to mathematically combine the second law of thermodynamic analysis with the economic factors which predict the unit cost of product such as electricity and quantifies monetary loss due to irreversibility. One of the other important objects in optimizing the thermodynamic systems like power cycles is applying the exergy analysis which submits the thermodynamic performance of an energy system and the efficiency of the system components by accurately quantifying the entropy-generation of each component in power plant. The third crucial object which an engineer face in designing the operating parameter of power plant is achieving acceptable properties due to the first law of thermodynamic such as reaching to maximum power, maximum efficiency and controlling the dependent parameters. Considering all of these objectives simultaneously will lead to optimum and precise results which conclude an acceptable providence in use of energy and predict optimum plan for enterprises. During last decades, a variety of methods have been developed which was not limited to traditional probabilistic and stochastic methods and involved advanced computational technologies, information and prediction models in order to increase the power plant's efficiency[3]. Cammarata *et al.*[4] formulate the objective function, the sum of capital, and the operational and maintenance cost of a district heating network using exergioeconomic concepts. Gorji and Ebrahimian[5] analyzed a gas turbine power plant using exergioeconomic principles and mathematic modeling. Bhargava *et al.*[6] analyzed an intercooled reheat gas turbine for the co-generation applications using exergioeconomic principles and mathematical models. Attala *et al.*[7] used exergioeconomic principles as a design tool for the realization of gas-steam combined power plant principle; whereas Mirsa *et al.*[8-9] optimized a single and double effect $H_2O/LiBr$ vapor absorption refrigeration systems.

There are also many optimization models which utilized algorithmic stochastic searching, prediction methodologies and advance soft computing techniques. Wang *et al.*[10] developed a parametric optimization design for supercritical CO_2 power cycles using Genetic Algorithm (GA) and Artificial Neural Network (ANN). Gorji and Goodarzian[11] optimized a gas turbine power plant operating parameters using a Multi Objective Genetic Algorithm (MOGA). Valdes *et al.*[12] developed a thermoeconomic optimization of combined cycle gas turbine power plants using Genetic Algorithm (GA). Lee and Mohamed[13] proposed a real-coded genetic algorithm involving a hybrid crossover method for power plant control system design and there are many different computational programming in the case of optimizing power plants. As it was expressed the feedback of new research papers obvious that soft computing techniques and machine learning methodologies attract incremental attention of scientists because of their reliability and robustness in the field of optimizing.

In the next part the characteristics of Mahshahr power plant will be scrutinized. In step 3 the governing equations related to optimizing the power plant will be implemented and the engineering limits and constraints for optimizing the system will be expressed mathematically. At the next step the power plant will be optimized using proposed methodology and the results will be exposed. At the end, obtaining results will be compared to base operating parameters for making a contrast.

1. POWER PLANT DESCRIPTION

In this paper, the applicability and efficiency of operating parameters of Mahshahr gas turbine power plant will be verified using proposed method. This part of power plant plays an important role by supplying over than 117 MW electricity for industrial, agricultural, civil and domestic regions in various provinces.

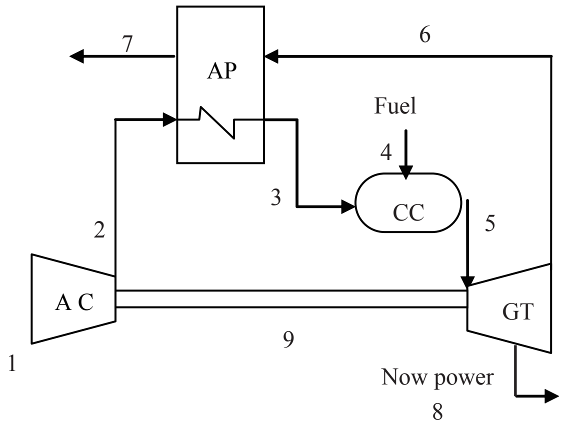

Figure 1
Gas Turbine System

Figure 1 indicates the schematic diagram of gas turbine plant and shows the work, exergy flows and the state points which was accounted for in this analysis. In this model, the net power generated by the system is 117 MW. This model is treated as the base case with following nominal properties which make an important role in proper analyzing:

- amount of compression pressure ratio is : r_p=10.26
- the isentropic efficiency of compressor is : η_{sc}=85%
- the temperature of combustion products entering the turbine is: T_5=1320 K
- the isentropic efficiency of turbine is : η_{sc}=88%
- environmental condition of the air at the inlet are : P_0=1.013bar and T_0=2991.1K
- the power plant operates at steady state
- fuel is assumed to be pure Methane (CH_4)
- air and combustion gasses are considered as ideal gas with variable specific heats
- the exit temperature is above the dew point temperature of the combustion products
- the pressure drop in the air preheater and combustion chamber is 4% and
- the effectiveness of the air preheater is 75%

It must be notion that standard air is an ideal gas consists of 78.1% nitrogen, 20.95% oxygen, 0.92% argon and 0.03% carbon dioxide.

2. THE PROBLEM STATEMENT

In general, a thermal system has three conflicted objectives: (1) maximizing the power output and first law efficiency, (2) increasing the exergetic efficiency and (3) decreasing the product cost. In order to derive to precise results, all of nominated objectives must satisfy simultaneously. The first two objectives are governed by thermodynamic requirements and the last one derived from economic constraints. Therefore, total objective function should be defined in a manner that the optimizing procedure satisfied all of requirements. For that, the optimization problem should be formulated as a minimization or maximization problem. The exergioeconomic analysis gives a clear picture about the costs related to the exergy destruction, exergy losses, maximum power output, optimum exergy efficiency and *etc*. Mahshahr power plant as a thermodynamic system follows the above rules, so the objective function for this system is defined as minimizing a total cost function $C_{p,tot}$ and maximizing the power output (efficiency of first law) and exergetic efficiency which can be derived a model that will be explained.

2.1 Objective Function Model

The proposed optimization model possesses three different objective functions which will be scrutinized in following sections.

2.1.1 Minimizing Total Cost

All cost due to owning and operating a plant depend on the type of financing, required capita, expected life of a component and *etc*. The levelized cost method of Moran[14] is used here. By hiring the capital recovery factor CRF(i, n) and present worth factor PWF(i, n), the levelized annual cost may be written as:

$$\dot{C}[\$\ per\ year] = [PEC - (SV)PWF(i,n)CRF(i,n)] \quad (1)$$

where SV=0.1PEC,$CRF\ (i,n) = \dfrac{i}{1-(1+i)^{-n}}$,

PWF(i,n)=(1+i)$^{-n}$,and PEC is purchased-equipment cost. Equations for calculating the purchased-equipment costs for the components of the gas turbine power plant are:

- air compressor

$$PEC_{AC} = \left(\frac{71.1\dot{m}_a}{0.9-\eta_c}\right)\left(\frac{P_2}{P_1}\right)\ln\left(\frac{P_2}{P_1}\right) \quad (2)$$

- combustion chamber

$$PEC_{CC} = \left(\frac{46.08\dot{m}_a}{0.995-\frac{P_5}{P_3}}\right)[1+\exp(0.018T_5 - 26.4)] \quad (3)$$

- gas turbine

$$PEC_{GT} = \left(\frac{479.34\dot{m}_g}{0.92-\eta_T}\right)\ln\left(\frac{P_5}{P_6}\right) \times [1+\exp(0.036T_5 - 54.4)] \quad (4)$$

- air preheater

$$PEC_{AP} = 4122\left(\frac{m_g(h_6-h_7)}{0.018\Delta T}\right)^{0.6} \quad (5)$$

where mathematically expressed as:

$$\Delta T = \frac{(T_7-T_2)-(T_6-T_3)}{\log\left(\frac{(T_7-T_2)}{(T_6-T_3)}\right)} \quad (6)$$

Dividing the levelized cost by annual operating seconds obtained the capital cost rate for the K_{th} component of power plant:

$$\dot{Z}_K[\$\ per\ hour] = \frac{\emptyset_k \dot{C}_K}{8000 \times 3600} \quad (7)$$

The maintenance cost is taken into consideration through the factor $\emptyset_k = 1.1$ for each plant components whose expected life is assumed to be 20 years and the interest rate is 17%. The numbers of hours of plant operating per year and maintenance factor utilized in this study are the typical numbers employed in standard exergioeconomic analysis[15]. The objective function for minimizing the costs can be written as following:

$$\dot{C}_{p,tot} = \dot{C}_{F,tot} + \sum_k \dot{Z}_k \quad (8)$$

$$\dot{C}_{F,tot} = c_{F,tot}\dot{m}_f LHV \quad (9)$$

where *LHV* is the fuel low heating value[16] and $C_{F,tot}$ is 0.000004 \$ /*Kj*.

$$\text{Min } F_1 = \dot{C}_{p,tot} \quad (10)$$

where k is the number of components that is 4 in this case and is the total fuel cost.

Additional standard engineering equations, known as exergioeconomic variables, that was vital for evaluating the performance of thermal systems are listed as following:

- average unit cost of the fuel

$$c_{f,K} = \frac{\dot{C}_{f,K}}{\dot{E}_{f,K}} \quad (11)$$

- average unit cost of product

$$c_{P,K} = \frac{\dot{C}_{P,K}}{\dot{E}_{P,K}} \quad (12)$$

- exergy destruction

$$\dot{C}_{D,K} = \dot{c}_{f,K}\dot{E}_{D,K} \quad (13)$$

- exergy economic factor

$$f_k = \frac{\dot{Z}_K}{\dot{Z}_K + \dot{C}_{D,K}} \quad (14)$$

2.1.2 Maximizing the Exergetic Efficiency

Exergy balance equation, applicable to any component of a thermal system may be formulated by utilizing the first and the second law of thermodynamics[17]. The thermodynamical exergy stream may be decomposed into its thermal and mechanical components. Ebadi and Gorji [18] applied these rules and derived to following exergy balances equation for analyzing any gas power plants:

$$\dot{E}_i^m - \dot{E}_o^m = \left(\dot{E}_i^T - \dot{E}_o^T\right) + \left(\dot{E}_i^{MEC} - \dot{E}_o^{mMEC}\right) \quad (15)$$

where the subscripts *i* and *o* , respectively, denote exergy flow streams entering or leaving the plant component.

The thermal and mechanical components of the exergy stream for an ideal gas with constant specific heat may be written as following:

$$\dot{E}^T = \dot{m}C_P[\left(T - T_{ref}\right) - T_{ref}ln\frac{T}{T_{ref}}] \quad (16)$$

$$\dot{E}^{MEC} = \dot{m}RT_{ref}ln\frac{P}{P_{ref}} \quad (17)$$

With the decomposition defined by equation (15), the general exergy balance can be written as follows:

$$\dot{E}^{CHE} + \left(\sum_{inlet}\dot{E}_i^T - \sum_{outlet}\dot{E}_o^T\right) + (\sum_{inlet}\dot{E}_i^{MEC} - \sum_{outlet}\dot{E}_o^{MEC}) + T_{ref}(\sum_{inlet}\dot{S}_i - \sum_{outlet}\dot{S}_o + \dot{Q}_{CV}/T_{ref}) = \dot{E}^W \quad (18)$$

The term $\dot{E}^{CHE}$ denotes the rate of exergy flow of fuel in the plant and $\dot{Q}_{CV}$ in the fourth term denotes the heat transfer between the component and the environment.

The exergy balance equations for each component in the gas turbine plant can be derived from general exergy balance equation given equation (18). The exergy balances for the components of gas turbine are:

- air compressor

$$(\dot{E}_1^T - \dot{E}_2^T) + (\dot{E}_1^{MEC} - \dot{E}_2^{MEC}) + T_0(\dot{S}_1 - \dot{S}_2) = \dot{W}_{AC} \quad (19)$$

- combustion chamber

$$\dot{E}^{CHE} + \left(\dot{E}_3^T + \dot{E}_f^T - \dot{E}_5^T\right) + \left(\dot{E}_3^{MEC} + \dot{E}_f^{MEC} - \dot{E}_5^{MEC}\right) + T_0\left(\dot{S}_3 + \dot{S}_f + \dot{S}_5 - \frac{\dot{Q}_{CC}}{T_{ref}}\right) = 0. \quad (20)$$

- gas turbine

$$(\dot{E}_5^T - \dot{E}_6^T) + (\dot{E}_5^{MEC} - \dot{E}_6^{MEC}) + T_0(\dot{S}_5 - \dot{S}_6) = \dot{W}_{GT} \quad (21)$$

- air preheater

$$\left(\dot{E}_2^T - \dot{E}_3^T + \dot{E}_6^T - \dot{E}_7^T\right) + (\dot{E}_2^{MEC} - \dot{E}_3^{MEC} + \dot{E}_6^{MEC} - \dot{E}_7^{MEC}) + T_0\left(\dot{S}_2 - \dot{S}_3 + \dot{S}_6 - \dot{S}_7 + \frac{\dot{Q}_{AP}}{T_{ref}}\right) = 0. \quad (22)$$

According to above equation there is relationship between network power output and exergy flow stream. The total power output can be formulated as following:

$$\dot{W}_{net} = |\dot{W}_{GT}| - |\dot{W}_{AC}| \quad (23)$$

The objective function for maximizing exergetic efficiency can be written as:

$$\varepsilon = \frac{\dot{W}_{net}}{\dot{E}^{CHE} + \dot{E}_f^T + \dot{E}_f^{MEC}} \quad (24)$$

$$\text{Max } F_2 = \varepsilon \quad (25)$$

2.1.3 Maximizing the Power Output and Energy Efficiency

Obtaining optimum performance of power plant is strongly related to maximizing the power output and energy efficiency. Gorji and Ebrahimian[16] and Gorji *et al.*[19] applied following policies for analyzing the energy efficiency of steam power plant under these conditions:

- the heat leakage during the process is take into considered for gaining more accurate solution
- variable specific heat applied during process
- kinetic and potential energies are neglected because they are not important
- in order to simplify the calculation, for each component the average temperature will be utilized in determination of variable specific heat which can be defined[20]:

$$T_{av} = \frac{T_i - T_j}{\ln\left(\frac{T_i}{T_j}\right)} \tag{26}$$

where i and j are respectively the final and prior temperature of each component.

- following common approximation applied for determining the gas enthalpy

$$h_{state}=C_P T_{state} \tag{27}$$

- due to trivial amount of Methane in mixture gas (), the effect of fuel (Methane) can be neglected

General conservation equation and energy balance can be written as follows:

$$\dot{Q} + \dot{W} + \sum_{i=1}^{n} \dot{m}_i h_i = \sum_{e=1}^{m} \dot{m}_e h_e \tag{28}$$

The conservation equation and energy balance will be applied for the operating components:

- air compressor

$$-\dot{W}_{AC} + m_a h_1 = m_a h_2 \tag{29}$$

$$m_g=m_a+m_f \tag{30}$$

- combustion chamber

$$\dot{Q}_{CC} + m_a h_3 + m_f h_4 = m_g h_5 \tag{31}$$

$$\dot{Q}_{CC} = \dot{m}_f \times LHV \tag{32}$$

- gas turbine

$$-\dot{W}_{GT} + m_g h_5 = m_g h_6 \tag{33}$$

- air pre heater

$$-\dot{Q}_{AP} + m_a h_2 + m_g h_6 = m_a h_3 + m_g h_7 \tag{34}$$

By pursuing the above equations, the energy efficiency can be defined:

$$\eta_I = \frac{\dot{W}_{net}}{m_f \times LHV} \tag{35}$$

The last objective function is:

$$\text{Max } F_3 = \eta_I \tag{36}$$

2.2 Controller Rules and Constraints

2.2.1 Economic Constraints

For a component receiving a heat transfer and generating power, cost balance equation may be written as[11]:

$$\text{A}\sum_e \dot{C}_{e,K} + \dot{C}_{W,K} = \dot{C}_{Q,K} + \sum_i \dot{C}_{i,K} + \dot{Z}_K \tag{37}$$

where $\dot{C}$ denotes a cost rate associated with an exergy stream and the variable $\dot{Z}$ represents non-exergetic costs.

The formulation of cost balance for plant components leads to following constraints:

- air compressor

$$\dot{C}_2 = \dot{C}_1 + \dot{C}_9 + \dot{Z}_{AC} \tag{38}$$

- combustion chamber

$$\dot{C}_5 = \dot{C}_4 + \dot{C}_3 + \dot{Z}_{CC} \tag{39}$$

- gas turbine

$$\dot{C}_6 + \dot{C}_9 + \dot{C}_8 = \dot{C}_5 + \dot{Z}_{GT} \tag{40}$$

$$\frac{\dot{C}_6}{\dot{E}_6} = \frac{\dot{C}_5}{\dot{E}_5} \tag{41}$$

- air preheater

$$\dot{C}_3 + \dot{C}_7 = \dot{C}_2 + \dot{C}_6 + \dot{Z}_{AP} \tag{42}$$

$$\frac{\dot{C}_6}{\dot{E}_6} = \frac{\dot{C}_7}{\dot{E}_7} \tag{43}$$

Auxiliary equations (42) and (43) are written assuming the same unit cost of incoming and outgoing fuel exergy streams. Additional auxiliary equation (44) will be formulated based on the concept that both the net power exported from the system and the power input to the compressor, consume same energy cost.

$$\frac{\dot{C}_8}{\dot{E}_8} = \frac{\dot{C}_9}{\dot{E}_9} \tag{44}$$

Note that the cost of fuel stream to the system ($\dot{C}_4$) is taken as 0.1 $\$$ *per kg* and a zero unit cost is allocated to air entering to the air compressor. Mathematically, these are expressed as:

$$\dot{C}_4 = 3067.2\$\, per\ hour \ \ \&\ \ \dot{C}_1 = 0\,\$\, per\ hour \tag{45}$$

2.2.2 Physical Constraints

The admissible ranges of mechanical operating parameters are considered as following:

$$8 \le rp \le 16 \tag{46}$$

$$0.75 \le \eta_T \le 0.92 \tag{47}$$

$$0.75 \le T_c \le 0.92 \tag{48}$$

$$1400 \le T_5 \le 1600 \tag{49}$$

$$600 \le T_3 \le 1500 \tag{50}$$

$$450 \le T_2 \le 700 \tag{51}$$

$$300 \le T_1 \le 480 \tag{52}$$

$$400 \le m_a \le 530 \tag{53}$$

$$8 \le m_f \le 9.5 \tag{54}$$

The governing mechanical constraint can be modeled as well as economic ones:

$$T_2 > T_1 \tag{55}$$

$$T_3 > T_2 \tag{56}$$

$$T_5 > T_3 \tag{57}$$

$$T_5 > T_6 \tag{58}$$

Nonideality in APs structure, leads to following engineering constraints:

$T_6 > T_3$ & $T_6 > T_3$ (59)

In addition, due to the interaction in AP:

$T_6 > T_7$ (60)

Following constraints are set due to the information that reported in Mahshahr power plant data base and[3]:

$T_2 - T_1 \geq 30$ (61)

$T_3 - T_2 \geq 50$ (62)

$T_5 - T_3 \geq 100$ (63)

$T_6 - T_7 \geq 40$ (64)

Considering all of the above constraints turned the problem to a high complex multi-modal problem that makes the decision making too hard and complicate. For that in last papers, many researchers omitted some of these constraints for a convenient decision making. However, neglecting these constraints lead to an imprecise decision. In the next part, we introduced a new method that is able to make a suitable engineering decision by considering all of the modeled objective functions and their constraints.

2.3 Applying Synchronous Parallel Shuffling Self Organized Pareto Strategy (SPSSOPS)

Application of hybrid evolutionary-learning algorithms begin by Michalski's[21] researches who hired machine learning technique and evolutionary algorithm to generate new population. These types of algorithms are simply called Learnable Evolutionary Models (LEMs). After that many researchers focused on this concept and developed new models and improvements.

Ammor and Rettinger[22] applied Self Organizing Map, sometimes known as Kohonen map, (SOM) to improve diversity and avoiding from fast convergence. SOM approximates the probability of density of input data distribution. Kobuta *et al.*[23] developed SOM for reproduction new seeds in GA.

In this paper a Time Adaptive Self Organizing Map (TASOM) method that utilizes a conscience mechanism fused to Elitism NSGA-II in order to conserve the diversity of populations. Besides an Artificial Bee Colony applied in asynchronous parallel model which improved the data processing speed and increase the local search ability (intensity) because of the greedy instinct of honey bees. The population is sorted and entered in each phase based on a random shuffling procedure. The results indicate that an adjustable random data sharing between these two algorithms, called shuffling process, expand the robustness of proposed method explicitly. In following sections we interpreted the detailed of ***SPSSOPSA*** more closely.

2.3.1 Time Adaptive Self Organizing Map

TASOM proposed by Shah-Hosseini and Safabakhsh[24] is a modification of SOM that automatically adapts the learning rate and neighborhood function of neuron weights independently. One of its explicit dominance comparing to classic SOM is its ability to normalize all distance calculation between any input vector and the neuron's weight vector since the basic SOM often fails to provide a suitable topological ordering for input distribution. Figure 2 exposes a schematic of weight adaption during the process. TASOM with conscience mechanism used following learning rule:

$$W_j^{n+1}(t) = W_j^n(t) + y_j(t).h_j(n).\left(R_i^n(t) - W_j^n(t)\right)$$

t=1,2,…,T (65)

where is sub-generation in SOM network and represents the ***SPSSOPSA*** generation number. $y_i(t)$ is a controlling parameter that leads weight vectors to a none dominate solution which was transferred from external archive to network as an input. In other word if the input's, which is a non-dominate solution, fitness value f_R is lower than $f_{wj(n)}$ then $y_i(t)$=1 and neuron center moves toward the non-dominate solution (networks input) otherwise $y_i(t)$=0 and neuron center does not approach to the solution. Mathematically expressed as:

$$y_j(t) = \begin{cases} 1 \; if \; R(t) \; dominate \; Wj(t) \\ 0 \qquad otherwise \end{cases} \quad (66)$$

$W_j^{n+1}(t)$ refers to updated weight vector and $W_j^n(t)$ is the old weight vector. $\|R_i^n - W_j^n\|$ represents the distance between input vectors where R_i^n is the *i-th* none dominate solution in *n-th* generation.

The learning rate which is a descending function defined as following:

$$h_j(t+1) = h_j(t) + \alpha\left(f\left(\frac{1}{s_f \, . sl(t)}\left\|R_j^n(t) - W_j^n(t)\right\|\right)\right) \quad (67)$$

The learning rate parameter $h_j(0)$ should be initialized with value close to unity. α obtains any arbitrary value between 0 and 1, and S_f is a descending constant and should be set due to the problem condition. In this paper we set [25].Function f (.) should be designed in a manner that following criteria derived appropriately:

$f(0)$=0, $0 \leq f(z) \leq 1$, and $\dfrac{df(z)}{dz} \geq 0$ for positive values of z.

In this paper $f(z)$ set as[25]:

$$f(z) = 1 - {}^{1}\!/_{1+z} \quad (68)$$

Shah-hosseini and Safabakhsh produced a scaling value for a 2-D input. In this paper scaling value is extended to a 9-D input due to the number of our decision parameters and our problem condition.

Scaling value sl adjusts using following equation:

$$sl(t+1) = \sqrt{\left(\sum_{i=1}^{9} E_k^i(t+1)^{10-i}(-1)^{i+1}\right)^+}, k = 1 \quad (69)$$

$$E_k^i(t+1) = E_k^i(t) + \mu_i\left(R_k^i(t) - E_k^i(t)\right) \qquad (70)$$

where i represents the number of variable in each solution. $E_k^i(0)$ initialized with some small random values.

Conscience mechanism is applied in order to revive the dead units (weights) in neuron center[26]. Dead unit is a term that refers to weights with a trivial chance of learning and adaption during the progress. The policy of repairing these units is often called conscience mechanism. In this paper a simple well-known mechanism is utilized which tuned the bios of each node (neuron) by following formula:

$$b_i(t+1) = \begin{cases} 0.8\, b_i(t) \\ or \\ b_i(t) - 0.3 \end{cases} \qquad (71)$$

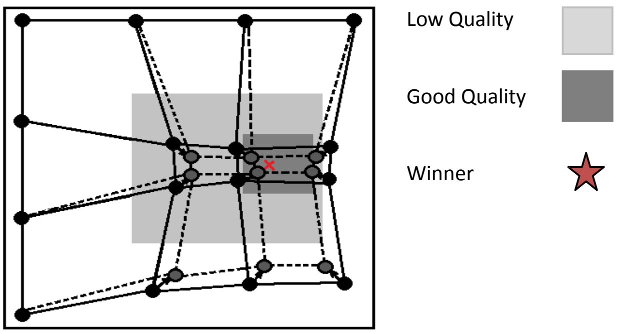

Figure 2
Weight Adaption During the Process

2.3.2 Synchronous Parallel Shuffling Self Organized Pareto Strategy

In this section, pseudo code and the schematic flowchart of proposed method will be given respectively:

- ***Step 0***: Define algorithm initial parameters such as mutation probability (P_{mut}), number of neurons (Nu_{GA} and Nu_{ABC}) in SOM center for each phase, sharing factor (ξ), pool size, number of generation, population size (P_s), descending constant (S_f), α, and stopping criterion. Set and start the process.
- ***Step 1***: Randomly generate P_s solution for the initial population P_1.
- ***Step 2***: Share (shuffle) the solutions into ABC phase and NSGA-II phase due to the sharing factor (ξ). ξ is a random number from a uniform distribution. Lead (1-ξ)* P_s of solutions in ABC operator phase (P_{ABC}) and the rest of them in genetic operator (P_{GA}).
- ***Step 3***: Evaluate the fitness of ABC solutions (foods) in P_{ABC} and rank them based on none dominate sorting and crowding distance.
- ***Step 4***: Define random weight vectors for SOM unit center in ABC operator phase (Nu_{ABC}) in a uniform stochastic distribution manner spanning to problem solution space. Evaluate the fitness of weight vectors.
- ***Step 5***: Train the weight vectors in SOM center ($W_j^n, j = 1,2,\ldots,Nu_{ABC}$) using obtained non-dominate solutions (elite bees) in the current n_{th} generation.
- ***Step 6***: Generate new weight vector W_j^{n+1}, using equation (80).
- ***Step 7***: if the new weights dominated old ones, replace old one with new ones. In other words move the SOM mobile units toward better area. If they do not dominate each other, save the new non-dominate weights in external archive.
- ***Step 8***: Apply the employed bees for neighbor search (as agents that perform near the P_{ABC})
- ***Step 9***: Evaluate the fitness of new obtained solutions.
- ***Step 10***: Sort the new solutions based on none dominate sorting and crowding distance to evaluate their fitness.
- ***Step 11***: Select a food source (solution) and employed the onlooker bees in order to perform a neighbor search near the chosen solution and a greedy selection based on the evaluated fitness.
- ***Step 12***: if all of the onlooker agents contribute in searching go to the next step, otherwise return to step 11.
- ***Step 13***: Export the obtained solutions in ABC phase to the collection site.
- ***Step 14***: Evaluate the fitness of GA solutions (chromosomes) in P_{GA} and rank them based on none dominate sorting and crowding distance.
- ***Step 15***: Perform a same treat for SOM center in GA phase. In other words regard instead of Nu_{ABC} and repeat steps 4 to 7 respectively.
- ***Step 16***: Generate a random number with uniform distribution. If the random number is less than $P_{mutation}$ produce children using mutation operator, and else produce children using crossover due to the pool size.
- ***Step 17***: Evaluate the fitness of produced solutions and combine them with old population. Rank all of the solutions using non-dominate sorting and crowd distance.
- ***Step 18***: Selectξ* P_s best solutions from current population.
- ***Step 19***: Export the obtained solutions in GA phase to the collection site.
- ***Step 20***: if the stopping criterion is satisfied, go to step 21, otherwise go to step 3.
- ***Step 21***: latest population, the weight vectors in both SOM centers and also the recorded solutions (archived ones) are considered as the final solution.
- ***Step 22***: Stop

Figure 3 indicates the flowchart of the SPSSOPSA.

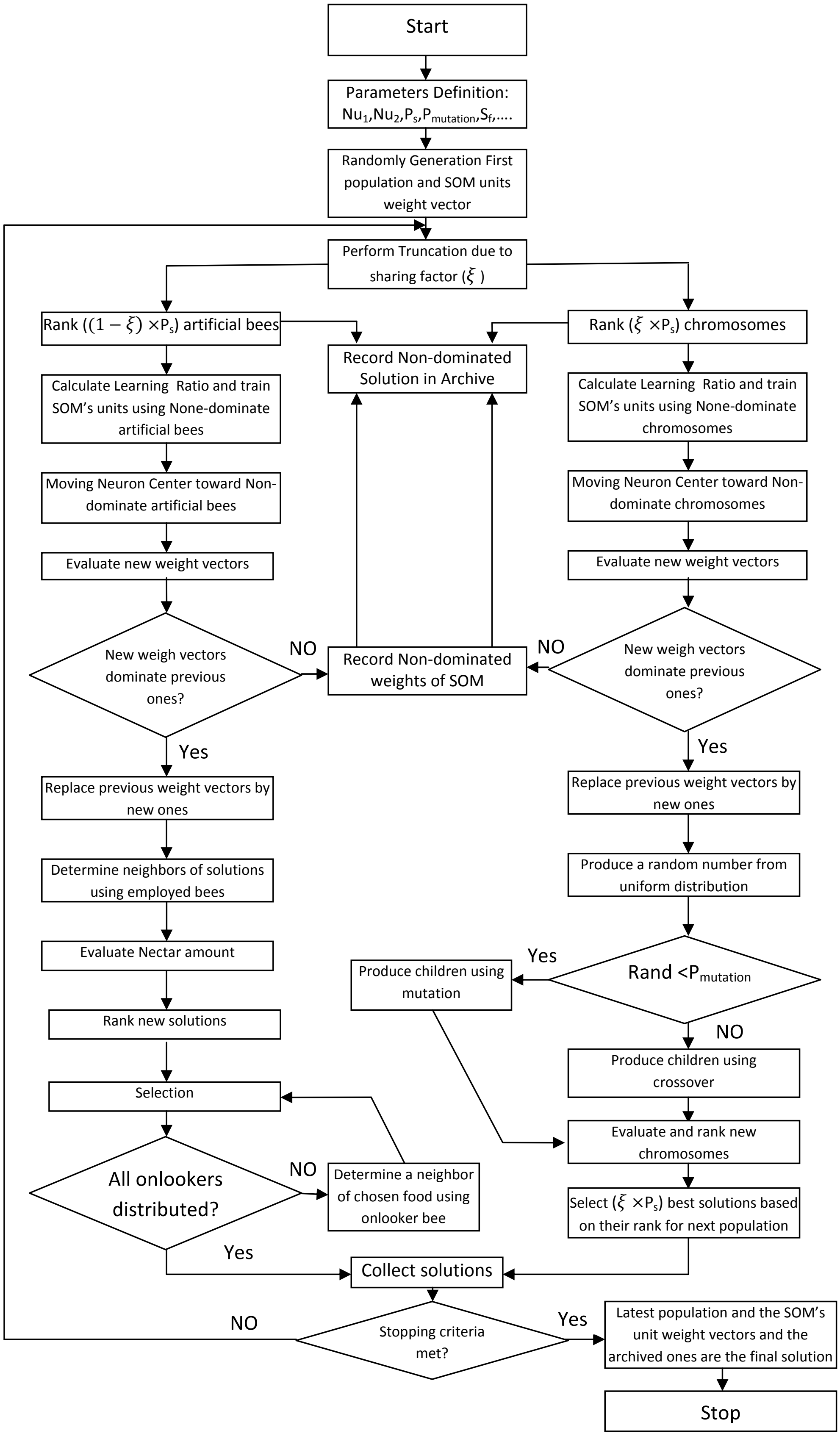

Figure 3
The Flowchart of SPSSOPSA

3. RESULT AND DISCUSSION

Figure 4(a) represents the Pareto optimal front obtained using SPSSOPSA. It seems that the proposed optimizing methodology achieve better Pareto solutions comparing to [11].

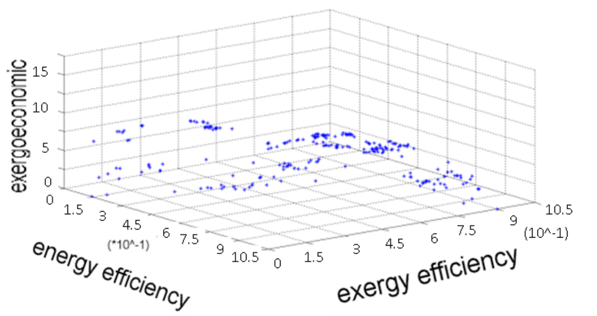

Figure 4(a)
The Non-Dominated Solutions Calculated Using SPSSOPSA

Figure 4(b) represents the variation of non-dominated solutions during the optimizing process. It is obvious that SPSSOPSA resulted in a significant increase in the number of non-dominated solutions in the last generations. This is because of the incremental capability of Time Adaptive Self Organizing Map (TASOM) center in finding better areas.

Table 1 represents the base chemical, thermal and mechanical exergy flow rates at various state points in Mahshahr power plant that reported in [18]. These flow rates were calculated based on the values of measured properties such as pressure, temperature, and mass flow rate at respective state points. Table 2 shows the net flow rates of various exergies crossing in the boundary of each component together with their respecting exergy destruction in gas turbine power plant. It must be mentioned that positive values indicate the exergy flow rate of product while negative values represent the exergy flow rate of resources or fuel.

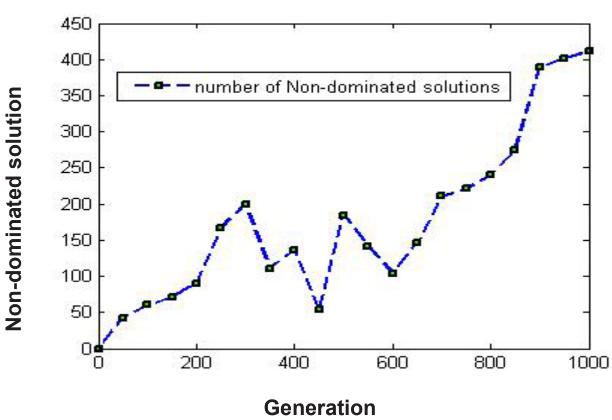

Figure 4(b)
Variation of Non-Dominated Solutions

Table 1
Base Property Values and Chemical, Thermal and Mechanical Exergy Flows at Various State Points

State	$\dot{m}$	T	ρ	$\dot{E}^{CHE}$	$\dot{E}^{T}$	$\dot{E}^{MEC}$
1	497.00	299.15	1.013	0.000	0.000	0.000
2	497.00	603.02	8.611	0.000	47.034	91.311
3	497.00	796.91	8.267	0.000	102.221	89.580
4	10.09	299.15	30.00	508.5	0.000	5.298
5	507.09	1320.0	8.019	0.000	335.76	91.015
6	507.09	861.54	1.075	0.000	143.181	2.613
7	507.09	695.18	1.032	0.000	83.699	0.488

Table 2
Base Net Exergy Flow Rates and Exergy Destruction in Power Plant in Rated Condition

Component	$\dot{E}^{W}$	$\dot{E}^{CHE}$	$\dot{E}^{T}$	$\dot{E}^{MEC}$	$\dot{E}^{D}$
AC	-154.814	0.000	47.034	91.318	13.462
AP	0.000	0.000	-4.295	-3.534	7.829
CC	0.000	-508.566	233.545	-3.863	278.88
GT	267.824	0.000	-192.585	-88.402	13.163
Total plant	116.010	-508.566	88.699	-4.481	313.338

Table 3 represents the base initial investment, the monetary flow rates and the capital cost rate for each component in the full load condition with the electricity output near 116.010 *MW*. These amounts play an important role in predicting and economic analyzing of thermal systems. In [5] these parameters and some famous methods such as Moran's method were used for analyzing production costs of Mahshahr, located in Iran, power plant altogether.

Table 3
Base Initial Investments, Monetary Flow Rates, and Capital Cost Rates Under Full Load Condition

Component	*PEC* ($\times 10^{-6}$)	$\dot{C}$ ($\times 10^{-6}$)	$\dot{Z}$ ($\times 10^{-6}$)
AC	9.69	2.36	869
AP	0.7	0.171	63
CC	0.97	0.236	87
GT	39.17	9.56	3519

In order to select an acceptable optimum solution among the feasible solutions, the obtained Pareto front has been checked precisely. Table 4 shows the selected optimum operating parameters together with the base parameters for making an engineering contrast.

Table 4
Comparison of the Decision Variables for Optimum and Base Case

Properties	*base*	*optimum*
Compressor pressure ratio	10.26	9.96
AC isentropic efficiency [%]	85	81
GT isentropic efficiency [%]	88	90
CC inlet temperature	796.91	770.8
CC product temperature	1320	1443.5
AC inlet temperature	299.15	300.4
AC product temperature	603.02	604.4
Air mass flow rate	497.00	442.2
Fuel mass flow rate	10.09	8.8

It is obvious that the compressor's pressure ratio decreased to 9.96 in optimum case. Also our method proposed using an AC with 81% isentropic efficiency which is more accessible comparing to the AC in base case with 85% isentropic efficiency. In addition, this element is a promising achievement in initial enterprise. The results evident the importance of utilizing a gas turbine with 90% isentropic efficiency for deriving to an optimum condition while providing a component with higher quality of isentropic efficiency, demands an increase in capital investment. But the increase in isentropic efficiency of GT in our proposed optimum case is just about 2%. Hence the increase in initial enterprises can be justified conveniently. The inlet temperature in combustion chamber decrease about 3.3%. This will lead to a lower thermal tension and consequence metallurgical damages in component and also an increase in total life of intake section in CC. Combustion chamber is the most important component from the exergioeconomic view. This is because it has the highest sum of capital investment ($\dot{Z}_{CC}$) and exergy destruction ($\dot{C}_{D,CC}$) and a lower value of exergioeconomic factor (f_{CC}). For that the component efficiency should be enhanced by increasing the capital investment. This can be achieved by increasing the combustion product temperature. Our optimum case proposed a product temperature about 1443.5 K which means about 9.36% increase comparing to base situation. Applying this operating policy will granted the appropriate engineering condition for compensating the shortcomings. The obtained change in AC inlet and product temperature in our optimum case has not any crucial impact on the performance of power plant. Therefore justifying their exergioeconomic and thermodynamical impacts will be neglected. The inlet air mass flow rate shows about 11.03% reduction in optimum case. Besides the fuel mass flow rate reduced about 12.78% that lead to one of the most promising elements among the obtained optimum operating variables. The effects of reduction in fuel mass flow rate of power plant in both economic and thermodynamical aspects will be scrutinized later. Table 5 represents the optimum thermal and mechanical exergy flow rates at various state points in Mahshahr power plant respecting to obtained operating parameters.

Table 5
Optimum Variables and Their Consequent Exergy Flows

State	$\dot{m}$	T	ρ	$\dot{E}^{CHE}$	$\dot{E}^{T}$	$\dot{E}^{MEC}$
1	442.20	300.40	1.013	0.000	0.000	0.000
2	442.20	604.40	8.611	0.000	41.700	81.590
3	442.20	770.8	8.267	0.000	93.221	80.036
4	8.80	299.15	30.00	508.5	0.000	4.650
5	451.00	1443.5	8.019	0.000	354.36	81.56
6	451.00	861.54	1.075	0.000	129.876	2.342
7	451.00	695.18	1.032	0.000	75.31	0.738

Table 6 shows the net flow rates of various exergies crossing from the boundary of each component together with their respecting exergy destruction in gas turbine power plant.

Table 6
Optimum Net Exergy Flow Rates and Exergy Destruction in Power Plant in Rated Condition

Component	$\dot{E}^{w}$	$\dot{E}^{CHE}$	$\dot{E}^{t}$	$\dot{E}^{MEC}$	$\dot{E}_{D}$
AC	-134.966	0.000	41.700	81.590	11.676
AP	0.000	0.000	-3.045	-3.158	6.203
CC	0.000	-508.566	261.15	-1.435	248.85
GT	307.082	0.000	-224.484	-79.218	3.383
Total plant	172.116	-508.566	75.321	-2.214	270.112

The results indicate explicit improvements in thermal properties of power plant components. The bold numbers in Table 6 dominate the properties of corresponding components in base condition. As it is shown AC consumes lower power and also its exergy destruction rate reduced about 13.2%. Optimum AP shows an advantage in reducing the released thermal and mechanical exergy flows. Its destructed exergy reduced about 23.07% comparing to base case. This reduction has not an explicit effect on minimizing the total destructed exergy since AP is a component that destructs a low amount of exergy flow comparing to AC and CC. The most concern should be focused on minimizing the exergy destruction in CC because of its crucial impact in destructing the exergy flow in power plant. Our optimum case leads to 10.8% reduction in CC which is obviously acceptable. The total results evident 48.36% increase in plants net power output and also 13.8% reduction in power plant exergy destruction. Table 7 indicates the optimum initial investments, the monetary flow rates and the capital cost rate for each component at rated condition. Consuming lower amount of fuel will lead to an obvious providence in investments. The total fuel cost reduced about 12.78% in optimum case. In addition the sum of capital investments for power plant components decreased approximately about 13.7%.

Table 7
Optimum Initial Investments, Monetary Flow Rates, and Capital Cost Rates Under Full Load Condition

Component	PEC (×10^{-6})	$\dot{C}$ (×10^{-6})	$\dot{Z}$ (×10^{-6})
AC	7.99	1.95	746
AP	0.22	0.054	21
CC	1.35	0.330	126
GT	33.24	8.82	3023

Following tables evident the cost-effective robustness of the Mahshahr power plant comparing to base case.

Table 8
Levelized Cost Rates and Average Cost per Unit of Exergy at Various State Points in Base Case

State point	$\dot{C}$ [\$ s^{-1}]	$\dot{C}$ [\$ GJ^{-1}]	$\dot{C}$ [\$ $kW^{-1}h^{-1}$]
1	0.000	0.00	0.000000
2	0.8036	5.808	0.020911
3	1.0174	5.304	0.019096
4	0.8000	1.556	0.005605
5	1.9043	4.461	0.016063
6	0.6503	4.460	0.016057
7	0.3755	4.460	0.016057
8	0.5370	4.628	0.016664
9	0.7167	4.629	0.016665

Table 9
Exergoeconomic Parameters of Gas Turbine Components

Component	c_p[\$ GJ^{-1}]	c_f[\$ GJ^{-1}]	$\dot{C}_D$[\$ GJ^{-1}]	f_k [%]
AC	5.808	4.628	0.0623	58.24
AP	6.012	4.461	0.0349	15.29
CC	4.461	2.399	0.6692	1.28
GT	4.628	4.461	0.0587	85.7

Table 8 represents the cost of stream under base operating parameters of power plant. It is obvious that gas turbine requires a higher monetary flow dedication comparing to other components. The base exergoeconimic parameters of Mahshahr power plant are shown in Table 9. These parameters play an important role for analyzing the economic behavior of components. Hence, in following tables, cited parameters will be tabulate for making an engineering contrast.

Table 10
Levelized Cost Rates and Average Cost per Unit of Exergy at Various State Points in Optimum Condition

State point	$\dot{C}$ [\$ s^{-1}]	C [\$ GJ^{-1}]	c [\$ $kW^{-1}h^{-1}$]
1	0.000	0.000	0.000000
2	0.5948	4.824	4.824
3	0.4638	2.676	0.009637
4	0.8000	1.556	0.005605
5	1.2764	2.927	0.010541
6	0.3871	2.927	0.010539
7	0.2226	2.940	0.010584
8	0.6633	3.853	0.013873
9	0.5202	3.854	0.013875

Table 11
Optimum Exergoeconomic Parameters of Gas Turbine Components

Component	c_p[\$ GJ^{-1}]	c_f[\$ GJ^{-1}]	$\dot{C}_D$[\$ s^{-1}]	f_k [%]
AC	4.824	3.853	0.0449	62.42
AP	5.023	2.927	0.0181	10.39
CC	2.927	1.305	0.3247	3.73
GT	3.853	2.927	0.0099	96.82

The bold numbers represents the achieved promotion after utilizing optimum parameters. As it is shown in Table 10, an explicit reduction occurred in the cost of each state. Nevertheless, the results show an ascendance in cost of 8th stream line. This is because of a supremacy that takes placed in the gas turbine power output in the optimum condition. It is important to mention that the resulted increment in the gas turbine net power output can justifies the higher monetary flow conveniently. Besides the exergoeconomic parameters have an improvement comparing to base properties. For example the combustion chamber derived to a lower value of $\dot{Z}_K+\dot{C}_{D,K}$ and higher value of exergoeconomic factor. This suggests an occurred predominance in saving the dissipated exergy flow and consequence improvement in capital investment.

According to gained results authors conclude that the proposed optimum operating variables shows an obvious robustness comparing to base operating variables as a view of exergy efficiency, net power output and exergioeconomic. Figure 5 indicates the different performance of power plant in base and optimum conditions.

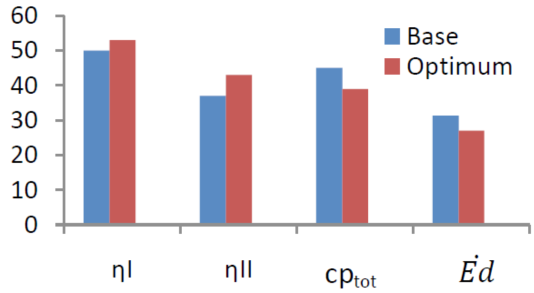

Figure 5
Comparing the Total Performance of Optimum and Base Cases

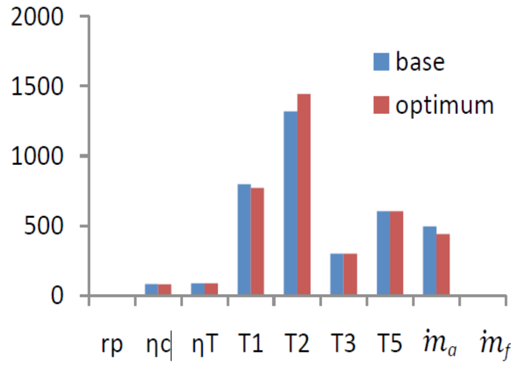

Figure 6
Variation of Operating Parameters

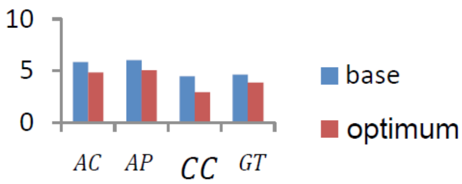

Figure 7
Variation of C_p

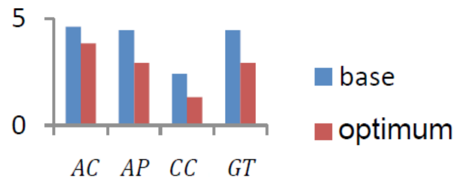

Figure 8
Variation of C_f

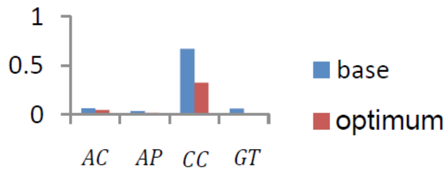

Figure 9
Variation of $\dot{C}_D$

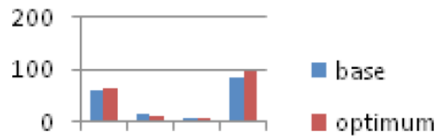

Figure 10
Variation of f_k

CONCLUSIONS

Combining the second law of thermodynamics with economics i.e. thermoeconomics using availability of energy and exergy for cost purposes provides a powerful tool for systematic study and optimization of complex energy systems like power plants. In this paper the maximum potential in performance of Mahshahr power plant investigated in a cost effective manner. Also it was indicated that an efficient optimizing of the operating parameters required a complex multi-objective and multi-modal simulated functions that makes the decision making process really complicated. Hence a new optimizing model proposed based on synthesizing the artificial bees and chromosomes which perform simultaneously. The results confirm that proposed model is a predominance optimizing method in analyzing and optimizing complicated real life engineering problems.

REFERENCES

[1] Gorji-Bandpy, M., Goodarzian, H., & Biglari, M. (2010). The Cost-Effective Analysis of a Gas Turbine Power Plant. *Energy Sources, Part B: Economic and Planning and Policy*, *5*(4), 348-358.

[2] Bejan, A., Tsatsaronis, G., & Moran, M. (1996). Thermal Design and Optimization. New York: John Wiley and Sons.

[3] Toffolo, A., & Lazzaretto, A. (2002). Evolutionary Algorithms for Multi-Objective Energetic and Economic Optimization in Thermal System Design. *Energy*, *27*(6), 549-567.

[4] Cammarata, G., Fichera, A., & Marletta, L. (1998). Using Genetic Algorithms and the Exergioeconomic Approach to Optimize District Heating Net works. *J Energy Resource Technology*, *3*(4), 241-246.

[5] Gorji-Bandpy, M., & Ebrahimian, V. (2006).

Exergoeconomic Analysis of Gas Turbine Power Plants. *I J. of Exergy*, *7*(1), 57-67.

[6] Bhargava, R., Bianchi, M., & Peretto, A. (2002). Thermoeconomic Analysis of an Intercooled, Reheat and Recuperated Gas Turbine for Cogeneration Application, Part I: Base Load Operation. *J Engineering for Gas Turbine and Power*, *124*, 147-154.

[7] Attala, L., Facchini, B., & Ferrara, G. (2001). Thermoeconomic Optimization Method Design Tool in Gas-Steam Combined Plant Realization. *J Energy Convers Mgnt*, *18*(4), 2163-2172.

[8] Misra, R., Sahoo, K., & Gupta, A. (2003). Thermoeconomic Optimization of a Single Effect Water/LiBr Vapor Absorption Refrigeration System. *I J Refrigeration, 2*(5), 158-169.

[9] Misra, R., Sahoo, K., & Gupta, A. (2005). Thermoeconomic Evaluation and Optimization of a Double-Effect H_2O/LiBr Vapor Absorption Refrigeration System. *I J Refrigeration*, *3*(6), 331-343.

[10] Wang, J., Sun, Z., Dai, Y., & Ma, S. (2010). Parametric Optimization Design for Supercritical Power Cycle Using Genetic Algorithm and Artificial Neural Network. *J AP ENERGY*, *87*, 1317-1324.

[11] Gorji-Bandpy, M., & Goodarzian, H. (2011). Exergoeconomic Optimization of Gas Turbine Power Plant Operating Parameters Using Genetic Algorithm: A Case Study. *J Thermal Science*, *15*, 43-54.

[12] Valdes, M., Duran, M.D., & Rovira, A. (2003). Thermoeconomic Optimization of Combined Cycle Gas Turbine Power Plants Using Genetic Algorithms. *J APPL THER ENG*, *23*, 2169-2182.

[13] Lee, K.Y., & Mohamed, P.S. (2002). A Real-Coded Genetic Algorithm Involving a Hybrid Crossover Method for Power Plant Control System Design. In *Proceedings of Congress on Evolutionary Computation* (pp.1069-1074). Honolulu: IEEE Press.

[14] Moran, M.J. (1982). Availability Analysis: A Guide to Efficient Energy Use. Englewood Cliffs: Prentice-Hall.

[15] Moran, M.J. (1982). Availability Analysis: A Guide to Efficient Energy Use. New Jersey: Prentice-Hall Englewood Cliffs.

[16] Gorji-Bandpy, M., & Ebrahimian, V. (2007). Exergy Analysis of a Steam Power Plant: A Case Study in Iran. *Int J Exergy, 4*, 54-71.

[17] Oh, S., Pang, H., Kim, S., & Kwak, H. (1996). Exergy Analysis for a Gas Turbine Cogeneration System. *J Eng Gas Turb Power, 118*(4), 782-791.

[18] Ebadi, M.J., & Gorji-Bandpy, M. (2005). Exergetic Analysis of Gas Turbine Plants. *Int J Exergy, 2*(4), 31-39.

[19] Gorji-Bandpy, M., Mozaffari, A., & Mohammadrezaei, S. (in press). Optimizing Maximum Power Output And Minimum Entropy Generation of Atkinson Cycle Using Mutable Smart Bees Algorithm. *IJCSE*.

[20] Ge, Y., Chen, L., & Sun, F. (2010). Finite Time Thermodynamic Modeling and Analysis for an Irreversible Atkinson Cycle. *J Therm Sci, 14*(6), 887-896.

[21] Michalaski, R.S. (2003). Learnable Evolution Model: Evolutionary Processes Guided by Machine Learning. *J Machine Learning*, *38*(7), 9-40.

[22] Amor, H.B., & Rettinger, A. (2005). Intelligent Exploration for Genetic Algorithms: Using Self-Organizing Maps in Evolutionary Computation. In *proceeding of GECOO* (pp.1531-1538).

[23] Kubota, R., Yamakawa, T., & Horio, K. (2004). Reproduction Strategy Based on Self-Organizing Map, for Real-coded Genetic Algorithm, Neural Information Processing. *Letters and Reviews*, *5*, 27-32.

[24] Shah-Hosseini, H., & Safabakhsh, R. (2000). TASOM: The Time Adaptive Self-Organizing Map. In *Proceeding of International Conference of Information Technology: Coding and Computing* (pp. 422-427). Las Vegas: IEEE Press.

[25] Shah-Hosseini, H., & Safabakhsh, R. (2000). The Adaptive Self-Organizing Map with Neighborhood Function For Bilevel Thresholding. In *Proceeding of AI, Simulation, and Planning in High Autonomy Systems Conference* (pp. 123-128). Tucson: AIS Press.

[26] Talaska, T., Wojtyna, R., Dlugosz, R., & Iniewski, K. Implementation of the Conscience Mechanism for Kohonen's Neural Network. In: *Mixed design of integrated circuits and systems* (pp. 310-315). Gdynia: IEEE Press.

