Journal of Natural Gas Science and Engineering 26 (2015) 303–312

Contents lists available at ScienceDirect

Journal of Natural Gas Science and Engineering

journal homepage: www.elsevier.com/locate/jngse

Optimization of mixed refrigerant systems in low temperature applications by means of group method of data handling (GMDH)

Reza Shirmohammadi [a], Bahram Ghorbani [b,*], Mohsen Hamedi [c], Mohammad-Hossein Hamedi [b], Luis M. Romeo [d]

[a] *Young Researchers and Elite Club, South Tehran Branch, Islamic Azad University, Tehran, Iran*
[b] *Mechanical Engineering Faculty, Energy Conversion Group, KNToosi University of Technology, Tehran, Iran*
[c] *Mechanical Engineering Faculty, KNToosi University of Technology, Tehran, Iran*
[d] *Research Centre for Energy Resources and Consumption (CIRCE) – Universidad de Zaragoza, CIRCE Building – Campus Río Ebro, Mariano Esquillor Gómez, 15, 50018, Zaragoza, Spain*

ARTICLE INFO

Article history:
Received 5 April 2015
Received in revised form
11 June 2015
Accepted 12 June 2015
Available online 26 June 2015

Keywords:
Consumed power
Cascade refrigeration systems
GMDH
Mixed refrigerant
Genetic algorithm (GA)

ABSTRACT

Over the past decades, increasing attention has been paid to optimal design and operation of energy intensive industries. In this paper, a multi-hybrid model with high estimation capability has been applied for prediction of optimum consumed power. Consumed power is the most important factor for cascade refrigeration systems in which efficient estimation of this factor in various operating conditions is essential. The purpose of this paper is to present a new multi-hybrid Model in which six input variables consist of methane, ethane, propane, and nitrogen components composition along with suction and discharge pressures have been employed in order to estimate and predict the optimal consumed power. Having replaced by pure ethylene cycle in the olefin plant of the Tabriz Petrochemical Complex, the one and two stage-cascade cycles are modeled continuously by the proposed model. A hybrid group method of data handling (GMDH) along with linking between Aspen HYSYS and MATLAB software, optimized with Genetic algorithm (GA), is herein proposed to obtain efficient polynomial correlation to estimate optimal consumed power for these two cascade cycles. Results show that the proposed multi-hybrid model is superior to non-linear programming techniques for obtaining the optimum consumed power of cascade refrigeration cycles and finding the values of optimizing variables.

NLP techniques are used to optimize the refrigerant composition at a given refrigerant flow rate and pressure (Lee et al., 2002). In addition, application of Neural networks, particle swarm optimization, genetic and the other evolutionary algorithms, and NLP techniques have received considerable attention in many research fields.

(Romeo and Gareta, 2006) presented the methodology of Neural Network (NN) design as well as application for a biomass boiler monitoring, and they indicated the advantages of NN in these situations. Neural network monitorizing results displayed an excellent agreement with real data. It is also concluded that NN is a stronger tool for monitoring than equation-based monitoring.

(Gareta et al., 2006) demonstrated that the Neural Network approach could be also used to forecast short-term hourly electricity pool prices. This methodology could help to improve power plant generation capacity management. Results were tested with extensive datasets and a good agreement is found between actual data and Neural Network results.

(Amanifard et al., 2008a) presented a quadratic model based upon some experimental results, using evolved GMDH-type neural networks for modeling of the transient evolution of spiky stall cells in an axial compressor. They concluded that the methodology applied in this work could sufficiently derive such complex model of unstable flow of rotating stall based on experimental input–output data. The prediction ability of such polynomial model has also been presented for some unforeseen data.

(Amanifard et al., 2008b) presented two metamodels based on the evolved group method of data handling (GMDH) type neural networks for modeling of both pressure drop (ΔP) and Nusselt number (Nu). It was shown that some interesting and important relationships as useful optimal design principles involved in the performance of microchannels can be discovered by Pareto based multi-objective optimization of the obtained polynomial metamodels representing their heat transfer and flow characteristics. They concluded that, such important optimal principles would not have been obtained without the use of both GMDH type neural network modeling and the Pareto optimization approach.

(Ghorbani et al., 2014a) proposed a hybrid group method of data handling (GMDH) artificial neural network, optimized with genetic algorithm (GA), to obtain efficient polynomial correlation to predict oil viscosity. This correlation was compared with 5 correlations presented in the previous research using the large set of Iranian oil data. They also provided a comprehensive computational and statistical result to evaluate the performance of the proposed methods. Results showed that these models were very good approximations for estimating the viscosity of crude oils.

(Ahmadi et al., 2015) proposed an intelligent approach to determine the output power and torque of a Stirling heat engine. The approach employs the GMDH method to develop an accurate predictive tool for determining output power and torque of a Stirling heat engine in manner that is inexpensive, fast and precise. Consequently, based on the output results, the GMDH approach can help energy experts to design Stirling heat engines with high levels of performance, reliability and robustness and with a low degree of uncertainty.

Many researches have been expended to the use of evolutionary methods as effective tools for system identification In order to predict and model the behavior of very complex systems based on given input–output data (Liu and Kadirkamanathan, 1999; Nariman-Zadeh et al., 2003; Jamali et al., 2009; Ardalan et al., 2009; Nariman-Zadeh et al., 2005a,b). GMDH algorithm is self-organizing approach by which complex models are generated gradually and the main idea of GMDH is to build an analytical function in a feed forward network based on a quadratic node transfer function whose coefficients are obtained using regression technique (Ivakhnenko, 1971; Ardalan et al., 2009; Jamali et al., 2009). In addition, the use of such self-organizing networks leads to successful application of the GMDH-type algorithm in abroad range of areas in engineering, science, and economics (Ivakhnenko, 1971; Nariman-Zadehetal., 2002a,b). Moreover, genetic algorithms have been recently used in a feed forward GMDH-type neural network for each neuron searching its optimal set of connection with the preceding layer. In the (Nariman-Zadeh et al., 2003), authors have proposed a hybrid use of genetic algorithm for a simplified structure GMDH-type neural network in which the connections of neurons are restricted to adjacent layers (Ardalan et al., 2009). Moreover, the use of HYSYS as the thermodynamic model and MATLAB as the optimizer is explored, in order to optimize the verified APCI LNG plant model (Alabdulkarem A et al., 2011).

The purpose of this paper is to apply a new multi-hybrid model i.e. GMDH neural network along with linking between HYSYS and MATLAB software, optimized by genetic algorithm, for modeling and predicting of optimum consumed power. In the following sections, after defining GMDH algorithms, evolved GS-GMDH (General structure) and CS-GMDH (Conventional structure) algorithms, employed for one and two-stage cascade cycle, are clarified.

2. GMDH algorithms

The GMDH algorithms are applied in a great variety of areas for forecasting as well as systems modeling and optimization. In addition, the GMDH algorithm can be considered from two different aspects, which are mathematical basis along with modeling theory and analysis of the system. Mathematically, the GMDH algorithm is rooted in analyzing Volterra function series to a quadratic two-variable polynomial. In this analysis, Volterra series is transformed into a set of chain recursive equations so that the algebraic substitution of each recursive relation by each other results in the re-establishment of Volterra series. A mathematical model can be represented as a set of neurons, in which different pairs in each layer are connected through a quadratic polynomial, so produce new neurons in the next layer. Mathematical modeling and its equation were presented in several publications such as (Nariman-Zadeh et al., 2003, 2005,).

In the second part, the GMDH algorithms are based on the modeling theory and analysis of systems, according to two general principles. The GMDH neural network is the manifestation of the GMDH algorithm, expressed in the form of a network. The GMDH neural network is a self-organizing, unidirectional structure with multiple layers, each of which is composed of several neurons that have a similar structure. Weight (w) is inserted inside each neuron as definite and constant values based on singular value decomposition method by solving normal equations (Nariman-Zadeh et al., 2003).

Additionally, Singular Value Decomposition (SVD) is employed to the design of such GMDH-type networks. SVD is a method for solving most linear least squares problems that some singularities might exist in the normal equations. The most popular technique for computing the SVD was originally proposed in (Golub and Reinsch, 1970).

2.1. Topology design of GMDH-type ANNs using genetic algorithm

Genetic algorithms as an evolutionary algorithm have been widely apply for different aspects of design in neural networks because of their unique capabilities of finding a global optimum in multi-modal and/or non-differentiable search space (Nariman-Zadeh et al., 2003; Jamali et al., 2009; Ardalan et al., 2009). On the other hand, there are two types of GMDH artificial neural networks, which are GS-GMDH and CS-GMDH neural networks. In the GS-GMDH neural networks Fig. 1 (a), neurons connections are able to occur between different layers, which are not necessarily adjacent ones. On the other hand, in the CS-GMDH neural networks, illustrated in Fig. 1 (b), such connections occur only between adjacent layers (Nariman-Zadeh et al., 2003, 2005a,).

Moreover, according to Fig. 2 (a) and (b), the crossover process is able to alter the building blocks information of such GS-GMDH neural networks. In this way, the two types of GS-GMDH and CS-GMDH neural networks can be altered to each other, as illustrated in Fig. 2 (b). In addition, mutation process is also able to convert a GS-GMDH neural network to a CS-GMDH neural network or vice versa (Nariman-Zadeh et al., 2003, 2005a; Madandoust et al., 2010).

2.2. Two-target optimization using GA algorithm

Two-target optimization using GA algorithm along with mentioned methods in the previous parts has been used in present study in order to find optimum points. In two-target optimization using GA algorithm, first, initial generation (pool) is produced stochastically. After creating initial generation, children are produced by choosing from pool population. New children then are produced and added to the pool by using crossover and mutation function over selected population from previous step. In this point, objective function value is calculated for all the existing population in the pool to choose dominant answers and update Pareto set. Next, allocating 25% of new pool with best answers of current pool based on recovery overview and irreversibility index overview. Finally, new pool is completed by the rest of the answers from current pool (Salehi et al., 2012).

3. Cascade refrigeration systems

3.1. Low-temperature refrigeration cycles description

Low-temperature refrigeration system of olefin plant in Tabriz petrochemical complex is composed of two separate closed refrigeration cycles with pure refrigerants, which are propylene for the first cascade, ethylene for the second cascade, and an open loop methane cycle. Propylene cycle not only provides cooling for process streams of olefin plant to −35° C, also it has external cooling role as a condenser for ethylene cycle (second cascade cycle). Fig. 3 shows the second cascade cycle in refrigeration system of Tabriz olefin plant. Pure ethylene is compressed to 20.2 bar in this cycle. As exited superheated vapor of ethylene from compressor passes through heat exchanger (E504), its temperature decrease to approximately 33° C; it is then condensed by passing through heat exchangers E505, E506 and E507. The condensed ethylene after passing through throttle valve, its temperature and pressure is reduced, so it can supply required cooling for feed and reflux streams. In order to help to supply required cooling for feed and reflux streams in the olefin plant; cooling potential of tail gas, regeneration gas, and hydrogen rich gas, which are obtained from demethanizer tower upstream products, are employed. Figs. 4 and 5 show One and Two-stage cascade refrigeration cycles, proposed and simulated to replace by pure ethylene cycle of olefin plant in Tabriz petrochemical complex (Ghorbani et al., 2014b).

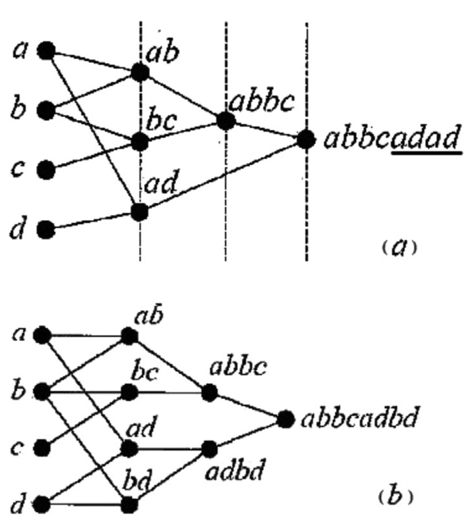

Fig. 1. Network structure of a chromosome (a) GS-GMDH type (b) CS-GMDH type.

3.2. One-stage cascade cycle

In this cycle Fig. 4, having compressed in compressor, the mixed refrigerant is cooled to approximately 33° C in cooling water condenser. Next, the mixed refrigerant is partially condensed by passing through the pre-cooling refrigeration cycle (propylene refrigeration cycle). It is then subcoolded in a multi-stream heat exchanger to approximately 33 °C and expanded by passing through throttle valve. The potential of cold stream is employed to supply the needed cooling of the cycle (Amidpour et al., 2015).

3.3. Two-stage cascade cycle

In order to reduce temperature difference in the length of heat exchanger, the heat transferring between cold and hot streams could be distributed by replacing some heat exchangers connected in series to each other. Idiomatically, each of these exchangers is called one stage. The needed cooling of each stage is supplied by separating the obtained vapor of each refrigerant as well as expanding and subcooling through passing the throttle valve. Fig. 5 shows a two-stage cascade of MRRC, replaced with the presented one-stage cascade in Fig. 4 in order to reduce the consumed power. In this cycle, just a part of refrigerant is employed in heat transferring among all of the heat exchangers. Consequently, this subject causes a reduction in exergy destruction among the heat exchangers (Amidpour et al., 2015).

3.4. Key parameters of mixed refrigerant refrigeration cycle

Achieving an efficient mixed refrigerant refrigeration cycle is possible by selecting appropriate design parameters such as refrigerants composition, operation pressures, and configuration of cycle. Operation pressures and components composition play an important role in refrigeration cycles design (Ghorbani et al., 2014b). Methane, ethane, propane, nitrogen discharge and suction pressure are the key parameters of mixed refrigerant cycle in the current study, considered as input parameters for modeling of system.

4. Modeling

4.1. Proposed multi-hybrid model

Since there are many variables involve in designing such cycle, the optimization was carried out in two stages as shown in Fig 6. In presented model, the correlation of each datasets is obtained from training datasets and is tested by the testing datasets, which are never observed throughout the training. About 90% of each dataset is used for training in order to derive empirical equation, and the

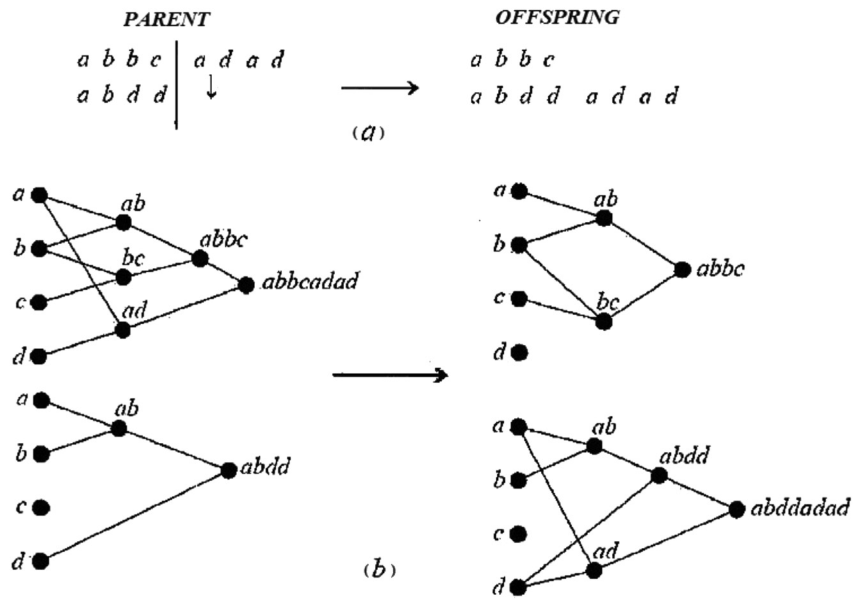

Fig. 2. Crossover operation (a) For two individuals in GS-GMDH networks (b) On two GS-GMDH networks.

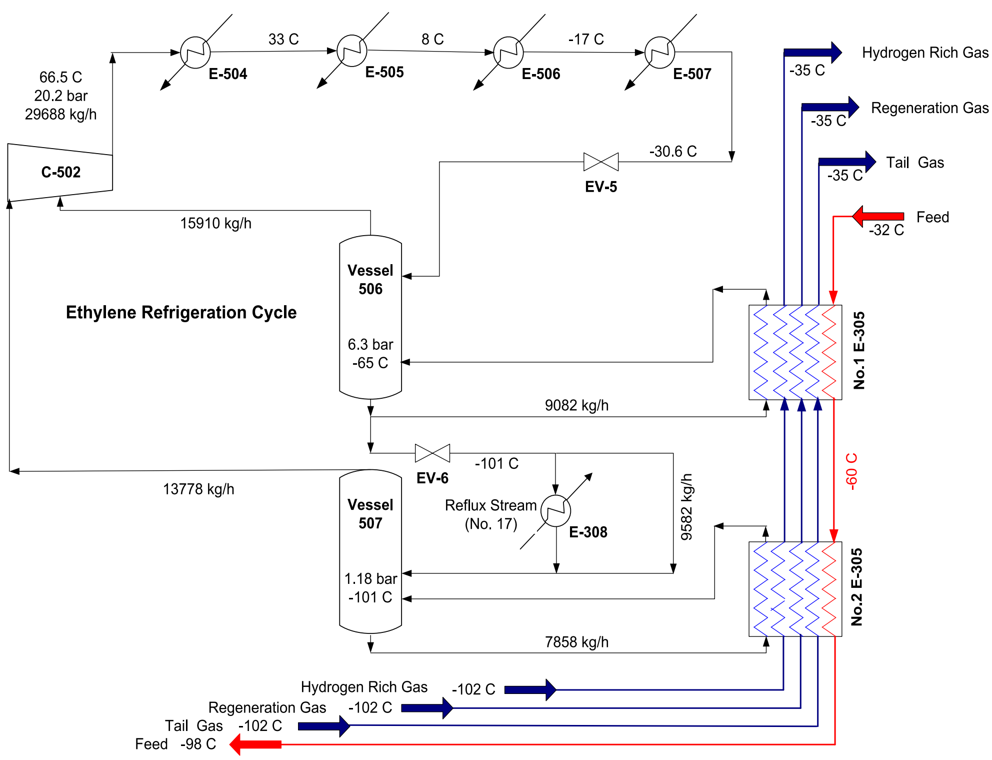

Fig. 3. Schematic diagram of olefin plant (ethylene cycle).

rest is used for validating the correlation. The best value that can be obtained for this variable is equal to 1. Having used the empirical equation, Genetic algorithm is employed to find optimum point i.e. consumed power. There are six values consist of x_1 to x_6 according to the obtained optimum consumed power. These six values are ported from Genetic algorithm to Aspen HYSYS software to produce a new value for consumed power. This step has been continued so that the value between optimum consumed power from Genetic algorithm and HYSYS close to zero value. In the next sections, modeling of one and two-stage cascade cycles using CS-GMDH and GS-GMDH will be presented, respectively.

4.2. Modeling of one-stage cascade cycle using CS-GMDH neural networks

In this paper, six input variables and an output variable are employed for modeling of one-stage cascade cycle using CS-GMDH neural networks. Six variables are recognized as primary input data

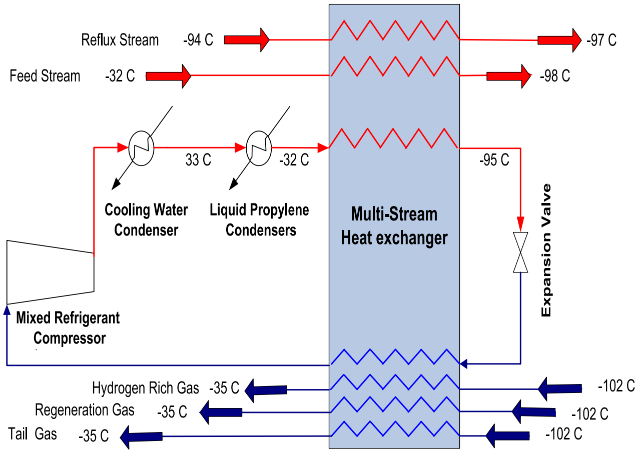

Fig. 4. Schematic diagram of One-stage cascade cycle.

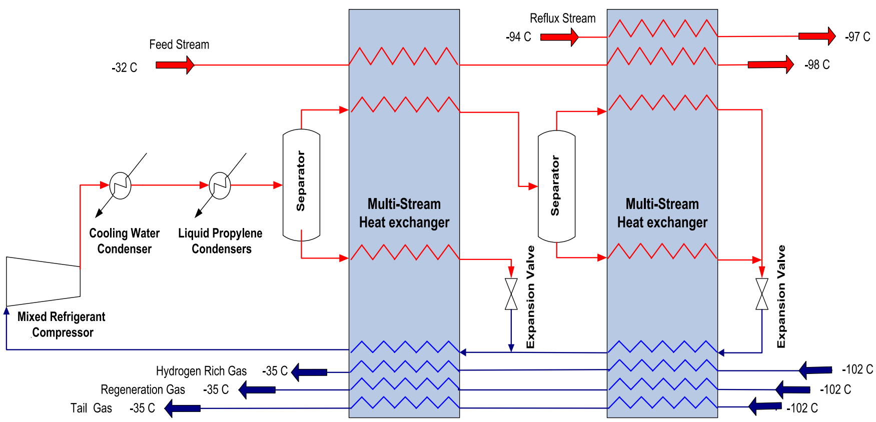

Fig. 5. Schematic diagram of Two-stage cascade cycle.

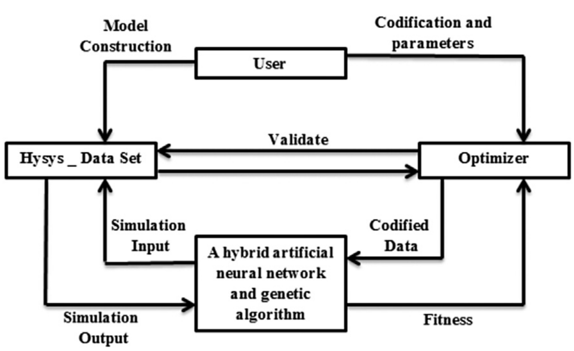

Fig. 6. Proposed optimization approach.

(nitrogencomposition,x_1; methane composition,x_2; ethane composition, x_3; propane composition, x_4; discharge pressure, x_5; suction pressure, x_6;) and an output data y_7, representing consumed power of cycle. There are 520 datasets consist ofx_1 to x_6, employed in this modeling. In addition, Pinch temperature difference in heat exchangers for this model should be more than 5 degree of Celsius, so this constraint is imposed to the Aspen HYSYS software. These datasets have been divided into training and testing sets to validate the forecast aptitude of the CS-GMDH neural networks. The training set, consisting of 468 out of 520 data, is employed for training and the rest i.e. testing set, comprising of 52 unanticipated data, is just employed for testing to indicate the forecast aptitude of the evolved CS-GMDH neural network model throughout the training process. The structure of the CS-GMDH, composed of two-hidden layer, is illustrated in Fig. 7 corresponding to the genome representations of y_7 for cycle-consumed power.

In this paper for one-stage cascade cycle, following constraints are imposed to the model:

$$1 < x_1 < 3$$

$$10 < x_2 < 35$$

$$25 < x_3 < 55$$

$$30 < x_4 < 50$$

$$x_1 + x_2 + x_3 + x_4 = 100$$

$$600 < x_5 < 1700$$

$$120 < x_6 < 300$$

Thus, corresponding polynomial representation of the model for one-stage cascade are drawn as follows:

where x_1 tox_4 are components composition, along withx_5 and x_6

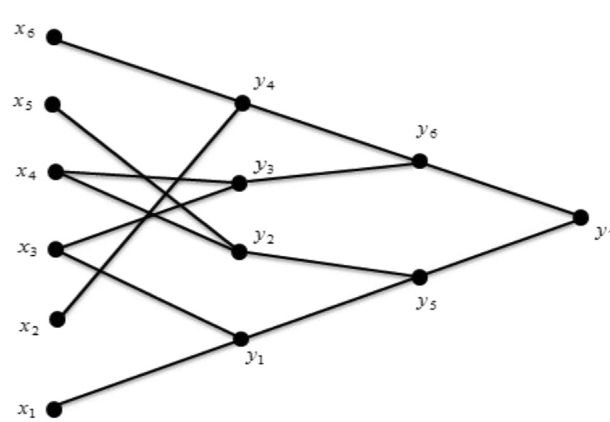

Fig. 7. Evolved structure of CS-GMDH neural network for One-stage cascade.

$a_1 = 2.048754239603699{*}10^3$
$a_2 = 0.008794111691933{*}10^3$
$a_3 = 0.038404475308063{*}10^3$
$a_4 = 0.000627137418052{*}10^3$
$a_5 = 0.000517566927166{*}10^3$
$a_6 = 0.000945869915507{*}10^3$
$a_7 = 1.477618487253145$
$a_8 = 42.275173224080554$
$a_9 = 0.940717735872928$
$a_{10} = -0.343464379258053$
$a_{11} = -0.000160585188215$
$a_{12} = -0.011834029744969$
$a_{13} = 3.857217584954775{*}10^3$
$a_{14} = -0.089132329367484{*}10^3$
$a_{15} = -0.058169371580979{*}10^3$
$a_{16} = 0.000812926401922{*}10^3$
$a_{17} = 0.000441474506898{*}10^3$
$a_{18} = 0.000957443045316{*}10^3$
$a_{19} = 2.318809599029221{*}10^3$
$a_{20} = -0.046061838195703{*}10^3$
$a_{21} = -0.002541438350099{*}10^3$
$a_{22} = 0.001053544690565{*}10^3$
$a_{23} = 0.000006886209337{*}10^3$
$a_{24} = -0.000042577635404{*}10^3$
$a_{25} = -0.004377982417473$
$a_{26} = 7.126616533645924$
$a_{27} = -6.651341009951328$
$a_{28} = -0.000095481826041$
$a_{29} = 0.004485999586462$
$a_{30} = -0.004029456499207$
$a_{31} = -200.028723444604077$
$a_{32} = -14.678137923007075$
$a_{33} = 16.215213719866817$
$a_{34} = 0.008010261219108$
$a_{35} = -0.001580248568533$
$a_{36} = -0.006798579385741$
$a_{37} = 0.000075376410827$
$a_{38} = 4.656166636569426$
$a_{39} = -4.224706505475592$
$a_{40} = -0.001211681992975$
$a_{42} = -0.000258164067726$

$$
\begin{aligned}
y_1 &= a_1 + (a_2{*}x_1) + (a_3{*}x_3) + \left(a_4{*}\left(x_1^2\right)\right) + \left(a_5{*}\left(x_3^2\right)\right) + (a_6{*}x_1{*}x_3)\\
y_2 &= a_7 + (a_8{*}x_4) + (a_9{*}x_5) + \left(a_{10}{*}\left(x_4^2\right)\right) + \left(a_{11}{*}\left(x_5^2\right)\right) + (a_{12}{*}x_4{*}x_5)\\
y_3 &= a_{13} + (a_{14}{*}x_3) + (a_{15}{*}x_4) + \left(a_{16}{*}\left(x_3^2\right)\right) + \left(a_{17}{*}\left(x_4^2\right)\right) + (a_{18}{*}x_3{*}x_4)\\
y_4 &= a_{19} + (a_{20}{*}x_2) + (a_{21}{*}x_6) + \left(a_{22}{*}\left(x_2^2\right)\right) + \left(a_{23}{*}\left(x_6^2\right)\right) + (a_{24}{*}x_2{*}x_6)\\
y_5 &= a_{25} + (a_{26}{*}y_1) + (a_{27}{*}y_2) + \left(a_{28}{*}\left(y_1^2\right)\right) + \left(a_{29}{*}\left(y_2^2\right)\right) + (a_{30}{*}y_1{*}y_2)\\
y_6 &= a_{31} + (a_{32}{*}y_3) + (a_{33}{*}y_4) + \left(a_{34}{*}\left(y_3^2\right)\right) + \left(a_{35}{*}\left(y_4^2\right)\right) + (a_{36}{*}y_3{*}y_4)\\
y_7 &= a_{37} + (a_{38}{*}y_5) + (a_{39}{*}y_6) + \left(a_{40}{*}\left(y_5^2\right)\right) + \left(a_{41}{*}\left(y_6^2\right)\right) + (a_{42}{*}y_5{*}y_6)
\end{aligned}
\tag{1}
$$

which are discharge and suction pressure, respectively. Besides, y_1 toy_6 are quadratic description of their correspond neurons in Fig. 7.

Fig. 8 depicts training and testing datasets of consumed power for one-stage cascade cycle. Not only does this CS-GMDH model have brilliant behavior, but also this model in terms of simple polynomial equations are able model and forecast properly the output of testing data that has not been employed throughout the training process as well Fig. 8.

4.3. Modeling of two-stage cascade cycle using GS-GMDH neural networks

Input and output data for two-stage cascade cycle are precisely the same as one-stage cascade cycle except for the amount ofx_2, considered as a constant input data. There are 478 datasets consist ofx_1 to x_6, employed in this modeling. The training set, consisting of 430 out of 478 data, is employed for training while the testing set, comprising of 48 unanticipated data, is just employed for testing to indicate the forecast ability of the evolved GS-GMDH neural network model throughout the training process. The structure of the GS-GMDH, composed of two-hidden layer, is illustrated in Fig. 9 corresponding to the genome representations of y_5 for cycle-consumed power.

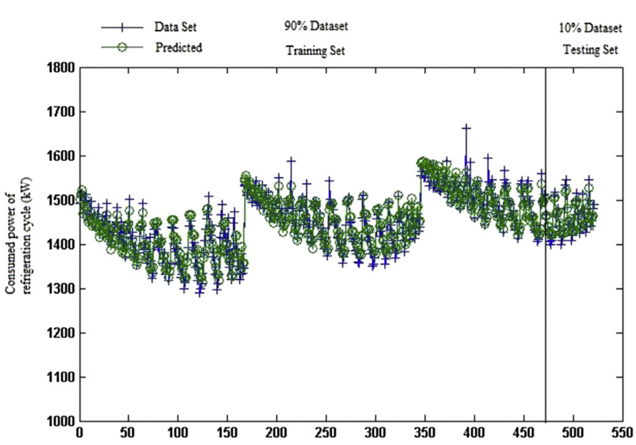

Fig. 8. Variation of consumed power with respect to input data (modeling & prediction) One-stage cascade cycle.

In this paper, following constraints are imposed to the model:

$1 < x_1 < 3$

$x_2 = 17.8$

$25 < x_3 < 55$

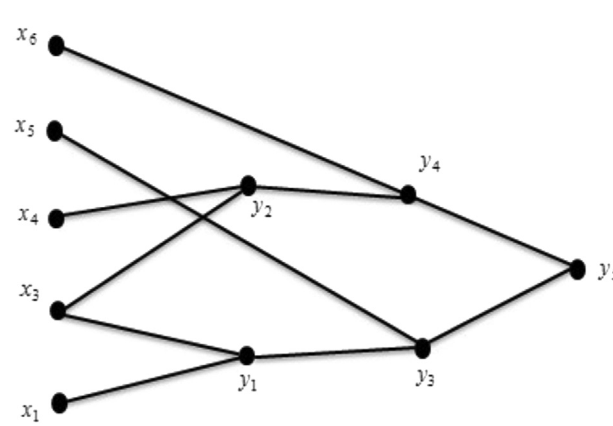

Fig. 9. Evolved structure of GS-GMDH neural networks for Two-stage cascade cycle.

$30 < x_4 < 50$

$x_1 + x_2 + x_3 + x_4 = 100$

$600 < x_5 < 1700$

$120 < x_6 < 300$

Thus, corresponding polynomial representation of the model for two-stage cascade are drown as follows:

$$
\begin{array}{ll}
a_1 = 2.336916511522821*10^3 & a_{16} = 0.000464905272013 \\
a_2 = 0.98113831449360*10^3 & a_{17} = -0.000452494508917 \\
a_3 = -0.039266213993667*10^3 & a_{18} = 0.000431079045985 \\
a_4 = -0.013169619440759*10^3 & a_{19} = 0.008303133867361 \\
a_5 = 0.000559251649690*10^3 & a_{20} = 2.373381544787244 \\
a_6 = -0.000131832607699*10^3 & a_{21} = 5.979125782315280 \\
a_7 = 5.842567259372625*10^3 & a_{22} = -0.000605105672830 \\
a_8 = -0.103305610279551*10^3 & a_{23} = 0.008454897939899 \\
a_9 = -0.138206142026768*10^3 & a_{24} = -0.005948147482195 \\
a_{10} = 0.000765824291461*10^3 & a_{25} = -600.003283302532715 \\
a_{11} = 0.00131196086815*10^3 & a_{26} = 7.402691626854500 \\
a_{12} = 0.001491636794569*10^3 & a_{27} = -6.914074617506103 \\
a_{13} = 0.002548245742804 & a_{28} = -0.000254542035099 \\
a_{14} = -2.041234451481583 & a_{29} = 0.003713972725346 \\
a_{15} = 2.278697042946432 & a_{30} = -0.003175447549008
\end{array}
$$

$$
\begin{aligned}
y_1 &= a_1 + (a_2*x_1) + (a_3*x_3) + \left(a_4*\left(x_1^2\right)\right) + \left(a_5*\left(x_3^2\right)\right) + (a_6*x_1*x_3) \\
y_2 &= a_7 + (a_8*x_3) + (a_9*x_4) + (a_{10}*) + \left(a_{11}*\left(x_4^2\right)\right) + (a_{12}*x_3*x_4) \\
y_3 &= a_{13} + (a_{14}*x_5) + (a_{15}*y_1) + \left(a_{16}*\left(x_5^2\right)\right) + \left(a_{17}*\left(y_1^2\right)\right) + (a_{18}*x_5*y_1) \\
y_4 &= a_{19} + (a_{20}*y_2) + (a_{21}*x_6) + \left(a_{22}*\left(y_2^2\right)\right) + \left(a_{23}*\left(x_6^2\right)\right) + (a_{24}*y_2*x_6) \\
y_5 &= a_{25} + (a_{26}*y_3) + (a_{27}*y_4) + \left(a_{28}*\left(y_3^2\right)\right) + \left(a_{29}*\left(y_4^2\right)\right) + (a_{30}*y_3*y_4)
\end{aligned}
\tag{2}
$$

where x_1 tox_4 are components composition, along withx_5 and x_6 which are discharge and suction pressure, respectively. Besides, y_1 toy_5 are quadratic description of their correspond neurons in Fig. 9.

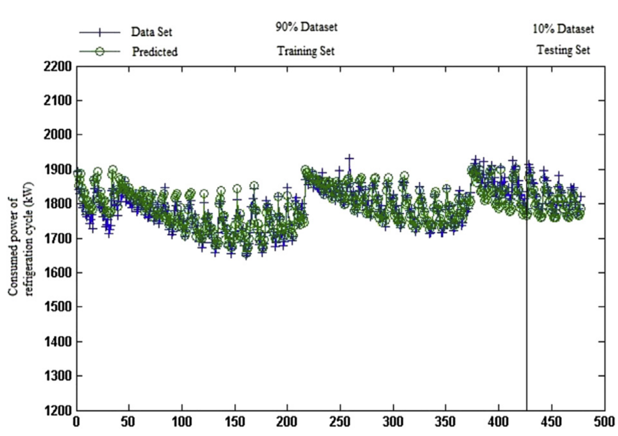

Fig. 10. Variation of consumed power with respect to input data (modeling & prediction) Two-stage cascade cycle.

Table 1
Accuracy of consumed power correlations for prediction.

Correlation	E_a	E_r	r
One-stage cascade cycle	0.948699	1248.974	0.948202
Two-stage cascade cycle	0.958893	1192.918	0.925382

Fig. 10 depicts training and testing datasets of consumed power for one-stage cascade cycle using GS-GMDH neural networks. Not only does this GS-GMDH model have wonderful behavior, but also the evolved GS-GMDH neural networks in terms of simple polynomial equations are able well model and forecast the output of testing data that has not been employed throughout the training process.

5. Optimization results

In this section, optimization results of one and two-stage cascades are discussed through using proposed approach in Fig. 6. The correlation of each datasets is obtained from training datasets and is tested using the testing dataset, which are never observed throughout the training. About 90% of each dataset is used for training and the rest is used for validating the correlation. The result of these correlations for one and two-stage cascades, tested using the available data, is depicted in Table 1.

In Table 1, E_a, E_i, and r stand for mean absolute relative error, mean relative error, and correlation coefficient, respectively. The values of these variables are attained using the equations in Appendix A. The correlation coefficient also known as r is a measure of the strength and direction of the linear relationship between two variables. The best value that can be obtained for this variable is equal to one. Unless this variable is acquired to be closer to one, correlation performance will be reduced consequently. According to the results in Table 1, the r-value of present study

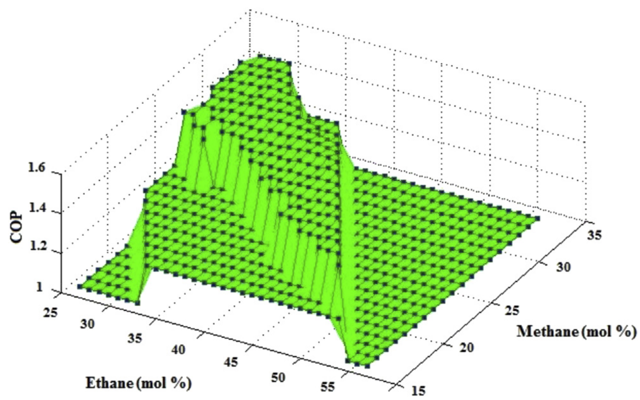

Fig. 11. Variation of cycle COP with respect to components composition (One-stage cascade cycle).

correlation for one-stage cascade cycle almost closer to one in comparison with two-stage cascade cycle.

Figs. 11 and 12 show the variation of one-stage cascade cycle COP and consumed power in terms of methane composition, x_2; ethane composition, x_3; respectively. In Fig. 11, optimum consumed power is equal to 1064.59, occurred in $x_2 = 31.09$ and $x_3 = 35.6$.

Fig. 13 shows variation of consumed power in terms of different amount of propane component. It is obvious that by increasing of different amount of propane, the consumed power will be increase consequently. The optimum amount of propane is equal to 32.2.

Figs. 14 and 15 show the cycle consumed power variation with respect to suction and discharge pressure for one and two-stage cascade cycle, respectively. According to Fig. 14, optimum consumed power for one-stage cascade is equal to 1064.59 kW, occurred in minimum pressure i.e. 272.667 kPa. On the other hand, according to Fig. 15, optimum consumed power for Two-stage cascade is equal to 1023.674 kW, occurred in maximum pressure i.e. 1349.18 kPa.

Optimum values for one and two-stage cascade cycles using presented model in this paper are illustrated in Table 2. In order to evaluate and compare this model, the results of (Amidpour et al., 2015) are presented in Table 3. Optimized operation parameters and consumed power for one and two-stage cascade cycles, based on a combination of mathematical methods and thermodynamic viewpoints, is obtained by non-linear programming techniques (Table 3). The supremacy of the presented model in this paper over NLP programming techniques is completely clear when it comes to consumed power. The consumed power of one-stage cascade was

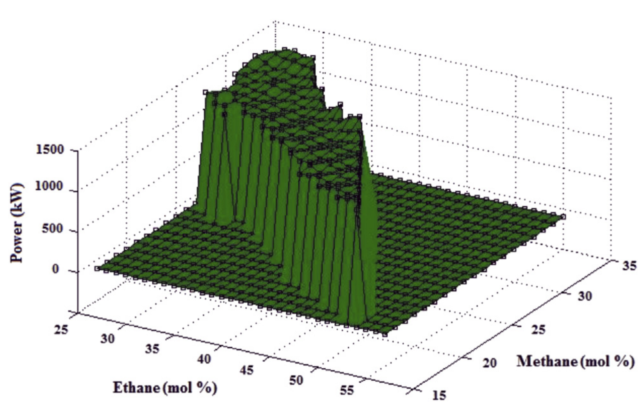

Fig. 12. Variation of cycle consumed power with respect to components composition (One-stage cascade cycle).

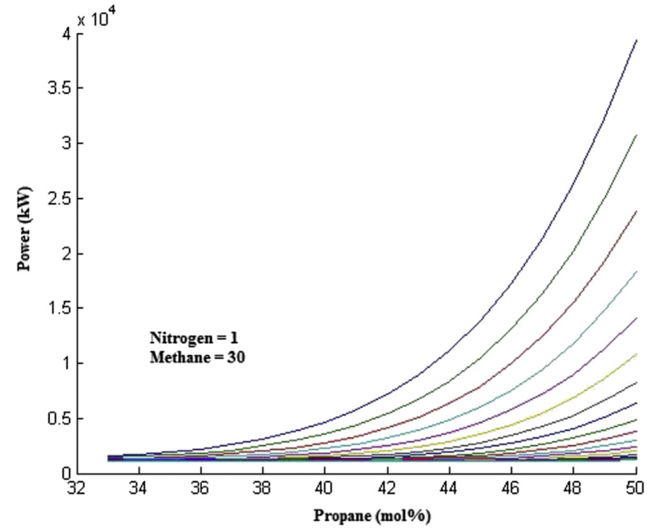

Fig. 13. Variation of optimized consumed power with respect to propane composition (One-stage cascade cycle).

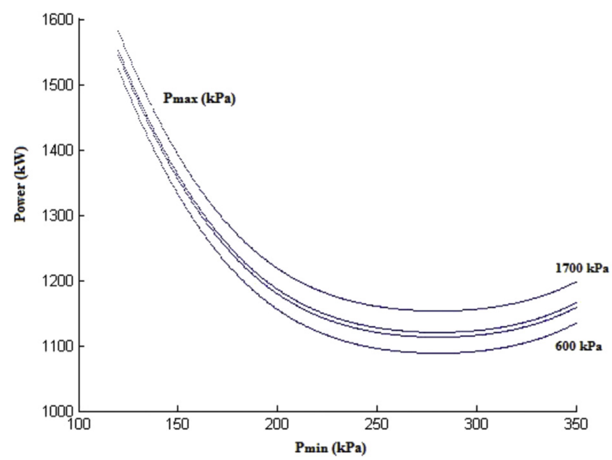

Fig. 14. Variation of optimized consumed power with respect to suction pressure (One-stage cascade cycle).

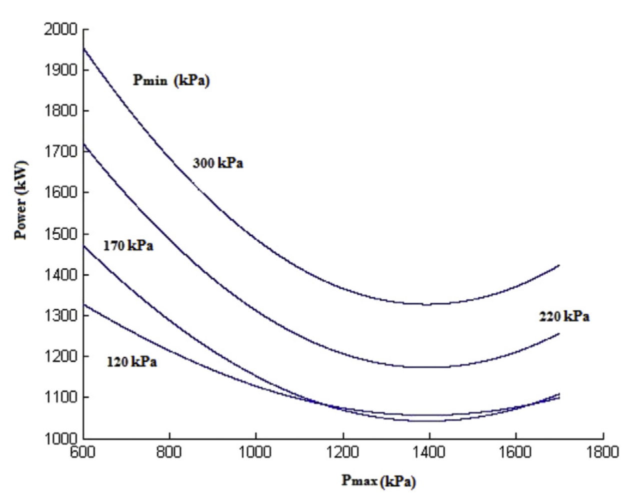

Fig. 15. Variation of optimized consumed power with respect to discharge pressure (Two-stage cascade).

Table 2
Optimum values for one and two-stage cascade cycles using presented model.

Cycle Configuration	Composition (mol%)				Operation pressure of cycle (kPa)		Consumed power of cycle (kW)
	Nitrogen	Methane	Ethane	Propane	Discharge	Suction	
One-stage cascade	1	31.09	35.63	32.27	649.91	272.66	1064.59
Two-stage cascade	1	17.8	35.1	46	1349.18	146.43	1023.67

Table 3
Optimized parameters for one and two-stage cascade cycles using NLP techniques (Amidpour et al., 2015).

Cycle Configuration	Composition (mol%)				Operation pressure of cycle (kPa)		Consumed power of cycle (kW)
	Nitrogen	Methan	Ethane	Propane	Discharge	Suction	
One-stage cascade	1	24	45	30	800	260	1239
Two-stage cascade	1	15	41	43	600	140	1230

declined from 1239 to 1064.59 kW. The same is true for the other cycle, so the consumed power of two-stage cascade was declined from 1230 to 1023.67 kW.

6. Conclusion

In this paper, the proposed multi-hybrid model with six input variables consist of nitrogen, methane, ethane, and propane components as well as discharge and suction pressure were employed to predict the optimum consumed power of two presented cascade cycles. The consumed power correlation was obtained for each cascade cycle. This correlation was trained and tested by a dataset with a wide range of input parameters. Genetic algorithm was then employed to optimize the correlation parameters for better performance. Results showed the proposed hybrid-model has correlation coefficient about 0.94 and 0.92 for one and two-stage cascade cycles, respectively. In addition, the accuracy of proposed model is compared to one well-known optimization method. Results showed that the proposed multi-hybrid model was superior to non-linear programming techniques for obtaining the optimum consumed power of cascade refrigeration cycles and finding the values of optimizing variables. In addition, the presented multi-hybrid model provides a saving of about 174.41 kW and 206.33 kW energy as compared with the NLP optimized case obtained for one and two-stage cascade cycles, respectively.

Nomenclature

E_i	Percent relative error
E_a	Percent mean absolute relative error
E_r	Percent mean relative error
S	Standard deviation
n	Number of data points
r	Correlation coefficient
$\overline{X}$	Mean value
i	Observation index

Appendix A. Statistical analysis

1. Percent relative error

$$E_i = \left(\frac{X_{\exp} - X_{est}}{X_{\exp}}\right)_i \times 100 (i = 1, 2, \dots, n)$$

2. Percent mean relative error

$$E_r = \frac{1}{n}\sum_{i=1}^{n} E_i$$

3. Percent mean absolute relative error

$$E_a = \frac{1}{n}\sum_{i=1}^{n} |E_i|$$

4. Standard deviation

$$S = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n} (E_i - E_r)^2}$$

5. The correlation coefficient

$$r = \sqrt{1 - \sum_{i=1}^{n} [X_{\exp} - X_{est}]_i^2 \Big/ \sum_{i=1}^{n} [X_{\exp} - \overline{X}]_i^2}$$

where

$$\overline{X} = \frac{1}{n}\sum_{i=1}^{n}\left[X_{\exp}\right]_i$$

References

Ahmadi, M.H., Ahmadi, M.A., Mehrpooya, M., Rosen, M.A., 2015. Using GMDH neural networks to model the power and torque of a Stirling engine. Sustainability 7, 2243–2255.

Alabdulkarem, A., Mortazavi, A., Hwang, Y., Radermacher, R., Rogers, P., 2011. Optimization of propane pre-cooled mixed refrigerant LNG plant. J. Appl. Therm. Eng. 31, 1091–1098.

Amanifard, N., Nariman-Zadeh, N., Farahani, M.H., Khalkhali, A., 2008a. Modelling of multiple short-length-scale stall cells in an axial compressor using evolved GMDH neural networks. Energy Convers. Manag. 49, 2588–2594.

Amanifard, N., Nariman-Zadeh, N., Borji, M., Khalkhali, A., Habibdoust, A., 2008b. Modelling and Pareto optimization of heat transfer and flow coefficient in microchannels using GMDH type neural networks. Energy Convers. Manag. 49 (2), 311–325.

Amidpour, M., Hamedi, M.H., Mafi, M., Ghorbani, B., Shirmohammadi, R., Salimi, M., 2015. Sensitivity analysis, economic optimization, and configuration design of mixed refrigerant cycles by NLP techniques. J. Nat. Gas. Sci. Eng. 21, 779–790.

Ardalan, H., Eslami, A., Nariman-Zadeh, N., 2009. Piles shaft capacity from CPT and CPTu data by polynomial neural networks and genetic algorithms. Comput. Geotechnics 36, 616–625.

Gareta, R., Romeo, L.M., Gil, A., 2006. Forecasting of electricity prices with neural networks. Energy Convers. Manag. 47, 1770–1778.

Ghorbani, B., Ziabasharhagh, M., Amidpour, M., 2014a. A hybrid artificial neural network and genetic algorithm for predicting viscosity of Iranian crude oils. J. Nat. Gas. Sci. Eng. 18, 312–323.

Ghorbani, B., Mafi, M., Shirmohammadi, R., Hamedi, M.H., Amidpour, M., 2014b. Optimization of operation parameters of refrigeration cycle using particle swarm and NLP techniques. J. Nat. Gas. Sci. Eng. 21, 779–790.

Golub, G.H., Reinsch, C., 1970. Sngular value decomposition and least squares solutions. Numer. Math. 14 (5), 403–420.

Ivakhnenko, A.G., 1971. Polynomial theory of complex systems. IEEE Trans. Syst. Man, Cybern. SMC-1, 364–378.

Jamali, A., Nariman-zadeh, N., Darvizeh, A., Masoumi, A., Hamrang, S., 2009. Multi-objective evolutionary optimization of polynomial neural networks for modelling and prediction of explosive cutting process. Eng. Appl. Artif. Intell. 22, 676–687.

Khan, M.S., Lee, M., 2013. Design optimization of single mixed refrigerant natural gas liquefaction process using the particle swarm paradigm with nonlinear constraints. J. Energy 49, 146–155.

Liu, G.P., Kadirkamanathan, V., 1999. Multi-objective criteria for neural network structure selection and identification of nonlinear systems using genetic algorithms. IEE Proc. Control Theory Appl. 146 (5), 373–382.

Madandoust, R., Ghavidel, R., Nariman-zadeh, N., 2010. Evolutionary design of generalized GMDH-type neural network for prediction of concrete compressive strength using UPV. Comput. Mater. Sci. 49, 556–567.

Mehrpooya, M., Vatani, A., Mousavian, S.M.A., 2010. Optimum design of integrated recovery plants by variable population size genetic algorithm. Can. J. Chem. Eng. 88 (6), 1054–1064.

Mokarizadeh Haghighi Shirazi, M., Mowla, D., 2010. Energy optimization for liquefaction process of natural gas in peak shaving plant. Energy 35, 2878–2885.

Nariman-Zadeh, N., Darvizeh, A., Jamali, A., Moeini, A., 2005a. Evolutionary design of generalized polynomial neural networks for modelling and prediction of explosive forming process. J. Mater. Process. Technol. 164–165, 1561–1571.

Nariman-zadeh, N., Atashkari, K., Jamali, A., Pilechi, A., Yao, X., 2005b. Inverse modelling of multi-objective thermodynamically optimized turbo engines using GMDH-type neural networks and evolutionary algorithms. Eng. Optim. 37 (5), 437–462. Taylor & Francis Group.

Nariman-Zadeh, N., Darvizeh, A., Ahmad-Zadeh, R., 2003. Hybrid genetic design of GMDH-type neural networks using singular value decomposition for modelling and prediction of the explosive cutting process. Proc. I MECH E Part' B J. Eng. Manuf. 217, 779–790.

Nariman-Zadeh, N., Darvizeh, A., Felezi, M.E., Gharababaei, H., 2002a. Polynomial modelling of explosive compaction process of metallic powders using GMDH-type neural networks and singular value decomposition. Model. Simul. Mater. Sci. Eng. 10 (6), 727–744 (18).

Nariman-zadeh, N., Darvizeh, A., Darvizeh, M., Gharababaei, H., 2002b. Modelling of explosive cutting process of plates using GMDH-type neural network and singular value decomposition. J. Mater. Process. Technol. 128 (1), 80–87 (8).

Romeo, L.M., Gareta, R., 2006. Neural network for evaluating boiler behaviour. Appl. Therm. Eng. 26, 1530–1536.

Salehi, G.R., Salehi, A., Ghorbani, B., Amidpour, M., Maleki, M., Kimiaghalam, F., 2012. A pareto front approach to Bi-objective of distillation column operation using genetic algorithm. Energy Sci. Technol. 3 (2), 63–73.

Stoecker, W.F., 1998. Industrial Refrigeration Handbook. McGraw-Hill, New York.

Vaidyaramana, S., Maranas, C., 2002. Synthesis of mixed refrigerant Cascade Cycles. Chem. Eng. Commun. 189, 1057–1078.