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An effective krill herd based optimal NN for parameter evaluation in Shell-And-Tube heat exchangers

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ABSTRACT

Helical baffles are employed increasingly in shell-and-tube heat exchangers for their significant advantages in reducing pressure drop, vibration, and fouling while maintaining a higher heat transfer performance. In order to make good use of helical baffles, serial improvements have been made by many researchers. In this paper create model of optimal NN for prediction analysis in parameters compared to existing works. This hidden layer and neuron optimization process fish asked KHO technique used. For more verification, KHO is applied to six design problems reported in the literature. Further, the performance of the KH algorithm is compared with that of various algorithms representative of the state-of-the-art in the area. The results of different algorithms are breaking down and stood out from comparative systems, and the finest results rising out of them are discovered by standing out the results from least MSE values. From the results our proposed method achieves minimum MSE compared to existing works and maximum prediction accuracy in optimization model.

1. INTRODUCTION

Heat is a form of energy. Heat transfer is the exchange of thermal energy between physical systems. For transferring heat by the process of conduction, heat exchangers are the most common equipment used in process industries [1]. Heat exchangers are the device that facilitating effective heat transfer between the two fluids by virtue of their temperature differences [2-3]. Here, shell and tube heat exchangers are used. In shell and tube heat exchangers, one fluid flows across the tube banks while other flows through the tubes, in which the heat transfer takes place between the shell and the tube side fluids [4]. Due to the important role of shell-and-tube heat exchangers, a variety of techniques have been proposed to the design optimization problem such as, numerical resolution and systematic screening of tube count tables [5]. In general, low-temperature geothermal heat sources are widely available but the electricity production efficiency is low due to the low temperature, [6] so that the Organic Rankine Cycle (ORC) method is introduced in this paper and thus can generate electricity from low-temperature heat sources using organic as a working fluid [7]. The main challenges of the ORC are the choice of an appropriate working fluid and of the particular cycle design with which the optimum objective function can be achieved [8].

ORC system driven by a low-temperature geothermal source optimizing the ratios of the total heat transfer area to the net power output and electricity production cost and also to have a fixed pressure drop, pinch-point temperature differences [9].

The main scope of the present work is to clarify the effect of flow, thermodynamic and geometrical parameters on energy loss in shell and coiled tube heat exchangers [10]. There are different methods for optimization design of shell and tube heat exchangers among that the traditional design approach is an iterative process based on the past experience and the constraints of working conditions, such as allowable fouling and pressure drops [11]. The selection of the working fluids relates the ORC performance with the distance between the critical temperature of the working fluid and the inlet temperature of the heat source [12]. Because of the complexity of the structure, the working condition is very difficult to obtain exact analytical solutions of heat transfer characteristics [13].

In recent years, numerous approaches for the performance design and optimization of practical thermodynamic cycles have been explored and applied in engineering [14] and also they developed a set of correlations for two-phase evaporators with a focus on ammonia as a working fluid that included the effect of chevron angle on the thermal and hydraulic performance [15]. Many studies on the configuration of shell and tube heat exchangers can be carried out. For example, systemic optimization designs of structures, equipment improvement, parameter optimization under different working conditions, and working fluids selection to increase power cycle efficiency [16]. From the brief review presented above, it can be concluded that the [17] proposed algorithm is applicable to find optimum and near optimum alternatives of the shell and tube heat exchanger configurations [18].

2. LITERATURE REVIEW

In 2016 Ashkan Alimoradi et al. [19] have proposed that the heat transfer of shell and helically coiled tube heat exchangers. To investigate the effect of physical properties of fluid, operational, and geometrical parameters, numerical and experimental methods were used on Nusselt numbers of both sides. Under the numerical and experimental analysis, 42 cases and 15 tests were investigated respectively. Depend on temperature, viscosity and thermal conductivity of working fluids were assumed. Result proved that if the pitch size is doubled, the shell side Nusselt number increases by 10%, at the same time coil side Nusselt numbers increases by only 0.8%. Based on results, two correlations were developed to predict the coil side and shell side these correlations were compared with experimental data for wide range of operational and geometrical parameters.

In 2016 Jian Wen et al. [20] illustrated that the optimization of shell and tube heat exchanger to overcome the dependence on empirical correlations and to achieve accurate results. Optimization parameters are helical angle, baffle overlap proportion and inlet volume rate in which the energy and cost are optimized by using Kriging met model based on multi-objective genetic algorithm. The results were obtained by the comparison between the optimum and a conventional shell and tube heat exchanger with segmental baffles and are beneficial to trade off the heat transfer rate and total cost of helical baffles. Finally, the shell and tube heat exchanger obtained a better performance with helical baffles and it can be concluded that are benefit for energy saving and cost reduction.

In 2016 Alessandro Scattina [21] analyzed that the mechanical process of tubes expansion used for the production of heat exchangers with two different aspects. Using finite element models, 2D model was used to study the influence of mandrel geometry and the 3D model was used to investigate geometrical errors in tubes. Force required for expansion in tube dimensions was investigated and the obtained results showed that the fillet radius is important factor of mandrel to reduce the expansion force. During tube expansion process, the influence of the tube geometrical errors was observed which can compromise the performance of the heat exchanger. It is concluded that the present study improves tubes expansion processes and heat exchanger production.

In 2016 Noémie Chagnon-Lessard et al. [22] demonstrated the optimization of Organic Rankine Cycle by means of numerical simulations. Optimization was performed with subcritical and transcritical thermodynamic cycles that maximizes the specific power output. The operating parameters such as pressures, mass flow rates and the working fluid were determined by the performance of 36 refrigerants. Optimized values are performed for a wide range of geofluid temperatures (from 80 to 180 C) and condenser temperature (from 0.1 to 50 C). The obtained results used for designing optimal geothermal power plants. To predict the maximum specific power output of an ORC a new correlation should be developed.

In 2015 Bin Gao et al. [23] analyzed the effects of flow resistance and heat transfer of several shell-and-tube heat exchangers with discontinuous helical baffles and compared with five different helix angle. The second-law of thermodynamics was employed to analyze these effects on the irreversible loss of heat exchangers. The irreversibility of heat exchanger was estimated by the theories of entropy generation and entransy dissipation. The result showed that the shell-side pressure drops and heat transfer coefficient of the heat exchanger with smaller helix angle are higher than those with larger helix angle and the flow resistance with larger helix angle is lower. In the heat exchange process, the shell-and-tube heat exchanger with smaller helix angle baffles produces less irreversibility.

In 2016 Shuangcheng Sun et al. [24] have proposed an inverse geometry design of two-dimensional complex radiative enclosures to satisfy a uniform distribution of radiative heat flux over the design surface using krill herd (KH) algorithm. Using the discrete ordinate method, the forward radiative heat transfer problem in irregular enclosures was solved. To optimize the geometric positions of the control points, five kinds of KH algorithms were utilized. Finally, KH algorithm proved to be more efficient than the micro genetic algorithm and particle swarm optimization algorithms. In an inverse geometry design, the influences of radiative properties of the media and the number of control points were also investigated.

In 2015 L.V. Kamble et al. [25] described the prediction of heat transfer from horizontal tube immersed in gas–solid fluidized bed of large particles by the neural network optimization. The effect of fluidizing gas velocity on the average heat transfer coefficient between fluidizing bed and horizontal tube surface was studied by the Artificial Neural Network modeling. For predicting the heat transfer coefficient, compare the performances of five training functions implemented in the neural network. Based on percentage relative error, coefficient of determination, root mean square error and sum of the square errors, the function has been selected among the five training function for the analysis.

3. PROPOSED METHODOLOGY

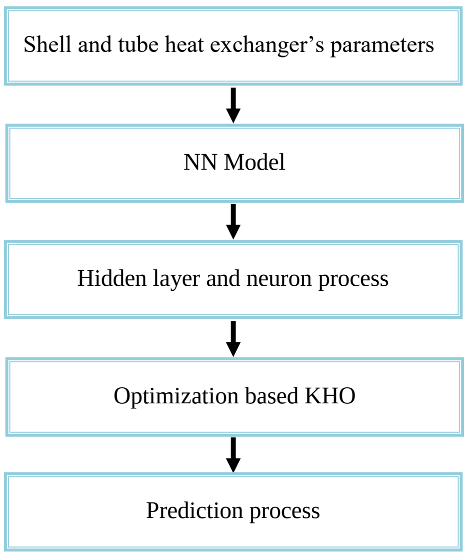


Figure 1. Schematic diagram for proposed work

A Heat Exchanger (HX) is a gadget used to exchange warm between at least one liquids. The liquids might be isolated by a strong divider to avoid blending or they might be in direct contact Organic Rankine cycles (ORCs) is taken by improving the cycle parameters together with the design of shell-and-tube heat exchangers. In our two existing research papers different techniques utilized to identify the HX parameters the techniques are optimal mathematical modeling and optimal Neural Network (NN). In our third research paper we can improve the accuracy level and performance of three parameters compared to existing works. This third work considers the input parameters such as tube configuration, different fluids, surface, and temperature. Here also we have used NN structure with relevant optimization model. Hidden layer and hidden neuron optimization inspired technique that is Krill herd optimization (KHO). The krill herd algorithm is new heuristic algorithms presented for solving optimization tasks. In the algorithm, three main factors define the position of the krill individuals that are movement induced by the presence of other individuals, foraging activity, and random diffusion. The KHO algorithm has better performance for optimization problem, but sometimes it may trap into the local optima. Figure 1 demonstrates the schematic graph of propose approach.

3.1 Neural Network (NN)

ANN models usually do not allow the calculation of statistical parameters and diagnostics for a detailed assessment of the quality of the model, as in the case of linear regression. It is therefore necessary to use other methods, to verify whether the model is appropriate for description of the phenomenon under study. Neural network is a very flexible instrument and can easily lead to a situation where the model will suspiciously well describe (fit) the data, but not the phenomenon (variables relationship) as a whole. This is reflected in very poor prediction of the values of the dependent variables for the new independent variables that have not yet occurred in the data, although they may be located inside the interval of training data, NN model shown in figure 2. This structure optimizes hidden layer and neurons of the model fish based optimization technique used that is Krill herd Optimization (KHO) process.

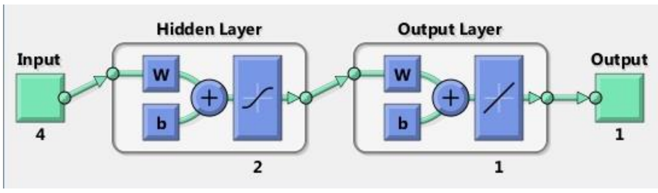


Figure 2. NN model

Steps involved in proposed work

Step 1: Initialize input parameters and number of hidden layers and neurons.
Step 2: Basic NN structure with evaluate basis function
Step 3: Find activation function
Step 4 Optimize hidden layers and neurons I n activation function.
Step 6: Optimization based on the krill herd fish optimization process
Step 7: Update krill herd behaviors
Step 8: If minimum MSE attained means the process will stopped otherwise repeat step 2 to 7.

3.2 Initialization process

This initialization process similar for our existing work process that is tube configuration, different fluids, surface and temperature, hidden layers and hidden neurons of Neural network model.

Basis function

$$B_f = \sum_{j=1}^{N} I_i \times \beta_{ij} \qquad (i = 1, 2, ..4) \qquad (1)$$

where B_f is a basics function, β_{ij} is an input layer weight and i is a number of inputs THAT $I_1 ....I_4$.

3.3 Activation function process

The question of deciding which activation function will require how many neurons to achieve a given order of approximation for all such functions. We will describe a very general theorem and explain how to construct networks with various activation functions. That is shown in below,

$$A_f = \sum_{j=1}^{h} \alpha_j * \left(\frac{1}{1 + \exp(-\sum_{i=1}^{N} I_i \beta_{ij})} \right) \qquad (2)$$

In condition (2) apply the all the output parameters in shell and heat exchangers modeling process. This Training and testing investigation diverse nine training algorithms are utilized as a part of NN structure.

3.4 Krill herd Optimization (KHO) for NN model

Predators remove individuals, reduce of the average krill density, and distance the krill swarm from the food location. Therefore, predation can be considered as the initialization of the optimization algorithm. The fitness of each individual in the natural system, is supposed to be the distances from the food centre and the highest density of the krill swarm [26].

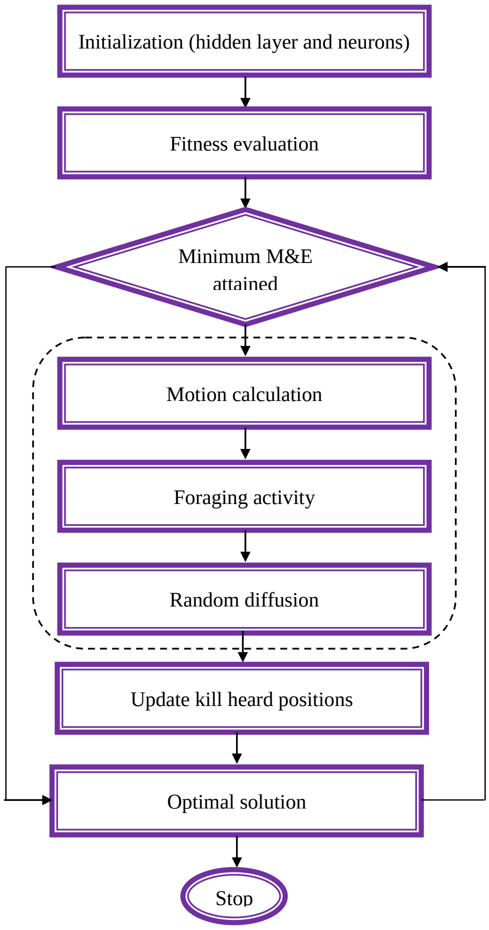


Figure 3. Flow chart for KHO

The Krill herd algorithm is a new optimization algorithm which is inspired the behavior of the krill swarms, this optimization technique to optimize hidden layer and neurons in prediction analysis. This KHO process consider two main goals such as Increasing krill density and Reaching food, so the herding behavior of increasing density and finding food. Figure 3 shows the flow diagram of KHO process.

KHO updating Procedure

The location of a krill individual is affected by the following three factors

- Movement induced by other krill individuals
- Foraging activity
- Random diffusion

The location of krill is expressed by the following Lagrangian model.

$$\frac{dA_i}{dt} = M_i + F_i + P_i \tag{3}$$

where , M_i the motion is induced by other krill individuals; F_i is the foraging motion, and P_i is the physical diffusion of the ith krill individuals.

3.4.1 Movement induced by other krill individuals

In the movement, the direction of motion of a krill individual is determined both by the local swarm density (local effect), a target swarm density (target effect), and a repulsive swarm density (repulsive effect). The krill movement can be defined as

$$M_i^{new} = M^{\max}\gamma_i + \omega_n M_i^{old} \tag{4}$$

where $\alpha_i = \alpha_i^{local} + \alpha_i^{target}$ (5)

In above equation (8) individual local search and target search are calculated by as following equation.

$$\alpha_i^{local} = \sum_{j=1}^{NN} B_{ij} O_{ij} \tag{6}$$

Here

$$O_{ij} = \frac{O_j - O_i}{\| O_j - O_i \| + \varepsilon} \tag{7}$$

In above equations the notations are explained as $M_{\max}$ is the maximum induced speed, ω_n is the inertia weight of the motion induced in the range [0, 1], M_i^{old} is the last motion induced, α_i^{old} is the local effect provided by the neighbors and α_i^{target} is the target direction effect provided by the best krill individual and NN is the numbers of individuals. In equation (8) the B_{ij} calculated based on the best and worst fitness values.

$$\alpha_i^{target} = G_{best} B_{i,best} O_{i\,best} \tag{8}$$

where, C_{best} is the effective coefficient of the krill individual with the best fitness to the i_{th} krill individual. This coefficient is defined since α_i^{target} leads the solution to the global optima and it should be more effective than other krill individuals such as neighbors. Herein, the value of G_{best} is defined as:

$$G_{best} = 2\left(rand + \frac{IA}{IA_{\max}} \right) \tag{9}$$

where rand is a random values between 0 and 1 and it is for enhancing exploration, IA is the actual iteration number and $IA_{\max}$ is the maximum number of iterations.

The sensing distance for each krill individual can be determined using different heuristic methods. Here, it is determined using the following formula for each iteration.

$$s_d = \frac{1}{5N} \sum_{j=1}^{N} \| O_i - O_j \| \tag{10}$$

For choosing the neighbor, different strategies can be used. For instance, a neighborhood ratio can be simply defined to find the number of the closest krill individuals. Using the actual behavior of the krill individuals, a sensing distance s_d should be determined around a krill individual shown in figure. Using equation (10), if the distance of two krill individuals is less than the defined sensing distance, they are neighbors.

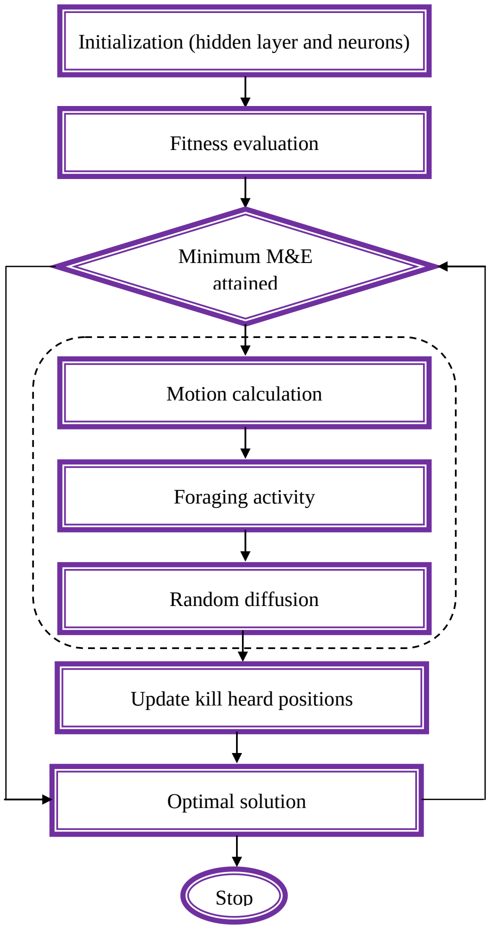


Figure 4. Fish sensing performance

3.4.2 Foraging motion

The foraging motion is formulated in terms of two main effective parameters. The first one is the food location and the second one is the previous experience about the food location. This motion can be expressed for the i^{th} krill individual as follows:

$$F_i = B_m \beta_i + \omega_m F_i^{old} \tag{11}$$

where $\beta_i = \beta_i^{food} + \beta_i^{best}$ (12)

Here F_m is the foraging speed, ω_m is the inertia weight of the foraging motion in the range [0,1], is the last foraging motion, β_i^{food} is the food attractive and β_i^{best} is the effect of the best fitness of the i^{th} krill so far. According to the measured values of the foraging speed it is taken 0.02 (ms-1).

Therefore, the food attraction for the i^{th} krill individual can be determined as follows:

$$\beta_i^{food} = G^{food} B_{i\,food} O_{i\,food} \tag{13}$$

where

$$O^{food} = \frac{\sum_{i=1}^{N} \frac{1}{B_i} O_i}{\sum_{i=1}^{N} \frac{1}{O_i}} \tag{14}$$

where C^{food} is the food coefficient, because the effect of food in the krill herding decreases during the time the food coefficients is determined as

$$G^{food} = 2\left(1 - \frac{IA}{IA_{\max}}\right) \tag{15}$$

The food attraction is defined to possibly attract the krill swarm to the global optima. Based on this definition, the krill individuals normally herd around the global optima after some iteration.

The effect of the best fitness of the i^{th} krill individual is also handled using the following equation:

$$\beta_i^{best} = B_{i\,best} O_{i\,best} \tag{16}$$

where $B_{i\,best}$ is the best already visited position of the krill individual.

3.4.3 Physical diffusion

The physical diffusion of the krill individuals is considered to be a random process. This motion can be express in terms of a maximum diffusion speed and a random directional vector. It can be formulated as follows:

$$P_i = P^{\max} \lambda \tag{17}$$

Here $P^{\max}$ is the maximum diffusion speed, and d is the random directional vector and its arrays are random values between -1 and 1.

3.4.4 Motion process of the KH

The physical diffusion performs a random search in the proposed method. Using different effective parameters of the motion during the time, the position vector of a krill individual during the interval t to $t + \Delta t$ is given by following equations.

$$O_i(t + \Delta t) = O_i(t) + \Delta t \frac{dO_i}{dt} \tag{18}$$

Dt Completely depends on the search space and it seems it can be simply obtained from the following formula.

$$\Delta t = S_t \sum_{j=1}^{NN} (UB_j - LB_j) \tag{19}$$

where NN is the total number of variables, and UB and LB are lower and upper bounds of the j^{th} variables $j = 0,1,2,.....NN$ respectively. Therefore, the absolute of their subtraction shows the search space. It is empirically found that S_t is a constant number between [0, 2].

3.4.5 Crossover

The crossover operator is first used in GA as an effective strategy for global optimization. A vectorized version of the crossover is also used in DE which can be considered as a further development to GA. The crossover rate calculation as follows.

3.4.6 Mutation

The mutation plays an important role in evolutionary algorithms such as ES and DE. The mutation is controlled by a mutation probability (Mp).

$$Mp = 0.5 / B_{i\,best} \tag{20}$$

Using this new mutation probability, the mutation probability for the global best is equal to zero and it increases with decreasing the fitness.

3.5 Optimal solution and MSE process

Rely on upon the previously mentioned process accomplish the ideal concealed layer and neuron. Furthermore, it is utilized to get the ideal wellness capacity which is spoken to as $F_{optimal}$ in this ideal wellness based get the yield.

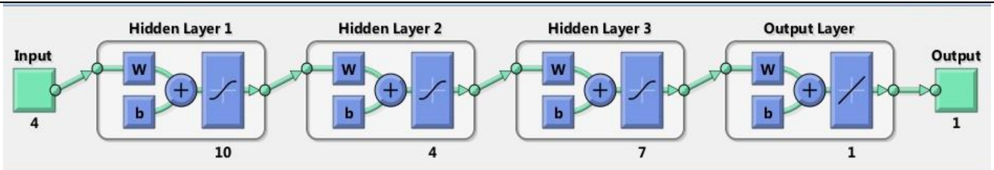
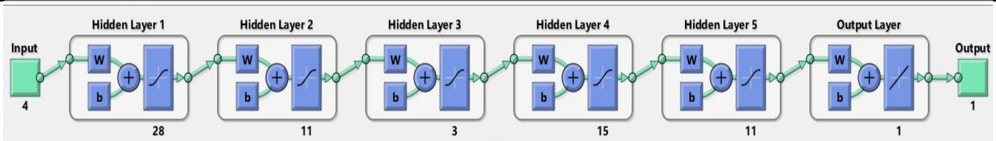
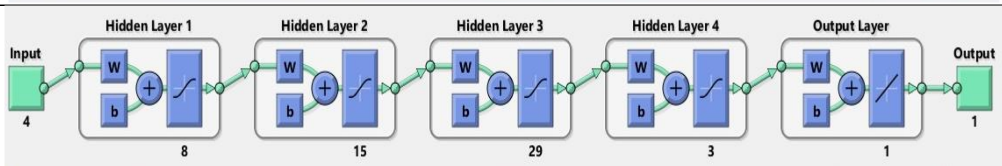
$$F_{i(optimal)} = \sum_{j=1}^{h} \alpha_j * \left(\frac{1}{1 + \exp(-\sum_{i=1}^{N} I_i \beta_{ij})} \right) \tag{21}$$

Based on equation (14) analyzed the all output parameters like, exegetic plant efficiency, energetic cycle efficiency and electrical power of shell and heat exchangers with minimum MSE value for prediction process.

4. RESULT AND DISCUSSION

The projected technique is executed in the stage of MATLAB 2015 with the framework setup is i5 processors with 4GB RAM which is utilized for fluffy and NN with streamlined foresee the yield parameters. This proposed execution parameters assessment contrasted with other advancement and existing strategy is like mathematical modeling with GWO, and NN with IGWO technique.

Table 1. Optimal NN for heat transfer parameters

Parameters	*Structure*	*Accuracy*
Exegetic plant efficiency		99.2
Energetic cycle efficiency		97.56
Electrical power		98.52

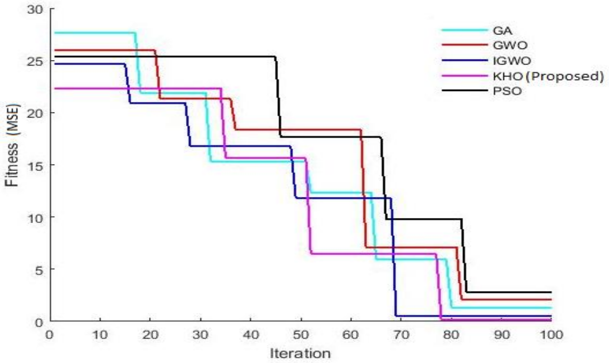


Figure 4. Convergence graph

Table 1 illustrates the optimal NN for heat transfer parameters. The table shows the clear structure for three parameters such as exegetic plant efficiency, energetic cycle efficiency and electrical power and finds the optimal accuracy. In the exegetic plant efficiency, the structure determines the 4 inputs, it gets 3 hidden layer neurons (1,2 and 3) In hidden layers the weight and the bias are optimized gets 10 neurons after that these 10 neurons goes to hidden layer 2 it optimized as 4 neurons and finally attains the output as 1 neuron. The accuracy obtained for exegetic plant efficiency is 99.2%. Similarly, energetic cycle efficiency gets 5 hidden layers the weights and bias are optimized to get output 1, the accuracy maintained for this parameter is 97.56%. The structure for electrical power shows 4 hidden layers and the accuracy level attains as 98.52%.

Figure 4 visualizes the convergence graph for five optimized algorithms (GA, GWO, IGWO, KHO, and PSO). The fitness value (MSE) has to be found for algorithms such as Genetic Algorithm (GA), Grey Wolf Optimization (GWO), Improved Grey Wolf Optimization (IGWO), Proposed Khrill Herd Optimization (KHO) and Particle Swarm Optimization (PSO) in different iterations. In the first iteration, all optimization techniques start in the MSE range of 23 to 28. The iteration value increases MSE range decreases it helps to find the best optimal fitness value. Compare to all these optimization techniques proposed KHO gets a better result than others. The optimal fitness value (MSE) attains in 78th iteration.

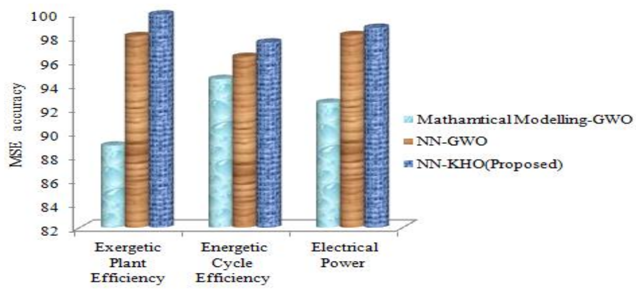
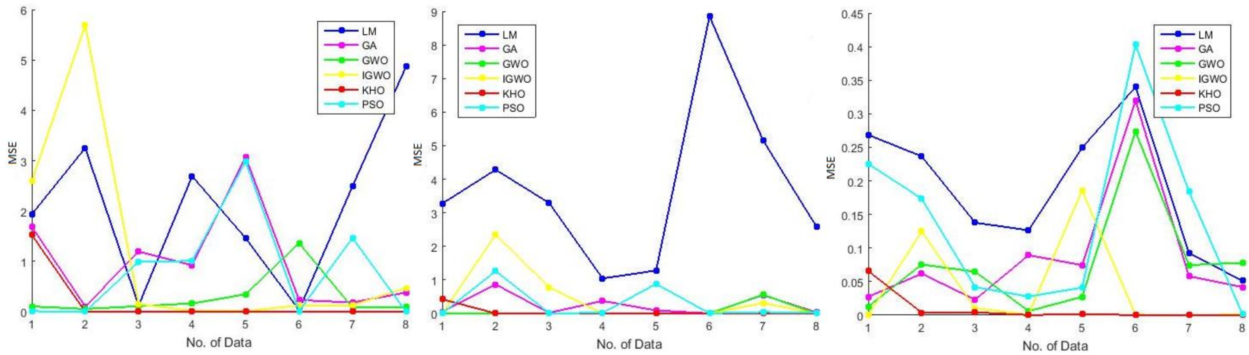


Figure 5. Comparative analysis



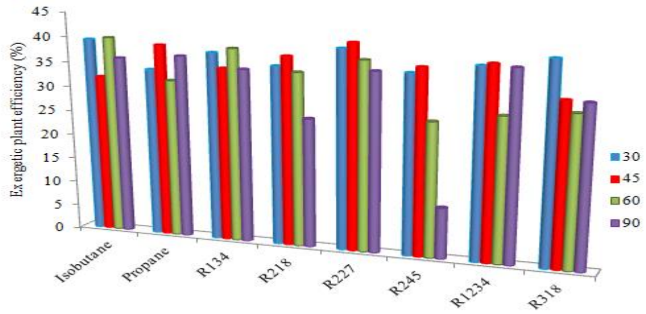
(a) Exegetic plant efficiency (b) Energetic cycle efficiency (c) Electrical power

Figure 6. MSE analysis for different parameters

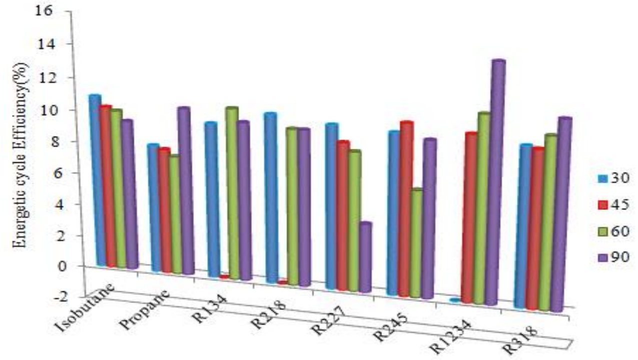
Figure 5 clearly shows the comparative analysis for three parameters (exergetic plant efficiency, energetic cycle efficiency, and electrical power). This graph compares the MSE accuracy of three techniques (mathematical modeling-GWO, NN-GWO, and NN-KHO) for three parameters. In exergetic plant efficiency, the MSE accuracy for GWO techniques as 89, NN-GWO gets 99 and NN-proposed KHO attains MSE as 100. Compare to these three techniques the neural network with proposed KHO algorithm as better optimal MSE than other techniques. Likewise, the energetic cycle efficiency and electrical power also obtain best fitness accuracy. The NN-GWO techniques also get good accuracy but don't get an optimal result so NN-proposed KHO technique is an optimal technique.

Figure 7(a) (b) and (c) illustrates that the Exergetic Plant Efficiency, Energetic Cycle Efficiency and Electrical Power of shell and tube heat transfers with dissimilar liquids. If the tube value is 30 then the effectiveness series is from 38.5 to 52.8 and the complete tube configuration can be achieved these values. By the help of Q, the heat is supplementary to the cycle. Five dissimilar cases are demonstrated; the first four cases (30, 45, 60 or 90) have the similar tube configuration in all heat transfers, and the last case uses the 30 configuration in the single-phase heat transfers (economizer, super heater and de super heater) and the 60 configuration in the two-phase heat transfers (evaporator and condenser), which will be indicate the 30- & 60-tube configuration in the remains. The outcome demonstrates that the 30- & 60-tube configuration carry out the finest 30- & 60-tube configuration and merge high heat-transfer coefficients with comparatively low pressure drop in single-phase configurations and two-phase flow, correspondingly. Figure (b) the cycle with R218 is a working fluid and the 40- & 60-tube configuration has an energetic cycle efficiency of 74.3%. By using the 40-tube configuration in all heat exchangers, the plant efficiency reduces to 75.86%.

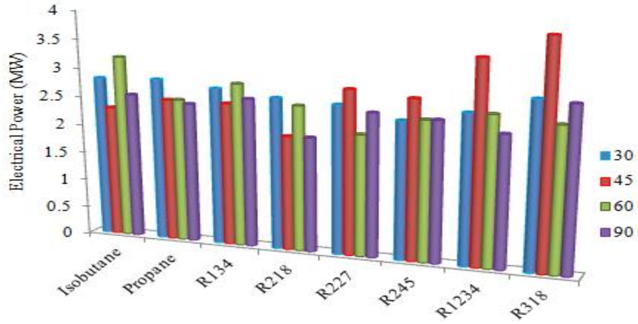
Table 2 show that real and forecast values of the projected KHO optimization method in shell and tube heat transformers. To amplify the tube configuration, the presentation will be changeable. If the tube configuration is 40 in liquid then the Isobutene of the Exegetic Plant Efficiency real value is 39.2 and projected method is 38.08. Likewise all the output limits values are attained in arithmetical modeling with IGWO optimization method compared to existing technique GWO AND IGWO technique.



(a) Exegetic plant efficiency



(b) Energetic cycle efficiency



(c) Electrical power

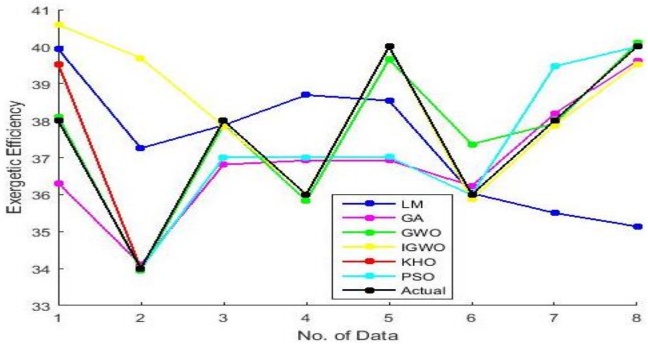
Figure 7. Parameters analysis based on tube configuration

Table 2. Parameter estimation

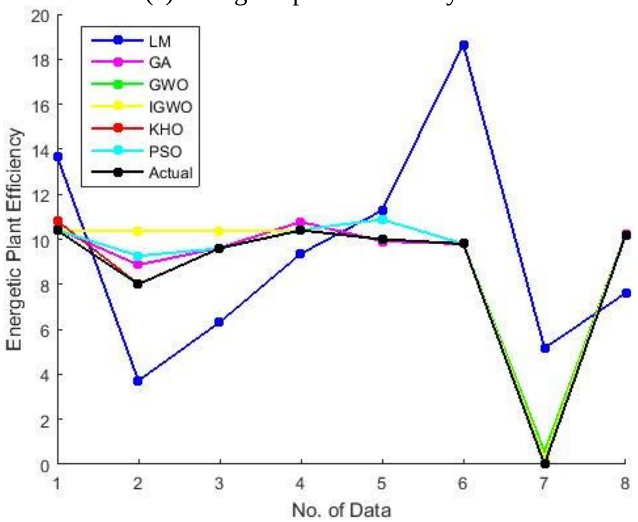
Inputs				Outputs					
Tube Configuration	**Different Fluids**	**Surface**	**Temperature**	**Exergetic Plant Efficiency**		**Energetic Cycle Efficiency**		**Electrical Power**	
				Actual	**proposed**	**Actual**	**proposed**	**Actual**	**proposed**
30	Propane	1000	125	40	39	10.2	10.8	2.88	3
30	R227	1000	125	38	38.2	9.6	10	2.55	2.58
45	R134	2000	125	40	3..99	10.2	9.8	2.8	2.89
45	R218	2000	125	32	33.2	7.8	1.2	2.3	2.45
60	R134	3000	125	36	36.9	10	9.2	2.6	2.64
60	R227	3000	125	36	35.6	9.6	9.4	2.55	2.89
90	R318	3000	125	34	33.5	9.4	9.1	2.45	2.8
90	R227	4000	125	36	36.2	9.4	9.85	2.5	2.45
90	R1234	4000	125	38	38.7	9.8	9.87	2.55	2.89

Figure 8(a) compares the actual and predicted values for exegetic plant efficiency and find the optimal algorithm. In data 1 actual value for exergetic efficiency as 38 but the efficiency value for GWO, GA and KHO get nearby actual values. For all the data (2 to 8) the efficiency increased by range i.e. 34 to 40.8. By the comparison of all the algorithms, KHO reaches nearly equal to the actual value.

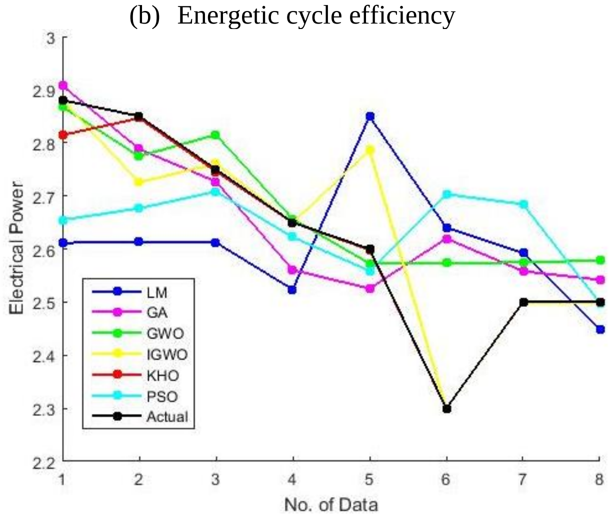
Figure 8(b) and c shows the analysis of Energetic cycle efficiency, Electrical power and compares the actual and predicted values. In both analyses, it is severely noted that the predicted value for KHO obtains same as the actual value in data 2 to 8. The data increases efficiency and the power also changed according to the actual value. The values of all optimization techniques are predicted based on the efficiencies.



(a) Exegetic plant efficiency



(b) Energetic cycle efficiency



(c) Electrical power

Figure 8. Actual vs predicted values

Figure 9 depicts the Graphical User Interface (GUI) process. It shows the output values for 30 tube configuration, 4 different fluids, the surface as 1000, temperature as 125 K. The output values for these inputs can be shown as below: For energetic plant efficiency, GA achieves 8.8641, GWO as 7.995, IGWO as 10.3497, LM attains 3.7181, and KHO achieves 8 and PSO as 9.2616. In this efficiency, the value for KHO reaches best optimal result than other algorithms. Similarly, the KHO obtained for energetic cycle efficiency and electrical power as 34, 1.5002. Likewise, the other configuration also attains the best optimal result in KHO techniques.

Figure 9. GUI

5. CONCLUSION

This study presents the successful application of a new algorithm for the optimal design of shell and tube heat exchangers. This algorithm is used in most thermal engineering problems that consist of several discrete and continuous variables and a large amount of discontinuity in the objective function. Depending on the applications, different design variables are optimized for minimum to MSE with better output parameters. Throughout this process, consider the dissimilar input restraints and the realistic output results are experiential to be almost equivalent to the data set smallest error value accomplished in the NN optimal structure along the different optimizations compared o existing mathematical modeling process. Exegetic Plant Efficiency, Energetic Cycle Efficiency and Electrical Power is 99.11%, 97.4% and 98.35% of the forecast process correspondingly in optimal NN in KHO process. In the future, heat transfer investigators will look towards additional incredible development methodologies for the achievement of reduced slip-up with their admirable methods for the presentation limits of the heat transfer process.

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