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Optimization of the Pool Boiling Heat Transfer in the Region of the Isolated Bubbles using the ABC Algorithm

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ABSTRACT

The region of the isolated bubble regime, in which the bubbling starts, is a very significant process for boiling heat transfer. In this study, Artificial Bee Colony algorithm (ABC), which is mainly based on the searching optimum foods sources for the bees, has been used for the optimization of the pool boiling heat transfer calculation. The ABC algorithm is very handy for numerical analysis. The ABC algorithm has been compared with a genetic algorithm as well as other well-known correlation models for pool boiling heat transfer calculation. The ABC algorithm is found to be useful for any boundary conditions. The boundary conditions have been changed in order to improve the results. Results show that the ABC algorithm works faster than the genetic algorithm for the given problem. The ABC algorithm also predicts less average absolute error when compared with other well-known correlations as well as the optimization using the genetic algorithm.

Keywords: ABC algorithm; Pool boiling; Heat transfer; Boiling optimization.

NOMENCLATURE

A	area
b	bulk
bb	bubble super-heating
c_1	the particular area engaged by the bubbles over heater surface area
c_2	the particular area engaged by the sliding bubbles over heater surface area
c_3	the particular area over the area at which transient heat conduction takes c4 Various of c3 and c2
d	the diameter of bubble separation
E	the relative error
f	the frequency of bubble separation
h	watt per square metre
h_f	g specific heat of vaporization
k	thermal conductivity
l	liquid
ls	sliding length
mic	micro-layer evaporation
N	nucleation site
Nc	natural convection
NU	the Nusselt number
OD	heater outside diameter
P0	ratio of the waiting period of the bubble to the total time of bubble formation
P1	the ratio of the area of influence to the projected area of the bubble at departure
P2	the ratio of mean bubble vapor area to the most project area
P3	the ratio of actual sliding length to the most theoretical distance between the max compact regular of nucleation site intensity
P_4	the ratio of area of radially forced convection influence to projected area of bubble at departure
P5	the ratio of sliding nucleation site density to actual nucleation site density
Pr	prandtl
q	heat
Re	the Reynolds number
T	temperature
T	time
u	velocity of the bubble
Rad	*f* radial forced convection
s	bubble sliding
stc	the heat conduction sliding transient
th	the thermocouple location inside the heater

trns	transient heat conduction	α	zHeat transfer coefficient
v	vapor	ρ	density
		τ	bubble cycle period

1. INTRODUCTION

Pool boiling is crucial process for many industrial applications. The pool boiling heat transfer coefficient can be affected by heater type characteristics, bubble dynamics, heat transfer and atmospheric feature. This phenomenon has been accepted by many scientists. Numerical study is an effective way to calculate the pool boiling heat transfer coefficient, and advanced computer technology makes this easier. In this century, the computer-aided technology is widely used for the optimization of industrial applications such as average heat transfer calculations. The ABC algorithm is widely used as an optimization technique for many systems Karaboga and Akay (2009). The ABC algorithm can be used for pool boiling heat transfer calculations.

Boiling heat transfer investigation due to the optimization were first carried out in 1997, and the genetic algorithm was used Castrogiovanni and Sforza (1997). Later in 2017, an optimization model using the genetic algorithm was made for the pool boiling Fazel (2017). Isolated bubble regime of the pool boiling heat transfer on the horizontal cartridge heaters was studied. This study is important because this was the first time when a genetic algorithm is used for the optimization of pool boiling.

Karaboga, and Basturk, compared some optimization algorithms, and they showed that the ABC algorithm works better than the other algorithms (Karaboga and Basturk 2007). Better numerical results have been obtained from the ABC algorithm comparing the other optimization algorithms Gao and Liu (2011), Gao *et al.* (2012). Sahin *et al.*, used the ABC algorithm for shell and tube heat exchangers design and economic optimization Sahin *et al*. (2011). Many empirical correlations have been found to estimate the heat transfer during saturated pool boiling of liquids. Mechanics, analogical and hydro-dynamical models have been made. Stephan and Abdelsalam studied on the natural convection of pool boiling and they added a new correlation to the literature (Stephan and Abdelsalam 1980). Van Stralen and Cole, experimentally studied bubble growing on the heater surface, and they found that microlayer bubble growth is affected by the heat transfer Cole *et al.* (1979). Olan-der and Watts found a new expression that shows the relation between microlayer thickness and bubble diameter Olander and Watts (1969). Sateesh *et al.* studied the microlayer evaporation and transient conduction during the sliding of bubbles for some geometries such as sloping surfaces and horizontal tubes Sateesh *et al.* (2005). Ghaisas *et al.* investigated the pool boiling characteristics of H2O with ethanol and 2- propanol at low heat fluxes Ghaisas *et al.* (2015). Fazel and Jamialahmadi studied heat transfer of pool boiling for various testing liquids. They improved a semi-empirical model for pool boiling heat transfer Fazel and Jamialahmadi (2013). Gorenflo *et al.*, reviewed prediction methods for pool boiling heat transfer. They compared eight different well-known estimation methods. They showed that pool boiling heat transfer prediction is proportional with heat flux, reduced pressure, and properties of the fluid Gorenflo *et al.* (2014).

Some researchers have used different techniques such as direct numerical simulations or machine learning for heat transfer and fluid flow problems. Tryggvason studied multi-phase flow using DNS Tryggvason (2016), Tryggvason *et al.* (2016), Ma *et al.* (2014). Ma *et al.* investigated bubbly flows using statical learning method Ma *et al.* (2016), Ma *et al.* (2015). Some researchers used the proper orthogonal decomposition technique for numeric model the heat transfer applications Podvin and Le Quéré (2001), Han *et al.* (2015). Varde *et al.* predicted the heat transfer coefficient by varying the temperature with data mining technique Varde *et al.* (2005). Ling *et al.* presented a new model of a Reynolds averaged turbulence using deep learning Ling *et al.* (2016).

Gorenflo *et al.* experimentally investigated nucleate boiling heat transfer for water and butanol mixtures, and no significant difference was observed for the measurements due to the mixtures Gorenflo *et al.* (2001). Fazel experimentally and numerically studied the optimization of pool boiling using rod heaters at the isolated vapor bubbles region Fazel (2017). The study is important since the pool boiling is optimized using the genetic algorithm. In this work the ABC algorithm has been chosen in order to optimize the pool boiling heat transfer in the isolated vapor bubbles region. Optimized heat transfer correlation has been compared with other well-known correlations. A performance analysis has been made between ABC and genetic algorithms. Required experimental data was obtained from Fazel's work Fazel (2017).

2. METHODOLOGY

In this study, an ABC algorithm model is presented to estimate the heat transfer in the isolated vapor bubbles region of pool boiling. This model stands for many heat transfer mechanisms including (1) latent heat to the evaporating micro layer, (2) transient conduction, (3) transient conduction of sliding bubbles, (4) radial forced and (5) natural convection.

The literature shows that boiling heat transfer has been a phenomena for many researchers. Researchers have been studying the boiling but the comprehensive treatment of nucleate pool boiling has many limitations Iida and Kobayasi (1970), Fujimoto *et al.* (2010), Yagov (2009). The main limitation of the present study that it only works for optimization of the isolated bubble region nucleate pool boiling heat transfer. Therefore, in the present model, the temperature differences from 5 to 10 degree can be used. It is valid when the bubbles are not capable of arriving to the free surface. The other limitation is to choose the type of the heater. The heater type used in the referenced article is cylindrical one Fazel (2017).

2.1 The ABC Algorithm

Some species live together as a group, form complex colonies. This species exhibit cleverly behavior in performing staminal tasks including foraging, mate-searching. They don't use any external or internal centralized mechanism for these purposes. In real honey bees colonies, the mentioned cleverly behavior is observed in their foraging pattern. This pattern is managed by three types of bees called; employed, onlooker and scout bees, respectively Karaboga (2005).

The employed bees are charged of exploiting the previously manned food sources and carrying the nectar which is obtained from the manned source. Just as employed bees turn back to the beehive, the nectar quality of the food sources and the location are shared with the onlooker bees via waggle dances. The onlooker bees stays and look at different waggle dances before selecting food source that is more abundant nectar, also additional high-lights by the employed bees. When the food source becomes valueless for exploiting no longer, the bees which previously worked at these sources become the scout bees. The scout bees search for the new food sources as randomly Karaboga and Akay (2009), Karaboga and Basturk (2007), Badem *et al.*(2018) Badem *et al.* (2017), Karaboga and Aslan (2016), Karaboga and Aslan (2018), Karaboga and Basturk (2008). The main motivations of the Artificial Bee Colony (ABC) optimization algorithm are the mentioned clever foraging behavior and communication mechanism between honey bees. The ABC algorithm has been proposed by Karaboga on these main motivations Karaboga (2005). The parameter vector which represents a candidate solution in the ABC algorithm is defined for individual food source. The amount of the nectar of the food source is also represented to the solution of the fitness value. The employed, scoot and onlooker bees cooperate to optimize the food sources by the iterative manner in the ABC algorithm Karaboga and Akay (2009), Karaboga and Basturk (2007), Badem *et al.* (2017), Karaboga and Aslan (2016), Karaboga and Aslan (2018), Badem *et al.* (2018), Karaboga and Basturk (2008). The fundamental steps of ABC algorithm are presented in Fig. 1.

ABC algorithm is initialized by generating SN different food sources or solutions with D random values as described in Eq. (1) Karaboga and Akay (2009), Karaboga and Basturk (2007), Karaboga and Basturk (2008);

$$x_{ij} = x_j^{\min} + rand(0,1)x_j^{\max} - x_j^{\min} \tag{1}$$

where x_{ij} is the j^{th} parameter of the solution of i^{th} parameter, x_j^{min} and x_j^{max} are lower and upper bounds of the j^{th} parameter, respectively.

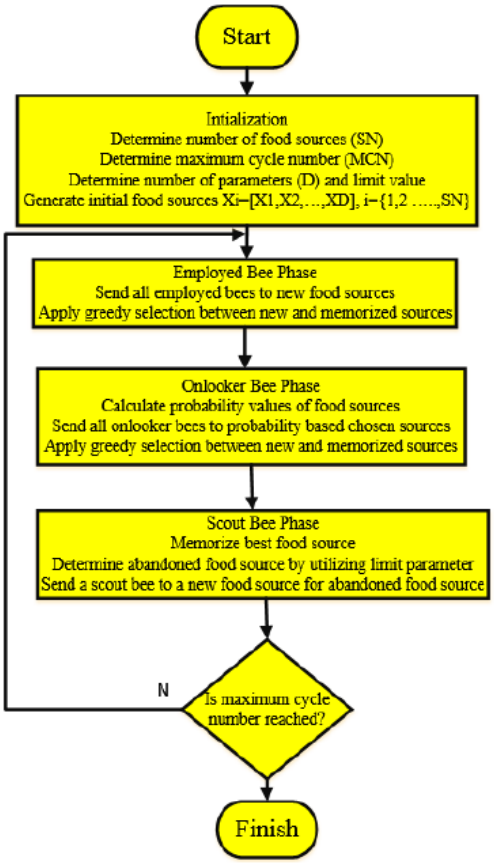

Fig. 1. Essential steps for the ABC algorithm.

As an employed bee handle with a food source, she works to find the candidate food source by using the positional information about the memorized and a randomly selected neighbor food source via below equation;

$$v_{ij} = x_{ij} + \phi_{ij}(x_{ij} - x_{kj}) \tag{2}$$

where k and j are randomly determined indexes. It should be noted that the sub index k must be different than the sub index i. The fitness value of the recently found food is compared with the own fitness value. If the new value is superior than the own one, the source information is changed with the information of the new food source. All employed bees come back to the hive after they are done with searching and share the new information of the food sources to onlooker bees. The on-looker bees pick an existed food sources according to probability values and then produce a new candidate food sources just as employed bees using Eq. (2). The values of the probability of any food sources are calculated below;

$$P_i = \frac{fitness_i}{\sum_j^{SN} fitness_j} \tag{3}$$

Exploitation and exploration operation must be provided in balanced for an outperform searching. Therefore, unless a food source can be advanced in a predetermined iteration, which is defined as the control parameter called the limit value in the ABC, the corresponded employed bee will become a scout bee. The scout bee generates a solution as randomly in search spaces via Eq. (3);

2.2 Microlayer Evaporating

Snyder and Edwards worked on the microlayer evaporation study Snyder and Edwards (1956). Hendricks and Sharp experimentally studied each individual bubbles using high speed camera, and they showed that the temperature drop was related to bubble growth Hendricks and Sharp (1964). The reference equation can be found in Jung and Kim (2016). As follows;

$$h^{mic} = \frac{\pi}{6} d^3 \rho_v h_{fg} \frac{N}{A} f \tag{4}$$

2.3 Transient Conduction

Han and Griffth investigated the pioneering work of the transient conduction Han (1962). The transient conduction of the bulk liquid after bubble departure was included to be the effect to the sum of the heat transfer. The equation is below;

$$(h)^{tms} = 2\sqrt{\frac{\rho_l k_l c_{pl}}{3t_w}} \Delta T \frac{N}{A} P_i \frac{\pi}{4} d^2 P_0$$

(5)

where

$$P_0 = \frac{t_w}{\tau} = t_w f \tag{6}$$

The numerical rate of P0 equals to 0.75 according to some researchers Manickam and Dhir (2012). Another dimensionless number P1 is used to be between 1.8 and 4 Sateesh *et al.* (2005), Han (1962), Manickam and Dhir (2012). In this study, P0 is calculated using the ABC algorithm.

2.4 Bubble Super-Heating

The superheated bubble heat transfer can be included in calculating the bubble formation frequency, its residence time and mean equivalent diameter, during the formation and ascension stages Campos and Lage (2000). Eq. (7) which contains all of these parameters is below;

$$(h)^{bb} = 2\sqrt{\frac{\rho_v k_v c_{pv}}{3t_g}} \Delta T \frac{N}{A} P_2 \frac{\pi}{4} d^2 (1-P_0) \tag{7}$$

2.5 Sliding Bubbles For Transient Conduction

Some researchers emphasize the importance of effective bubble sliding. The total heat flux is affected by bubble sliding, which is related to the bubble departure diameter, bubble lift-off diameter at the sliding time, active nucleation site intensity, waiting period besides the thermo-physical properties of fluids and bubble departure frequency Mohanty and Das (2017). The related equations are below;

$$l_s d = P_0 (\frac{N}{A})^{-\frac{1}{2} d} \tag{8}$$

$$(h)^{stc} = 2\sqrt{\frac{\rho_l k_l c_{pl}}{3t_w}} \Delta T \frac{N}{A} P_3 d (\frac{N}{A})^{-\frac{1}{2} P_0} \tag{9}$$

2.6 Radial Forced Convection

Paul and Abdel-Khalik studied boiling heat flux for the notable phase change process, natural and forced convections Paul and Abdel-Khalik (1983). They investigated the active nucleation site density, and their work showed that the linearity of the nucleation site density is a function of the boiling heat flux. The equations are below;

$$u^{radial} = \frac{d/2}{\tau_w} \tag{10}$$

$$Nu_r = 0.453 \mathrm{Re}_r^{\frac{1}{2}} . \mathrm{Pr}^{\frac{1}{3}} \tag{11}$$

$$\mathrm{Re}_r = \frac{\rho_l u^{radial} (d/2)}{\mu l} \tag{12}$$

$$\overline{Nu_r} = \frac{\int_0^r Nu_r 2\pi r dr}{\int_0^r 2\pi r dr} = (4/3) Nu_r \tag{13}$$

$$A_{a_{rfc}} = P_4 \frac{N}{A} \frac{\pi}{4} d^2 (1-P_0) \tag{14}$$

$$h^{rad_f} = h_r P_4 \frac{N}{A} \frac{\pi}{4} d^2 (1-P_0)(T_w - T_b) \tag{15}$$

2.7 Natural Convection

Zuber's pioneering work of natural convection is in nucleate boiling Zuber (1963). Many scientists studied the natural convection effect of pool boiling Zhang *et al.* (2015), Horie *et al.* (2015), Narayan *et al.* (2018), Kim *et al.* (2004), Kim *et al.* (2014), Roh (2014). Coefficient of heat flux can be calculated as follows;

$$h^{Nc} = \alpha_{Nc} c_{Nc} (T_w - T_b) \tag{16}$$

where

$$Nu = \frac{\alpha . d}{k} \tag{17}$$

$$\overline{Nu}_{OD} = (0.6 + \frac{0.387.(Grod.\mathrm{Pr})^{1/6}}{(1+((0.559/\mathrm{Pr})^{9/16}))^{8/27}})^2 \tag{18}$$

$$c_{Nc} = 1 - c_1 - c_2 - c_4$$

(19)

where

$$c_1 = \frac{N}{A} \frac{\pi}{4} d^2 \left[P_0 \frac{P_1 + P_2 + P_3 + P_4}{4} + (1-P_0) \right]$$

(20)

$$c_2 = \frac{\pi}{4} d^2 P_5 \frac{N}{A} \tag{21}$$

$$c_3 = \sqrt{\frac{N}{A}} P_3 d \tag{22}$$

$$c_4 = P_0 (c_3 - c_2) \tag{23}$$

The equations above (20, 21, 22, 23) and experimental data are taken from Fazel's work (see the article for more details) Fazel (2017).

3. RESULTS AND DISCUSSION

Both algorithms are compared using the conditions seen in Tables 1 and 2. The configuration steps of the genetic algorithm and the ABC algorithm are presented in Tables 1 and 2, respectively. Also, the ABC algorithm optimum NP value is detected NP number for the conditions seen Table 3. In this study, thirty runs have been made for all solutions. Some researchers have been investigated ABC algorithm to the genetic algorithm comparing their advantages and disadvantages. Their result shows that the ABC algorithm is better than the Genetic algorithm Pinninghoff *et al.* (2016), Sooda and Nair (2013).

Table 1. Configuration of Genetic Algorithm

Number of variable	6	
Bounds	[0 0.1 0.1 0.1 0.1 0.1]	[1 5 5 5 3 4]
Population type	double vector	6
Population size	120	3
Creation function	uniform	6
Fitness scaling	top	
Selection function	uniform	
Mutation function	adaptive feasible	
Crossover	constrained dependent	
Migration	forward	default
Hybrid function	none	
Stopping criteria	default	
Generations	50	
Stall test	average change	
Others	default	
Use random states from previous run	thick	
User function evaluation	in serial	

Table 2. Configuration of the ABC Algorithm

Number of variable	6	
Run time	30	
Np (the number of colony size)	120	
Max-cycle	50	
Bounds	[0 0.1 0.1 0.1 0.1 0.1]	[1 5 5 5 3 4]

Table 3 ABC model sensitivity to different types of NP

	MAX CYCLE	RUNS	NP(%50 employed bees %50 onlooker bees)
ABC1	50	30	100
ABC2	50	30	120
ABC3	50	30	150

The aim of this study is to reduce the error. The average absolute error can be calculated as follow;

$$E = \sum_{i=1}^{n} abs\left(\left[\frac{h_i^{optimized}}{h_i^{experimental}} - 1\right]\right) \tag{24}$$

Figure 2 shows the comparison of average absolute error for both genetic and ABC algorithms. On the other hand the error reduces for the ABC algorithm when the amount of run increases. The error stays constant for the genetic algorithm. It should be noted that slightly better results might be obtained

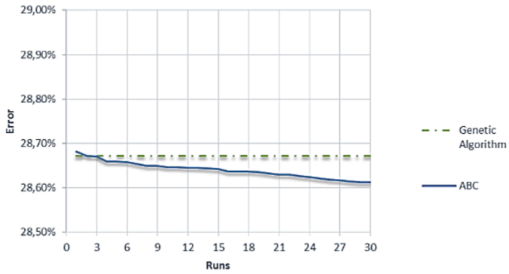

Fig. 2. Comparison of the Average Absolute Error.

by increasing the number of population and generation for the genetic algorithm and the number of colony size for the ABC algorithm. Figure 3 depicts the run time for both genetic and ABC algorithms. The results show that the ABC algorithm works faster than the genetic algorithm.

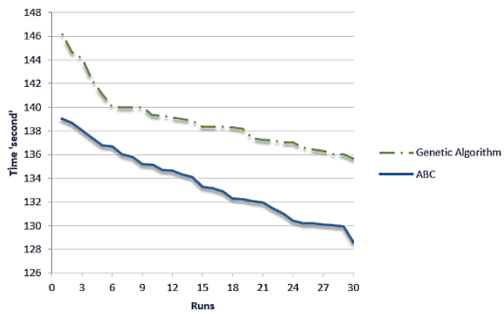

Fig. 3. Comparison of Run Time.

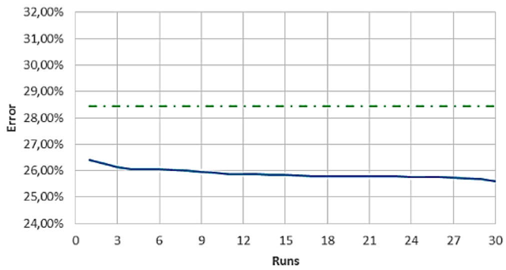

Fig. 4. Average Absolute Error with the New Boundary Condition.

Boundary conditions has been changed in order to improve the results. The new bounds [0 7,5] [0.01 7,5] [0 7,5] [0 7,5] [0 7,5] [0.01 7,5] have been used for both algorithms. Figure 4 displays the absolute error with the new boundary conditions for both the genetic and ABC algorithms. The error stays constants while the run number increases and has a value of approximately 28.4 percent. On the other hand, the error reduces from approximately 26.4 to 25.4 percent after thirty runs for the ABC algorithm. The best solution has been obtained by using the ABC algorithm. The minimum error has been calculated for the best parameters P [P_0=5.02][P_1=0.01] [P_2=7.5] [P_3=0.85] [P_4=7.49] [P_5=0.01]. These best parameters have been used for the calculated average absolute error of boiling heat flux. The best parameters reduce the percentage of the error.

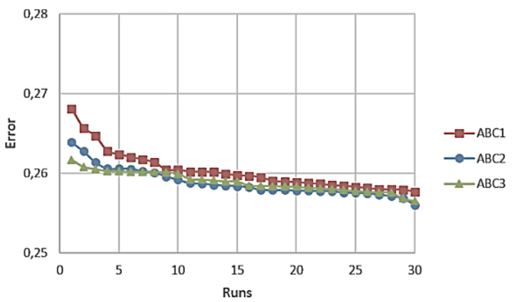

Fig. 5. Optimum NP value.

Nearly 120 NP value for the ABC optimization algorithm has been used by some researchers Karaboga and Basturk (2007). In our work, the new boundary conditions have been tested with different types of NP. Table 3 presents the properties of the each model with different NP value. Figure 5 shows the comparison of the different types of NP. The optimum NP value has been found the ABC2 model for this study, which has 120 NP as seen in Table 3.

Figure 6 depicts the comparison of the average absolute error of the nucleate boiling at the isolated bubble regime heat flux for well-known correlations including Fazel (2017), Stephan and Abdelsalam (1980), Gorenflo (1993), Mostinski (1963), and McNelly (1953). The experimental results for the coefficient of heat flux (h) from Fazel's work has been used for the calculations. The coefficient of heat flux has been calculated using these well-known correlations, and the error has been measured Fazel (2017). The solution of the ABC based optimization model has been involved in the analogy as well. The results show that the ABC optimized model provides better result among all correlations.

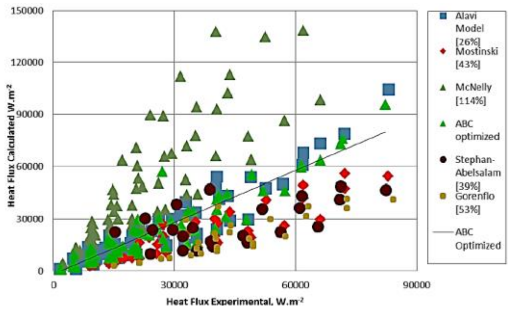

Fig. 6. Average Absolute Error Analysis.

4. CONCLUSION

In this study, pool boiling heat transfer in the region of the isolated bubbles has been optimized using the ABC algorithm. The ABC algorithm has been compared with the genetic algorithm as well as other well-known correlations model for pool boiling heat transfer calculation. Two main contributions have been made in this study. Firstly, the optimization using ABC algorithm predicts less error comparing with the genetic algorithm. Secondly, the ABC algorithm works faster than the genetic algorithm for boiling heat transfer in the same conditions. It has been determined that the ABC algorithm will yield better results in any case where the conditions are such as this article. The ABC optimized model has significantly less average absolute error comparing mentioned correlations models.

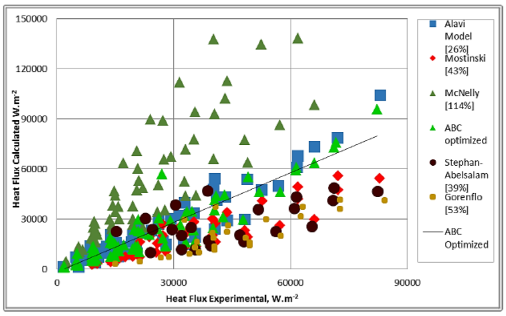

Fig. 6. Average Absolute Error Analysis.

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