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Hybridization of Cuckoo Search and Firefly Algorithms to Calculate the Interaction Parameters in Phase Equilibrium Modeling Problems

Merzougui, Abdelkarim*+•; Hasseine, A.; Regab, S.•; Laiadi, D.•
Department of Chemical Engineering, University of Biskra, ALGERIA

ABSTRACT:*Liquid-liquid equilibrium (LLE) problems such as: phase stability analysis, phase equilibrium calculations, chemical equilibrium calculations, binary interaction parameter identification of thermodynamic models and other problems of fluid characterization have been the core subject of many recent studies.This study introduces Cuckoo Search (CS), Firefly Algorithms (FA) and its variants as parameter identification methods for modeling the activity coefficients of 30 ternary systems using the NRTL and UNIQUAC models. In addition, we analyze and compare the performance of these algorithms to that of the other algorithms. The results show that the hybridization of CS and FA performs better in both speed and accuracy than similar problems based on the other met-heurists methods.*

KEYWORDS:*Liquid-liquid equilibrium; Optimization; Cuckoo Search; Firefly Algorithm; Hybridization.*

INTRODUCTION

In chemical engineering, optimization plays a key role in many areas such as: the design, operation of industrial reactors, separation processes and heat exchangers [1-5]. The key in engineering optimization problems are usually designed in a way that defines the global optimum and not just a local optimum. Furthermore, the most of chemical process optimization problems have a nonconvex feasible region (multiple local optima). Moreover, in some applications such as phase equilibrium problems, only the global optimum is the correct solution [6-8]. To overcomethese problems, some researchers have innovated optimization algorithms based on nature observation for searching the global optimum [9,10]. In recent years a number of stochastic global optimization methods have been proposed for solving thermodynamic problems (phase stability analysis, phase equilibrium calculations, chemical equilibrium calculations, simultaneous phase and chemical equilibrium calculations, calculation of critical points, calculation of azeotropes, parameter estimation of thermodynamic models and problems of fluid characterization) [1,11-16].

On the other hand, nature-inspired-based optimization algorithms are stochastic search methods that mimic the metaphor of natural biological evolution and/or the social behavior of species [17]. Examples include how ants find the shortest path to a source of food, how the behavior of fireflies which search for a mating partner by emitting

**To whom correspondence should be addressed.*
+E-mail:merzouguikarim@yahoo.com
•Other Address: Laboratoire de Recherche en Génie Civil, Hydraulique, Développement Durable et Environnement (LAR- GHYDE), University Mohamed Kheider- Biskra, ALGERIA
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a flashing light, how birds find their destination during migration and lifestyle of a bird family called cuckoo. The behavior of such species is guided by learning, adaptation, and evolution. To mimic the efficient behavior of these species, many researchers have developed computational systems that seek fast and robust solutions to optimization problems [17].

Until now, Harmony Search (HS), Cuckoo Search (CS),Firefly Algorithms (FA), Genetic Algorithm (GA), Simulated Annealing (SA), TabuSearch (TS), Differential Evolution (DE), Random Tunneling (RT) method and particle swarm optimization (PSO) have been successfully used for solving phase equilibria problems [18-30].

In particular, Srinivas and Rangaiah [1,18] studied DE and TS for non-reactive mixtures, and proposed two versions of DE with TabuList (DETL) to improve the performance of the optimization algorithm. *Merzougui et al.* [19] evaluated the Flower Pollination Algorithms in the parameter identification of UNIQUAC and NRTL models from ternary and quaternary systems relevant for food products mixtures. Flower Pollination Algorithms can locate the global optimum for most of the examples tested. In a recent study, *Bonilla-Petriciolet* and *Segovia-Hernández* [20] tested different versions of PSO for Phase equilibrium calculations for both reactive and non-reactive systems, and their results show that classical PSO is a reliable method with good performance.

Bhartiet al. [21] used Cuckoo Search algorithm (CS) for estimating binary interaction parameters of UNIQUAC and NRTL activity coefficient models for liquid-liquid ternary systems involving twelve Imidazolium and Phosphonium Ionic Liquids (IL). They concluded that CS was capable of estimating the parameters in models describing liquid–liquid phase behavior of multicomponent systems.

Saber and *Shaw* [22] proposed a global optimization computational method called Dividing Rectangles (DIRECT) to solve phase equilibrium problems. They concluded that DIRECT was successfully used as a predictive tool for ternary LLE data. *Ferrariet al*. [23] used PSO and SA algorithms for phase equilibrium of the UNIQUAC and the NRTL models for binary and multi-component LLE mixtures. They concluded that both optimization solvers were capable of modeling LLE data. *Bonilla-Petricioletet al*. [24] have used seven stochastic global optimization solvers; HS, PSO, GA, SA, DE, Differential Evolution with TabuList (DETL) and bare bones PSO (BBPSO), for modeling the mean activity coefficients of quaternary ammonium salts at 25°C using the e-NRTL model. The results indicated that SA, DETL and BBPSO offer better performance for solving phase equilibrium problems involved in the modeling of the thermodynamic properties of ILs. A harmony search algorithm (HSA) was applied by *Merzouguiet al*.[25] to calculate the binary interaction parameters of the NRTL model for 20 ternary liquid–liquid systems.

Merzouguiet al. [26] proposed a hybrid method based on a Genetic Algorithm (GA) combined with *Levenberg-Marquardt* (LM). The performance of HGA and GA are compared and discussed based on the reliability, their comparison shows that HGA method can be more efficient than GA. Bhargava *et al.* [27] studied the performance of Cuckoo Search (CS) for phase equilibria calculations and stability problems, the results show that Cuckoo Search (CS)offers a reliable performance for solving these thermodynamic problems.

In this paper, Cuckoo Search (CS) and Firefly Algorithms (FA) presented in Fig. 1 arereviewed and apply to the identification of binary interaction parameters based on NRTL and UNIQUAC models.

In order to improve the quality of solutions, a hybrid metaheuristic approach by hybridizing Cuckoo Search(CS) or Firefly Algorithms (FA) and Nealder-Mead-Simplex algorithm, namely, HCS and HFA respectively , are proposed to LLE calculation and interaction parameter estimation problems. The configuration of this paper is as follows. The CS and FA can be briefly described in the Sections, respectively. The detailed presentation of HCS and HFA are given and the both optimization solvers are tested using 30 ternary systems.

THEORITICAL SECTION

Cuckoo Search algorithm (CS)

Cuckoo Search (CS) is an evolutionary optimization algorithm developed by *Xin-she Yang*and *Suash Deb* in 2009 [31]. It was inspired by lifestyle of a bird family called cuckoo. Specifically, brood parasitism is a reproductive strategy followed by cuckoos in which they lay their eggs in the nests of other birds, which are usually other species. If these eggs are discovered by the host bird, it may abandon the nest completely or throw away the alieneggs [27].For example, if a host bird discovers

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Fig. 1: Schematic diagram of natural evolutionary systems.

theeggs are not their own, it will either throw these alien eggs away or simply abandon its nest and build a new nest elsewhere. Some cuckoo species such as the new world brood-parasitic Tapera have evolved in such a way that female parasitic cuckoos are often very specialized in the mimicry in colors and pattern of the eggs of a few chosen host species [32].

Cuckoo search (CS) uses the following representations [33]:

Each egg in a nest represents a solution, and a cuckoo egg represents a new solution. The aim is to use the new and potentially better solutions (cuckoos) to replace a not-so-good solution in the nests. In the simplest form, each nest has one egg. The algorithm can be extended to more complicated cases in which each nest has multiple eggs representing a set of solutions.

CS is based on three idealized rules:

1. Each cuckoo lays one egg at a time, and dumps its egg in a randomly chosen nest;

2. The best nests with high quality of eggs will carry over to the next generation;

3. The number of available hosts nests is fixed, and the egg laid by a cuckoo is discovered by the host bird with a probability $p_a \in (0,1)$. Discovering operate on some set of worst nests, and discovered solutions dumped from farther calculations.

Fig. 2, depicts flowchart of CS algorithm:

The firefly algorithm

The firefly algorithm is a metaheuristic algorithm, which is inspired by the behavior of fireflies which search for a mating partner by emitting a flashing light. It has been first proposed by *Yang* in 2007 [34, 35]. The brightness of the firefly is the key point of the algorithm, and is equivalent to the objective function under consideration. Three main assumptions were made when proposing the algorithm:

The development of firefly-inspired algorithm was based on three idealized rules [36]:

1- Artificial fireflies are unisex so that sex is not an issue for attraction;

2- Attractiveness is proportional to their flashing brightness which decreases as the distance from the other

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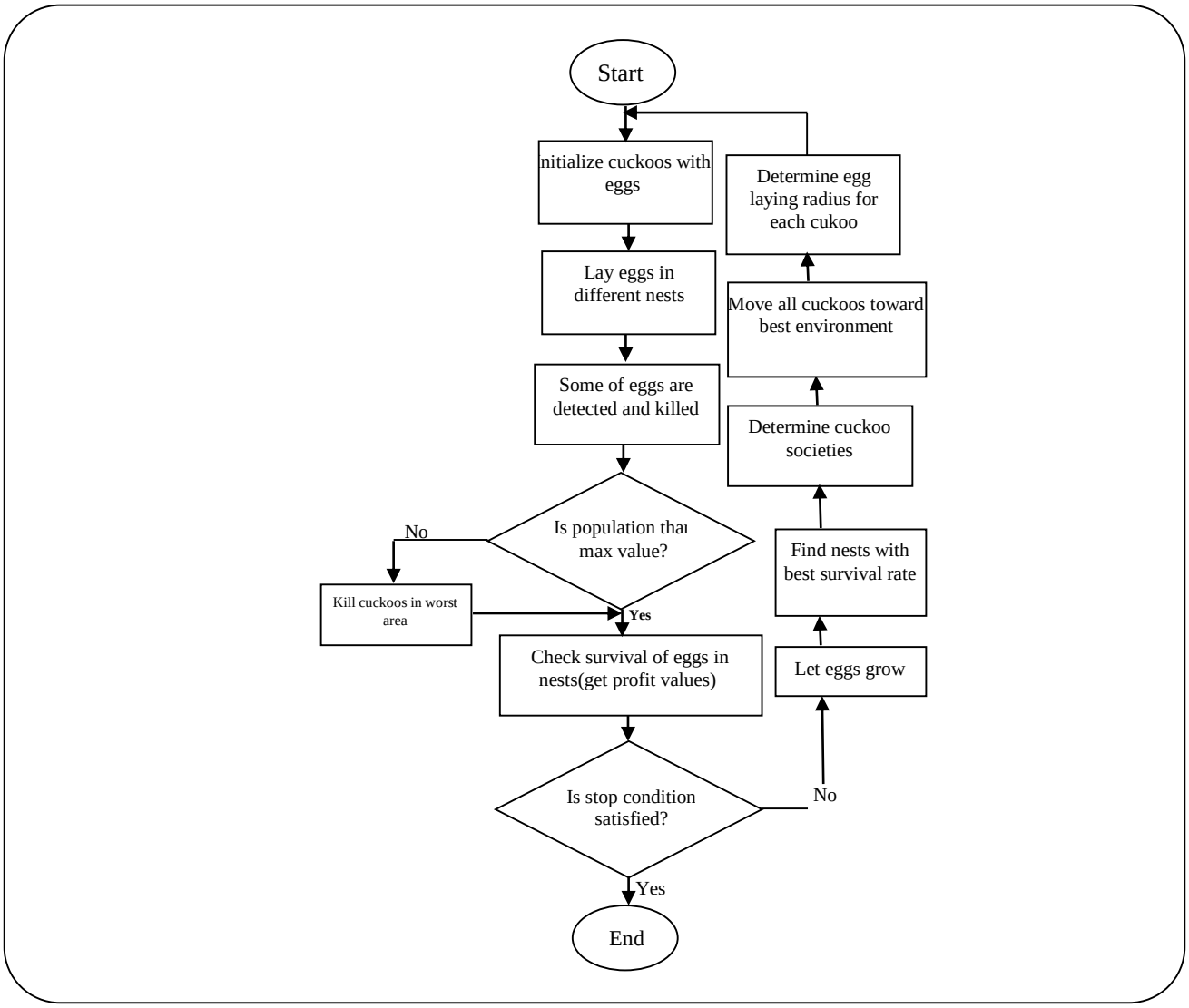


Fig. 2: Flowchart of Cuckoo Search algorithm.

firefly increases due to the fact that the air absorbs light. Since the most attractive firefly is the brightest one, to which it convinces neighbours moving toward. In case of no brighter one, it freely moves any direction;

3- The brightness of the flashing light can be considered as objective function to be optimized.

For minimization problems, the light intensity is inversely proportional to the value of the fitness function. The flow chart for FA is shown in Fig. 3 while the important steps are summarized below.

Hybridization of naure-inspired metaheuristics

Hybrid metaheuristics combine algorithmic components from various optimization algorithms aiming to improve the performance of the original metaheuristics in solving optimization problems [37]. A hybrid method combining Cuckoo Search (CS) and the Firefly algorithms (FA) with Nelder-Mead simplex algorithm is proposed in this work. The main idea of this combined algorithm is that CS or FA is applied to the optimization problem to explore the entire search space until one or more good solutions are found, which can no longer be improved through the random operations. The Nelder-Mead simplex algorithm is then invoked in the second phase to further improve the solutions.

The flow diagram of HCS or HFA is shown in Fig. 4. In the first stage CS or FA algorithm finish its training (Figs. 2 and 3), then Nelder-Mead simplex algorithm starts training with the weights generated by CS or FA algorithm

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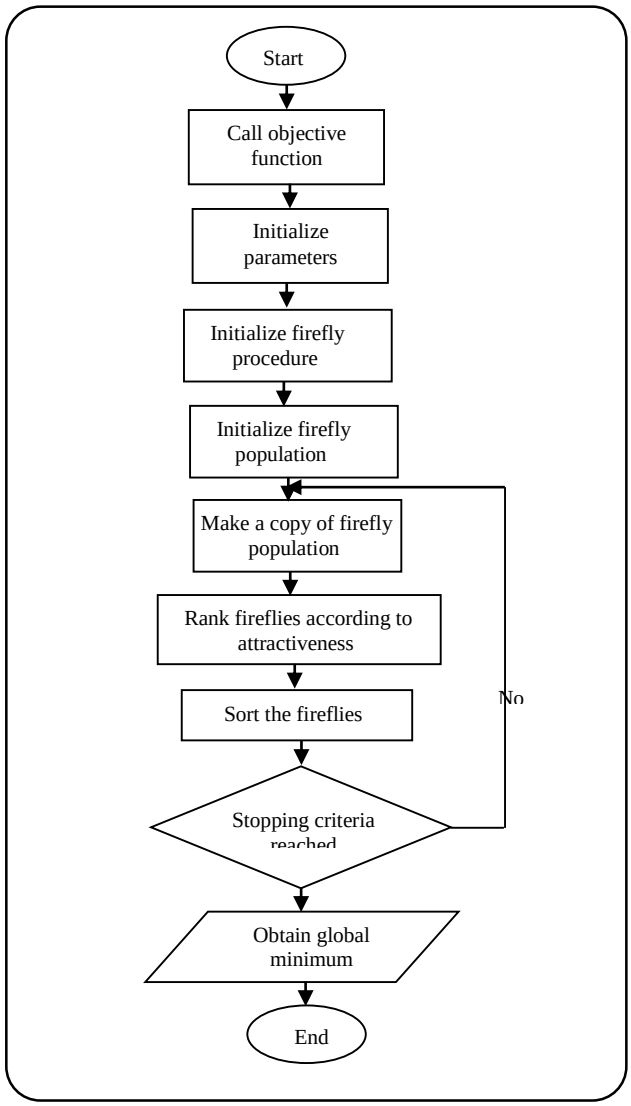


Fig. 3: Flowchart of FA algorithm.

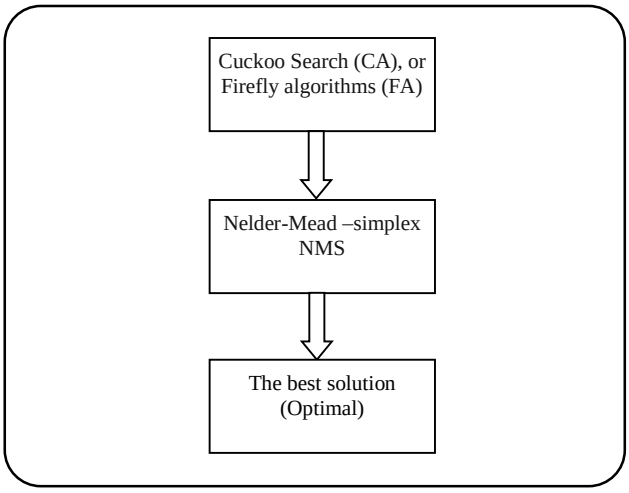


Fig. 4: The proposed hybridization algorithm.

and the Nelder-Mead simplex train the network until the stopped condition is satisfied.

RESULTS AND DISCUSSION

The performance of CS, FA, HCS and HFA algorithms is tested using several thermodynamic problems related to the modeling of phase equilibrium in non-reactive systems such as, phase equilibrium calculation and interaction parameter estimation. These problems are multivariable, highly non-linear, its objective function is non-convex with several local optimums. In this work, we used the experimental LLE data of several ternary systems for illustrating the use of CS, FA and its variants in the calculation of the binary parameters of NRTL and UNIQUAC models. These selected systems are listed in Table 2 along with their references and temperatures.

The benchmarking system involves the predictions of LLE for water (1)–methanol (2)–dichloromethane (3) ternary system at 293.15K°C.

Empirical study of the impact of CS and FA parameters on convergence behavior

The mathematical models and the objective function used for running the simulation have been defined in the previous work [19,25,26,41,42]. The simulation has been made by studying the evolution of the algorithms solution over generations under different settings of the parameters of these algorithms.

Identifying appropriate setting of FA parameters

The first experiment aimed to investigate the appropriate setting of the FA parameters via experimental design analysis. Those factors are the combination of the amount of {Number of Fireflies (NF) or population size, Number of generations (MaxIter), the light absorption coefficient (γ), the randomization parameter (α) and the maximum attractiveness value ($ß_0$) }.

These parameters were tested with respect to the variations in the accuracy of the final results. Each parameter was tested, and when one was tested, the other one was fixed. Later, the number of fireflies (population) used was modified, to verify the impact of the number of fireflies on the representation of the best solution. Table 2 summarizes the information about initial and final values [43, 44], as well as the rate of variation of each parameter.

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Table 1: Ternary systems at different temperatures used for parameter identification.

No.	System	T, K	Reference
1	water (1) + methanol (2) + dichloromethane (3)	293.15	[25]
2	water (1) + ethanol (2) + dichloromethane (3)	293.15	[25]
3	water (1) + 1-propanol (2) + dichloromethane (3)	293.15	[25]
4	soybean FAME (1) + glycerol (2) + methanol (3)	303.15	[38]
5	soybean FAME (1) + glycerol (2) + methanol (3)	318.15	[38]
6	soybean FAME (1) + glycerol (2) + methanol (3)	333.15	[38]
7	soybean FAME (1) + water (2) + methanol (5)	303.15	[38]
8	soybean FAME (1) + water (2) + methanol (5)	318.15	[38]
9	soybean FAME (1) + water (2) + methanol (5)	333.15	[38]
10	soybean FAME (1) + water (3) + glycerol (4)	303.15	[38]
11	soybean FAME (1) + water (3) + glycerol (4)	318.15	[38]
12	soybean FAME (1) + water (3) + glycerol (4)	333.15	[38]
13	soybean FAEE (1) + glycerol (2) + methanol (3)	303.15	[38]
14	soybean FAEE (1) + glycerol (2) + methanol (3)	318.15	[38]
15	soybean FAEE (1) + glycerol (2) + methanol (3)	333.15	[38]
16	soybean FAEE (1) + water (2) + methanol (5)	303.15	[38]
17	soybean FAEE (1) + water (2) + methanol (5)	318.15	[38]
18	soybean FAEE (1) + water (2) + methanol (5)	333.15	[38]
19	soybean FAEE (1) + water (3) + glycerol (4)	303.15	[38]
20	soybean FAEE (1) + water (3) + glycerol (4)	318.15	[38]
21	soybean FAEE (1) + water (3) + glycerol (4)	333.15	[38]
22	Linoleate (1) + anhydrous ethanol (5) + glycerol (6)	323.15	[39]
23	Linoleate (1) + anhydrous ethanol (5) + glycerol (6)	353.15	[39]
24	Oleate (1) + anhydrous ethanol (5) + glycerol (6)	323.15	[39]
25	Oleate (1) + anhydrous ethanol (5) + glycerol (6)	353.15	[39]
26	Palmitate (1) + anhydrous ethanol (5) + glycerol (6)	323.15	[39]
27	Palmitate (1) + anhydrous ethanol (5) + glycerol (6)	353.15	[39]
28	Laurate (1) + anhydrous ethanol (5) + glycerol (6)	323.15	[39]
29	Laurate (1) + anhydrous ethanol (5) + glycerol (6)	353.15	[39]
30	Glycerol (1) + Ethanol (2) + Soybean Biodiesel (3)	293.15	[40]

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Table 2: Experimental tests with the FA algorithm parameters.

Parameter	initial value	final value	increment
γ	0	1	0.1
α	0. 1	1	0.1
ß$_0$	0.1	1	0.1
NF	5	80	10

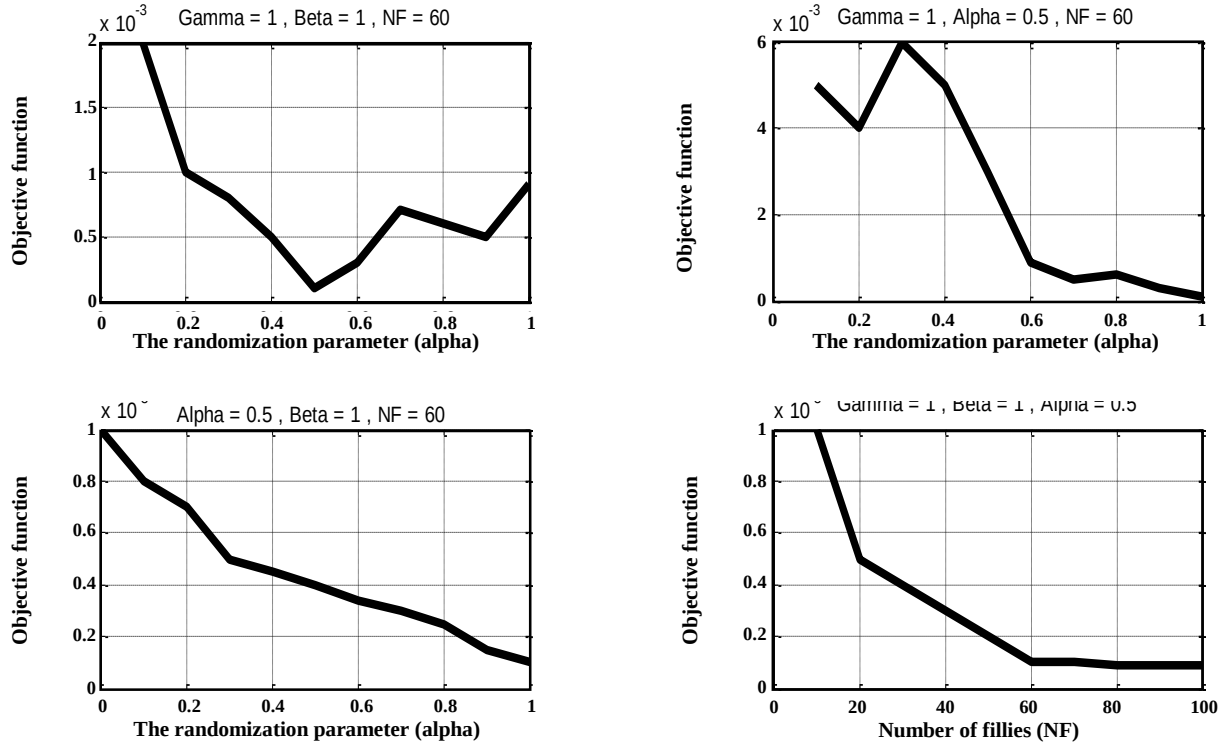


Fig. 5: Ilustration of the effect of the different FA parameters in the LLE parameter identification of water (1)–methanol (2)–dichloromethane (3) ternary system at 293.15K.

The Fig. 5, illustrates the best performance for the Firefly algorithm was obtained (considering the range selected for the firefly parameters to our application) with the values:

α = 0.5, ß$_0$ = 1, γ = 1 and NF= 60. The value of objective function (*F*), always decrease when the value of ß$_0$ increases (except when ß$_0$ =0.3), for fixed values for α and γ. On the other hand,when ß$_0$ and γ are fixed and α is variable, the value of objective function decreases between values of 0.1 and 0.5, with a minimum at 0.5. The γ variation indicated a decrease of objective function when γ increases.

The MaxIter is directly related with the problem size imposed. The high value of this combination usually increases the probability of getting the optimal solution but requires longer computational time. The improvement procedure of the best solution in FA as iteration continues is illustrated in Fig. 6. It is observed that 2000 generation is sufficient to give a very good set of parameters in the NRTL model and does not improve any further up to 2000 iterations.

Identifying appropriate setting of CS parameters

One of the very important aspects of a search algorithm is how much it is susceptible to variations in the tuning parameters, to check the robustness of CS, a number of searches are initiated with different tuning parameters and results are recorded.

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Table 3: Experimental tests with the CS algorithm parameters.

Parameter	initial value	final value	increment
Nn	10	100	10
p_a	0. 1	0.5	0. 1
ß	1	2	1.1
MaxIter	1	500	1

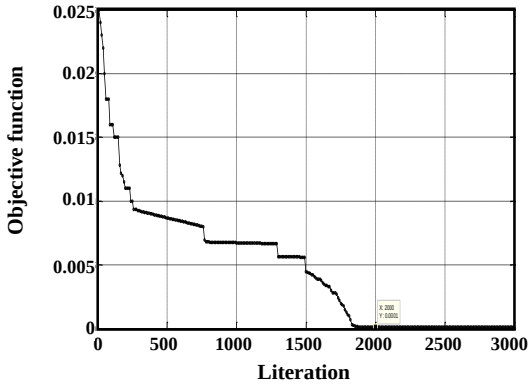


Fig. 6: Convergence profiles of Firefly algorithm (FA) during LLE parameter identification of water (1)–methanol (2)–dichloromethane (3) ternary system at 293.15K.

The effects of the variation of Number of nests (Nn), Discovery rate of alien solutions (p_a), Levy exponent (ß) and Maximum Iteration (MaxIter) are investigated by executing a many different searches for the each of the following cases (Table 3):

For each case the value for the objective function is recorded. Table 2, shows the output of the CS search when running using different values for tuning parameters [45,46]. Fig. 7, shows the convergence of the Cuckoo Search using different values of each parameter on quality of the proposed algorithm.

The results of a sensitivity analysis of Nn, p_a and ß are showing in Fig. 7. From our tuning of CS algorithm parameters, we found that (Nn= 60, P_a=0.2 and ß=1.5) produces the better solution (the value of function objective is low).

The Fig. 8, show the improvement procedure of the optimal solution in CS algorithm as iteration continues for the NRTL model. This figure, also demonstrate that the solution obtained in less than 600 iterations is a near global optimum and does not improve any further up to 500 iterations. It is observed that 500 generation is sufficient to give a very good set of parameters in the model.

Hybridization of CS and FA and compared with other optimization methods

Based on the results of tuning parameters of CS and FA obtained in the previous subsection, the HCS and HFA methods are investigated in this section. To make a practical comparison between different methods, all the experiments were conducted on the same conditions.

The parameter estimation results and the LLE calculation of seven existing optimization methods, SA, GA, HS, HSA, HGA, FA and CS, were compared with the proposed HFA and HCS. All methods were executed 50 times independently. Fig. 9, presents the overall performance of these methods. For 50 runs, the Average Root-Mean-Square Deviation (ARMSD) value of the HFA and HCS method was better compared to the other methods. So it is selected to adjust values of tie lines of (water + methanol + dichloromethane).

The interaction parameters values obtained using HCA and HFA for the benchmarking ternary systems are given in Tables 4-5. Since these new values in this work are different from the ones reported by reference [25,47] and these parameters lead to a lower value of the RMSD relative to the other results.

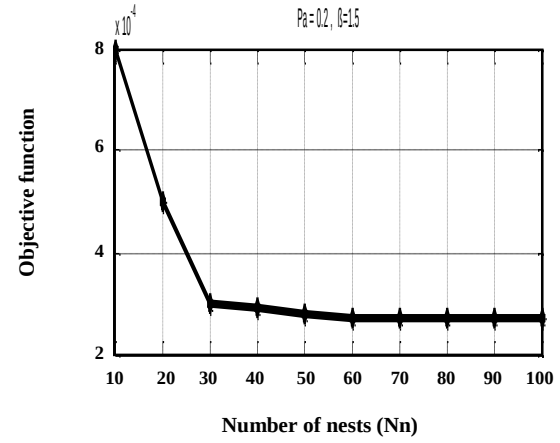
Figs. 10-11 presents the ternary equilibrium diagram for water + methanol + dichloromethane system at 293.15K with experimental data and correlated values, using NRTL and UNIQUAC models.

The experimental and calculated LLE data agreed very well as shown in the figures, as for the ternary systems, the strategy using hybridization of CA or FA in the correlation of liquid–liquid equilibrium data employed in the previous work is shown to be reliable, so the results of the present work correspond to the new and more optimal solution.

Finally, Fig. 12 shows the mean modeling errors (e_i) for the prediction of LLE behavior of selected ternary mixtures. These modeling errors ranged from 13.2 to 55.1 % for CS-UNIQUAC, from 12.6 to 51.3 % for FA-UNIQUAC, from 11.7 to 42.6 % for HCS-UNIQUAC and from 10.8 to 38.8 %

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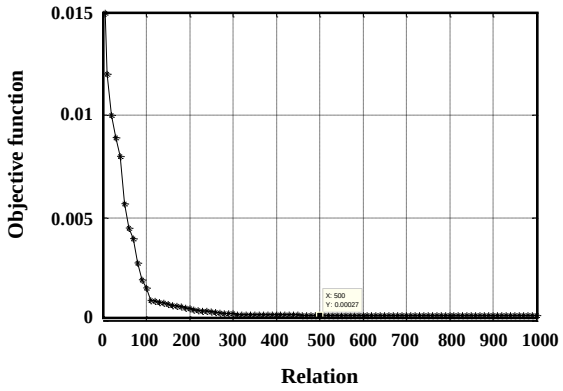
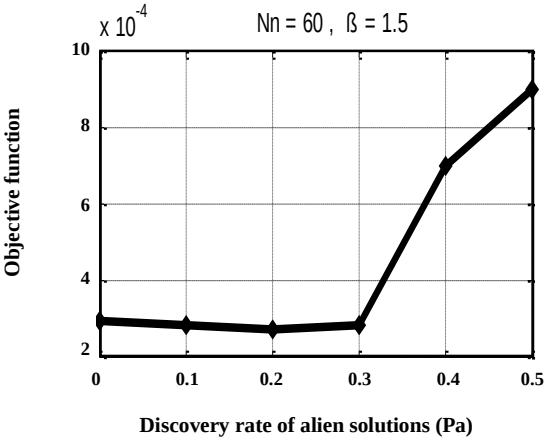


Fig. 8: Convergence profiles of Cuckoo Search (CS)during LLE parameter identification of water (1)–methanol (2)–dichloromethane (3) ternary system at 293.15K.



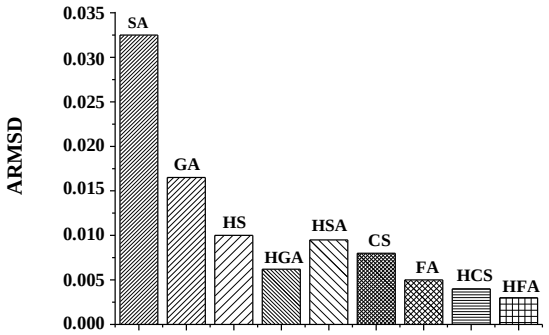


Fig. 9: Comparison of ARMSD values for several algorithms using NRTL model for water –methanol – dichloromethane system at 293.15 K.

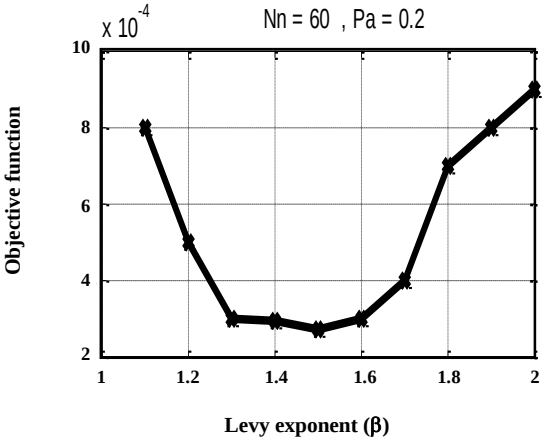


Fig. 7: Ilustration of the effect of the different CS parameters in the LLE parameter identification of water (1)–methanol (2)–dichloromethane (3) ternary system at 293.15K.

for HFA-UNIQUAC. It is clear that the modeling performance of both hybrid solvers was better than those obtained without hybridization.

COCLUSIONS

In the present work, the new hybrid optimization called HFA and HCS are introduced. The proposed methods combined the Cuckoo Search and Firefly Algorithms with the Nelder-Mead simplex method. The proposed methods are used to phase equilibrium calculation and interaction parameters estimation problems. The experimental results showed that the accuracy and speed performance of HFA and HCS had significantly outperformed the results produced by SA, GA, HS, HSA, HGA, FA and CS methods. Moreover, the convergence analysis showed that

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Table 4: The optimal NRTL binary interaction parameters and RMSD values for the selected ternary systems.

Sys. No.	NRTL interaction parameters using optimization solvers, K						FA	CS	HFA	HCS	Lit.
	A_{12}	A_{21}	A_{13}	A_{31}	A_{23}	A_{32}					
1	469.053	709.047	912.887	1350.478	-258.53	1220.247	0.0021	0.0034	0.0016	0.0027	
2	1346.257	-183.441	1295.735	983. 412	-600.163	-354.221	0.0091	0.0096	0.0082	0.0090	
3	284.057	1207.183	1087.087	1005.754	1183.503	-285.048	0.0048	0.0063	0.0040	0.0060	
4	856.953	-568.745	1125.054	87.954	458.654	1253.213	0.0018	0.0029	0.0010	0.0023	
5	884.584	-624.538	1090.32	91.556	470.650	1214.053	0.0018	0.0038	0.0013	0.0031	
6	905.845	-593.478	1125.405	88.965	456.214	1169.112	0.0024	0.0032	0.0018	0.0028	
7	1302.533	-895.652	1123.660	653.213	1025.362	318. 215	0.0022	0.0036	0.0015	0.0028	
8	1386.224	-983.234	1119.452	632.855	1043.181	317. 234	0.0018	0.0048	0.0012	0.0045	
9	1385.861	-205.028	1125.531	623.815	1042.772	313. 885	0.0035	0.0042	0.0022	0.0035	0.0114
10	733.67	-238.16	1311.38	302.77	1245.43	1019.73	0.0018	0.0020	0.0011	0.0015	0.0608
11	733.51	-230.63	1308.71	301.30	1244.35	1021.36	0.0019	0.0029	0.0013	0.0023	0.0359
12	669.73	-219. 86	1303.16	299.05	1241.84	1038.93	0.0036	0.0051	0.0026	0.0042	0.0015
13	-350.17	-715.52	1214.60	252.36	746.79	-1024.60	0.0022	0.0033	0.0016	0.0025	0.0014
14	-286.25	-734.21	1212.50	254.57	775.56	-1012.48	0.0030	0.0028	0.0021	0.0023	0.0029
15	-262.67	-742.12	1117.09	259.23	723.86	-1051.36	0.0019	0.0032	0.0013	0.0025	0.0017
16	843.454	942.934	1092.020	637.119	796.495	-530.204	0.0023	0.0043	0.0016	0.0035	0.0025
17	733.185	925.720	1081.974	646.228	771.266	-557.858	0.0025	0.0036	0.0015	0.0021	0.0037
18	863.464	901.831	1059.112	622.635	780.894	-516.024	0.0022	0.0037	0.0012	0.0017	0.0027
19	-825.02	249.14	1010.120	496.304	870.069	-656.604	0.0023	0.0042	0.0015	0.0035	0.0020
20	-917.25	216.84	1045.154	482.915	837.057	-645.728	0.0031	0.0062	0.0022	0.0042	0.0042
21	873.36	235.89	1023.82	453.258	559.129	-637.579	0.0018	0.0038	0.0010	0.0035	0.0020
22	1057.58	-611.92	1105.45	439.37	950. 165	629.13	0.0027	0.0068	0.0018	0.0061	0.0026
23	1180.64	-629.62	1205.98	487.80	938.174	571.91	0.0021	0.0035	0.0013	0.0028	0.0017
24	953.63	-682.86	1081.31	416.04	822.642	568.72	0.0023	0.0042	0.0011	0.0034	0.0012
25	-836.65	-218.26	1160.70	865.247	673.82	-524.92	0.0024	0.0042	0.0018	0.0032	0.0031
26	-893.22	-269.37	1157.22	840.425	659.35	-531.44	0.0028	0.0039	0.0014	0.0034	0.0015
27	620.35	271.74	296.32	725.934	358.28	231.11	0.0023	0.0038	0.0011	0.0022	0.0011
28	-359.326	655.130	1285.397	1025.57	-425.39	1301.302	0.0022	0.0033	0.0015	0.0025	0.0023
29	-335.524	630.494	1175.061	1158.32	-490.73	1293.654	0.0018	0.0041	0.0010	0.0032	0.0025
30	183.358	-538.820	1050.48	889.36	937.38	-543.284	0.0026	0.0037	0.0012	0.0028	0.0045
											0.0037
											0.0033
											0.0024
											0.0023
											0.0021
											0.0028
											0.0022
											0.0026

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Table 5: The optimal UNIQUAC binary interaction parameters and RMSD values for the selected ternary systems.

Sys. No.	UNIQUAC interaction parameters using optimization solvers, K						FA	CS	HFA	HCS	Lit.
	A_{12}	A_{21}	A_{13}	A_{31}	A_{23}	A_{32}					
1	-52.365	-387.510	421.825	331.684	789.012	-282.402	0.0061	0.0058	0.0055	0.005	0.0747
2	903.28	-58.305	223.687	589.522	-102.541	246.084	0.0052	0.0098	0.0046	0.009	0.0447
3	1345.147	-135.357	1008.152	873.043	-38.027	478.576	0.0056	0.0083	0.0054	0.0078	0.0068
4	-189.32	645.85	-534.50	687.80	892.97	1280.10	0.0026	0.0025	0.0017	0.0030	0.0020
5	-181.67	637.52	-527.50	680.28	885.37	1273.96	0.0036	0.0034	0.0025	0.0040	0.0014
6	-172.97	633.31	-518.86	676.68	876.46	1265.72	0.0024	0.0042	0.0017	0.0020	0.0029
7	55.80	556.05	1033.73	897.82	478.35	-154.81	0.0042	0.0039	0.0034	0.0035	0.0017
8	51.22	547.61	1018.71	893.15	469.90	-152.05	0.0027	0.0033	0.0021	0.0028	0.0025
9	47.83	538.78	1000.07	882.62	458.93	-149.47	0.0049	0.0047	0.0043	0.0042	0.0037
10	769.20	541.12	850.41	603.56	1103.86	1085.09	0.0031	0.0025	0.0020	0.0018	0.0034
11	760.33	530.56	843.80	592.18	1098.33	1076.48	0.0027	0.0036	0.0022	0.0028	0.0030
12	751.84	525.08	834.55	584.91	1087.49	1064.61	0.0048	0.0045	0.0040	0.0038	0.0043
13	642.04	493.06	1201.36	942.49	475.83	365.94	0.0022	0.0030	0.0012	0.0020	0.0020
14	633.22	483.87	1193.82	935.11	470.44	361.08	0.0043	0.0040	0.0036	0.0035	0.0030
15	622.89	472.34	1185.07	926.75	462.41	354.64	0.0030	0.0028	0.0021	0.0018	0.0040
16	358.37	-176.41	1056.32	806.04	313.18	597.68	0.0026	0.0020	0.0016	0.0015	0.0022
17	353.76	-165.88	1041.17	802.36	309.21	590.04	0.0036	0.0032	0.0026	0.0023	0.0036
18	348.25	-160.83	1025.83	795.58	296.93	575.76	0.0039	0.0035	0.0031	0.0030	0.0021
19	283.44	89.65	1131.55	974.45	469.26	505.95	0.0032	0.0028	0.0022	0.0020	0.0016
20	273.76	83.06	1122.85	966.33	461.93	496.11	0.0031	0.0028	0.0024	0.0025	0.0026
21	127.21	-142.70	1109.52	557.62	677.82	395.83	0.0030	0.0027	0.0021	0.0020	0.0031
22	118.56	-133.22	1081.52	545.37	665.08	380.71	0.0028	0.0022	0.0016	0.0015	0.0022
23	184.12	165.08	1265.37	773.49	637.17	164.33	0.0026	0.0020	0.0015	0.0013	0.0026
24	171.66	155.92	1252.37	761.11	627.52	151.98	0.0027	0.0022	0.0019	0.0017	0.0021
25	150.58	990.53	1042.19	1063.47	986.08	167.41	0.0023	0.0018	0.0014	0.0012	0.0016
26	146.12	984.75	1033.93	1051.03	980.86	159.33	0.0028	0.0022	0.0018	0.0016	0.0015
27	382.23	781.61	871.12	1111.15	1063.68	904.33	0.0018	0.0034	0.0010	0.0028	0.0019
28	368.95	770.04	864.76	1102.14	1050.33	886.62	0.0035	0.0030	0.0026	0.0025	0.0014
29	-783.34	98.95	1135.08	860.42	644.12	-512.83	0.0023	0.0030	0.0015	0.0024	0.0018
30	-771.10	89.28	1128.91	851.86	635.38	-502.05	0.0018	0.0036	0.0013	0.0032	0.0030

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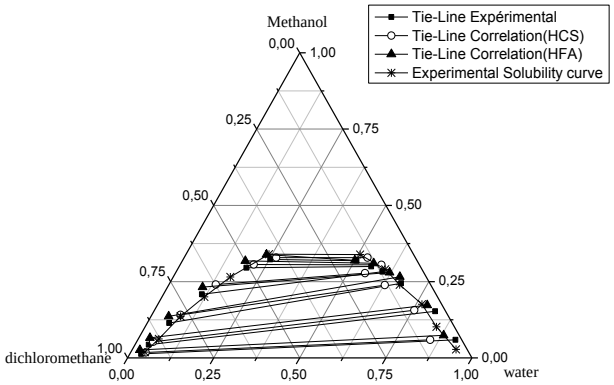


Fig. 10: Comparison of experimental and NRTL correlated Tie-Line data for the ternary system {water (1) + methanol (2) + dichloromethane (3)} at 293.15 K.

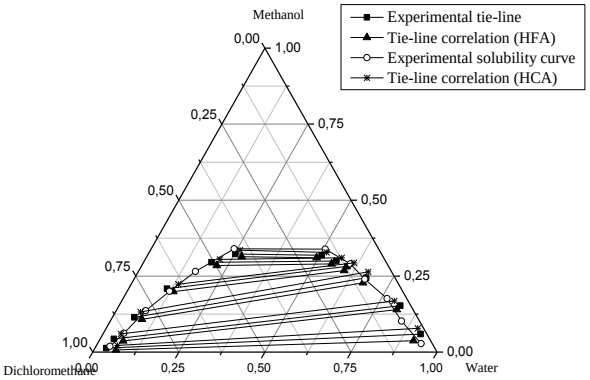


Fig. 11: Comparison of experimental and UNIQUAC correlated Tie- Line data for the ternary system {water (1) + methanol (2) + dichloromethane (3)} at 293.15 K.

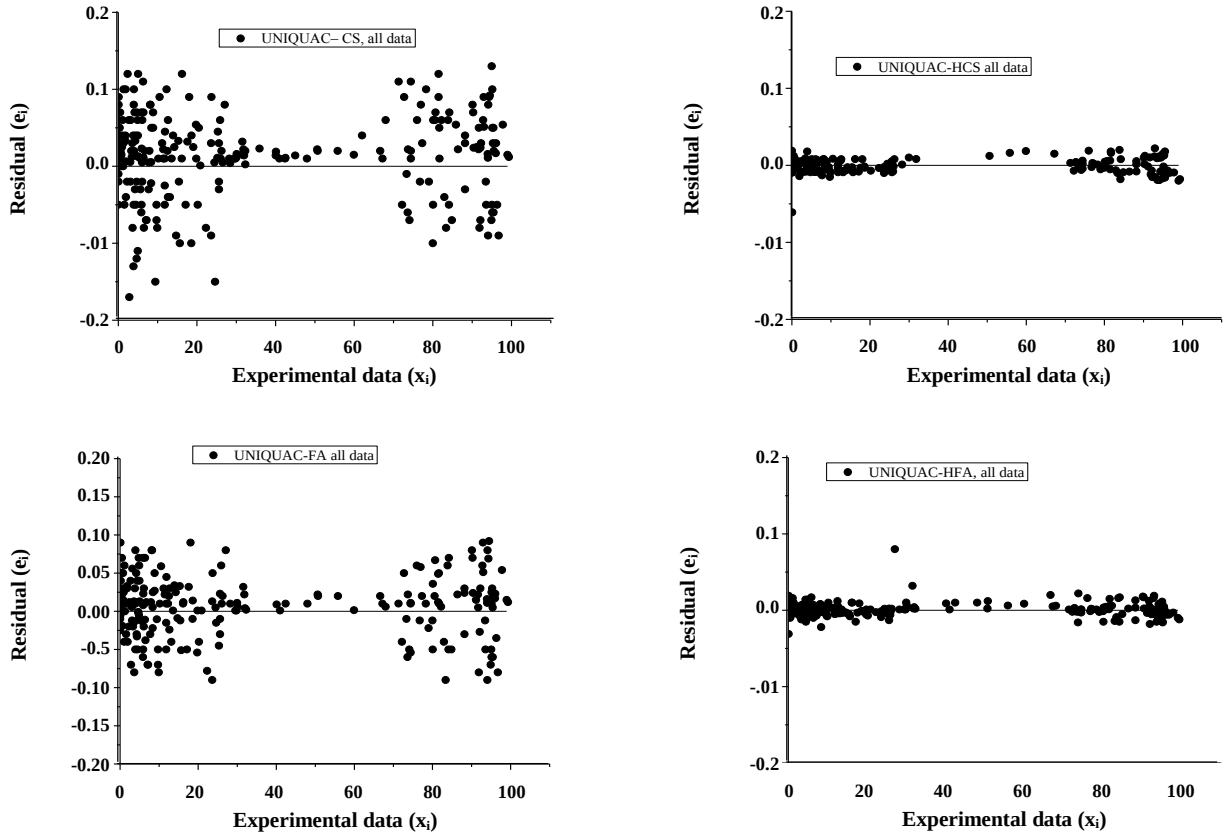


Fig. 12: Residual plots of tie-line of selected ternary systems.

optima more effectively.Furthermore, the research also investigated the effect of variation of the tuning parameters of Cuckoo Search and firefly algorithm on the quality of search, it has been shown that within a wide range, CS and FA can be an efficient search algorithm.

For the future research, several improvements are suggested to further enhance the performance of the proposed method. Firstly, the drawbacks lies with fixed values of different parameter of CS and FA can be eliminated bychange these parameters dynamically

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withthe number of generation. Secondly, we plan to incorporate the hybridization of CS, FA and other metaheuristics such as the bee algorithm and particle swarm optimization in phase equilibria optimization problems. Lastly, the proposed methods should be tested in variety problems of liquid-liquid or liquid-vapor equilibrium.

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