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Prediction of flow characteristics in the bubble column reactor by the artificial pheromone-based communication of biological ants

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Abstract

In order to perceive the behavior presented by the multiphase chemical reactors, ant colony optimization algorithm was combined with CFD data. This intelligent algorithm creates a probabilistic technique for computing flow and it can predict various levels of three-dimensional bubble column reactor. This artificial ant algorithms is mimicking the real ant behavior. We found that this method can anticipate the flow characteristics in the reactor using almost 30 % of whole data in the domain. Following discovering the suitable parameters, the method is used for predicting the points not being simulated with CFD, which represent mesh refinement of Ant colony method. In addition, it is possible to anticipate the bubble-column reactors in the absence

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of numerical results or training of exact values of evaluated data. The major benefits include reduced computational costs and time savings.

Keywords: Flow pattern, machine learning, computational fluid dynamics, ant colony optimization, swarm intelligence

1 Introduction

Multiphase Bubble Column Reactor (BCR) types are highly important for different industries because of their applications and efficiency[1-3]. A BCR's structure is composed of a cylindrical vessel with a gas distributor at the bottom section so that the gas bubbles are fed into the reactor[4-7]. Therefore, the gas is sparked in other phase for separation or chemical reaction. Moreover, this phase may have two forms; i.e., liquid-solid mix and liquid phase[8-11]. The bubble column is particularly beneficial in petrochemical, chemical, metallurgical, and biochemical industries, and they are utilized as multiple reactors and contactors since these fluid structure domains give a large surface area. The BCRs in different industries such as pharmaceutical or biochemical are used in the processes that involve reactions such as chlorination, oxidation, polymerization, hydrogenation, and alkylation, which are advantageous for the production of synthetic fuels[12-15]. The Fischer-Tropsch process is considered as a major application of the mentioned reactors in the chemical industries[16, 17]. It is the process of indirect coal liquefaction, resulting in various kinds of fuels like synthetic fuels, methanol synthesis, and transportation fuels[18, 19]. The production of these kinds of fuels is environmentally advantageous compared to the fuels derived from petroleum [9, 20-22]. The

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BCRs are extensively used due to their specific operation and design. The high heat transfer coefficients are characteristics of the bubble columns [9, 23-26]. As the advantage of the bubble columns, it can be stated that a catalyst or other packing chemical components are able to stay a long period even though they are extensively used. Also, it is possible to add or remove the online catalyst easily[27-31]. Thus, the bubble columns are used in biochemical and chemical industries. In order to get effective BCRs, it is necessary to consider their design scale[32, 33]. Hence, if the reactors are improved by computation and simulation of the column's hydrodynamics, then a perfect understanding concerning the process can be provided [34-36]. Various numerical methods are available for estimation of the multiphase flow in the BCRs. Nevertheless, the scholars have difficulties in the simulation of the full gas movement [37-39]. In order to numerically stimulate complex turbulence behavior in the two phase reactor, often the super computers (sometimes they contain more than 150,000 processor cores with sophisticated facilities thermal cooling system and several racks/cabinets connected by a high-speed 3-D torus network) provide the opportunity to calculate the liquid flow in the very complicated geometries. In experimental observation, If the fluid flow is needed to be measured during operation, because of the requirement for the high-speed microscopic cameras and modern probes, it is not economical [40-44]. Moreover, the other constraint of the approach in the prediction of large BCRs is related to the computational costs at varying operational conditions and different times[45-50]. These limitations gave way to application of the intelligent algorithms for simulation of BCRs [40, 51-55].

Support vector machines, neural networks, simulated annealing, and evolutionary algorithms are some of the soft computing approaches that can be applied for predicting and simulating the chemical processes[56-58]. This system can direct the complicated relationships[59]. Using this approach, a smart way is provided for estimation of the complicated mechanisms in engineering. A suitable example in this regard is the regulation of robotic movements in risky cases[55, 60, 61]. Thus, this approach is useful in order to control the robots in the cases that the chemical reactions may be dangerous for the people[52-54].

As mentioned, soft modeling approaches pursue a smart process; thus, it is useful in decision-making because of its comprehensiveness and complex algorithm[62]. In addition, they can be devoid of various errors including the accuracy in monotonous conditions. In addition, using the different inputs and output procedure is beneficial when the output - input association is inherently meaningful[63]. Therefore, the method's learning process is completely dependent on the data both for experimental or simulated cases. The recent research works have been mainly focused on a specific dimension of soft computing methods used for flow patterns production in the BCRs. According to the research works, the relationship between the machine learning and computational fluid dynamics (CFD) results in important concepts for the computation of different properties of BCRs. Pourtousi et al[40, 51, 64]. used different type of big data in the bubble column reactor in the machine learning algorithm and they predicted pattern recognition of gas and liquid flow in the bubble column reactor. In this study we combined ant colony method to predict the flow pattern in the bubble column reactor. The application of ant colony algorithm is an appropriate alternative rather than using the CFD approach, which is costly in terms of computation, for the flow simulation in BCRs. We specifically train the flow characteristics in the bubble column reactor by pheromone-based communication of biological ants and compare the results with existing CFD data[65, 66].

2 Method

For simulation of bubbling flow in the bubble column reactor the Eulerian–Eulerian approach is used throughout the domain. This method can simulate the fraction of each phase in the domain and it is based on ensemble-averaged mass and momentum transport equations for each phase. For solving fluid flow in the bubble column reactor firstly we compute the continuity equation as following:

$$\frac{\partial}{\partial t}(\rho_k \epsilon_k) + \nabla(\rho_k \epsilon_k u_k) = 0 \tag{1}$$

Momentum transfer equation:

$$\frac{\partial}{\partial t}(\rho_k \epsilon_k u_k) + \nabla(\rho_k \epsilon_k u_k u_k) = -\nabla(\epsilon_k \tau_k) - \epsilon_k \nabla p + \epsilon_k \rho_k g + M_{I,k} \tag{2}$$

The total interfacial force scheme between main phases are mainly drag and turbulent dispersion force. The overall forcing scheme is written as:

$$M_{I,L} = -M_{I,G} = M_{D,L} + M_{TD,L} \tag{3}$$

The details description of interfacial force methods which are utilized used in this investigation can be observed in in Tabib et al[45]. For calculation of the turbulence flow characteristics the k–ε model is used. This model is utilized for over the past 20 years for calculation of turbulence behavior in the bubble column reactor. All turbulence model parameters are similar with k-e model in Pourtousi et al[40, 51]. Pefleger et al[67]. and Tabib et al[45].

2.1 Geometrical structure

A cylindrical bubble column reactor with a height and diameter of 2.6 m and 0.288 m, respectively is used, and single sparger point is used at the bottom of the column with 0.5 m height. The details description of boundary conditions such as slip boundary conditions and degassing pressure at the surface of the column in this investigation can be observed in Pfleger and Becker[67]. The source point boundary condition used for single sparger is identical with Tabib et al[45].

2.2 Grid

A structured grid based on hexahedral grid is utilized for calculation of the whole fluid structure and the interaction between liquid and gas.

2.3 ANT Colony

In this study, the ant colony optimization method (ACM) is a probabilistic technique for solving big data with complicated problem structure that can be decreased to discover good paths through graphs. Intelligent Ants or artificial algorithms of ant method stand for multi-agent methods to mimic the real behavior of ants. In this study we specifically used this method to predict the gas-liquid flow pattern in the column. More description about this method can be found in [68-90].

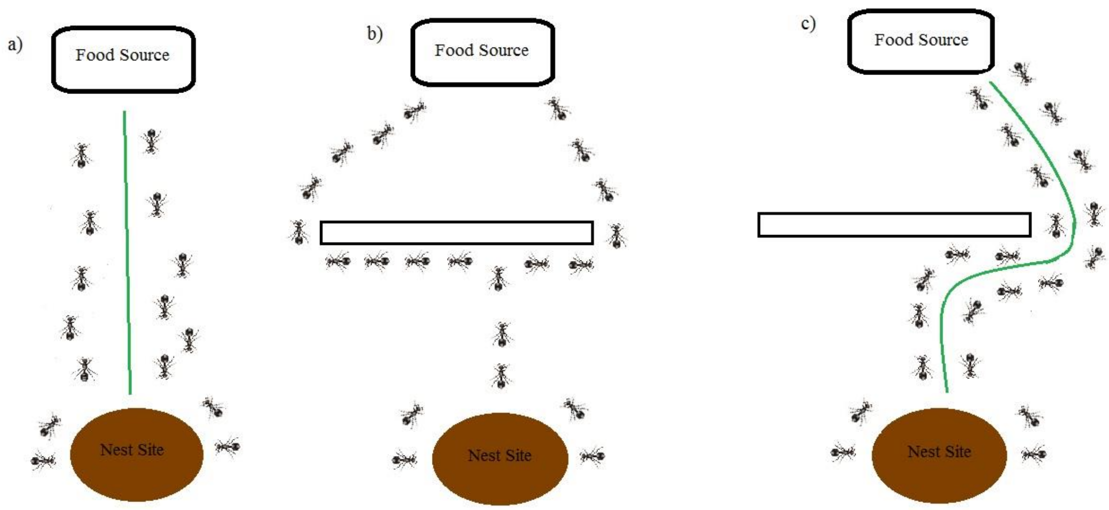

Figure 1: a) Ants food finding schematic; b) Ants with obstacle (starting problem); b) Ants with obstacle (best solution).

3 results

In the present study, through simulating a cylindrical bubble column (BCR) reactor by computational fluid dynamics (CFD), different parameters of the fluid were acquired as the outputs of the CFD method. Output parameters of the CFD method consist of the x, y, and z coordinates, pressure, air superficial velocity, and air volume fraction. In this study, the CFD outputs were assessed through combining the Fuzzy Inference System (FIS) with one of the artificial intelligence algorithms (ant colony algorithm).

To use the Ant colony algorithm, part of the CFD outputs were considered as input and the others were considered as output. In this research, five inputs were utilized; the first input was the x coordinate, the second input the y coordinate and the third was the z coordinate. The pressure which was one of the traits of the fluid inside the BCR is the fourth input; air superficial

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velocity another characteristic of the fluid inside BCR is the fifth input, whereas air volume fraction is considered as output.

To initiate the learning process by artificial intelligence (ant colony algorithm), the following conditions are assumed:

The maximum iteration is 100, the total data number is 1500, the value of p represents a percentage of the total data that has been used in the training process and is considered as 70%. In the training process, 70% of the data was involved and 100% of the data was evaluated in the training process. The clustering type was assumed as Fuzzy c-means (FCM).

With the Above mentioned assumptions, by considering the input of the x coordinates and the output of the air volume fraction, the training and testing processes were performed separately for 20, 30, and 40 numbers of ants. As presented in Fig. 2, the best Regression (R) value is 0.30 for a number of 30 ants which shows that FIS does not have sufficient intelligence in the learning process using the ant colony algorithm, and the change in the number of ants has made no significant enhancement in the intelligence of method.

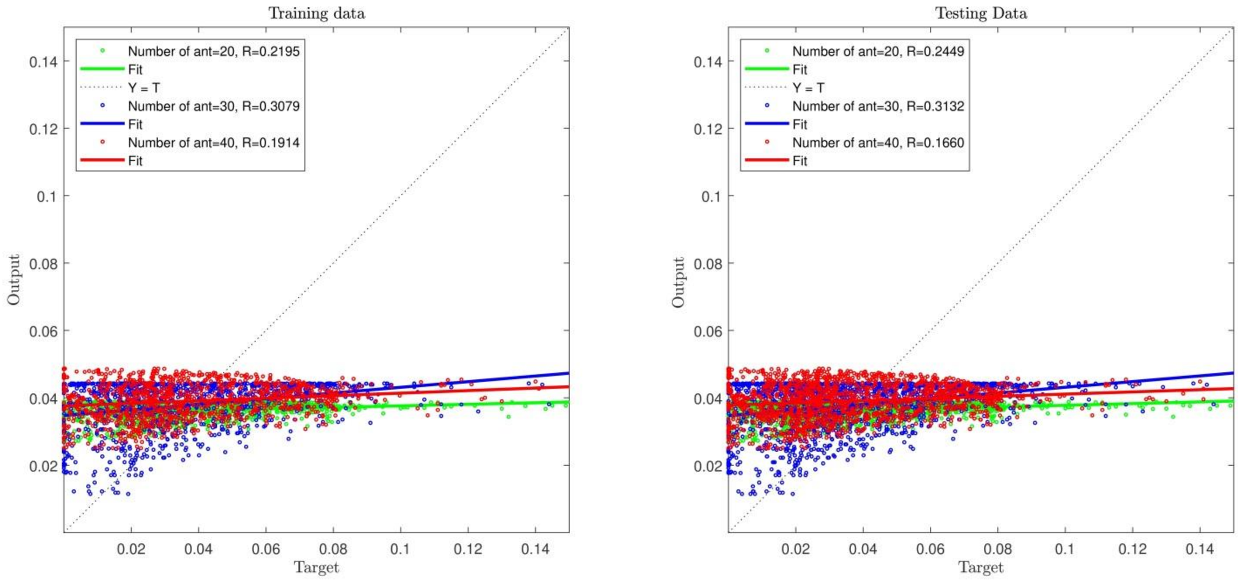

Figure 2: ant colony algorithm training and testing process with one input (number of ant =20, 30, 40; number of data=1500; max iteration=100; P=%70; FCM clustering).

To boost the system intelligence, the number of inputs was increased and evaluated; the x and y coordinates were considered as inputs, and training and testing processes were carried out for 20, 30, and 40 ants separately. Fig. 3 doesn't show much enhancement in system intelligence.

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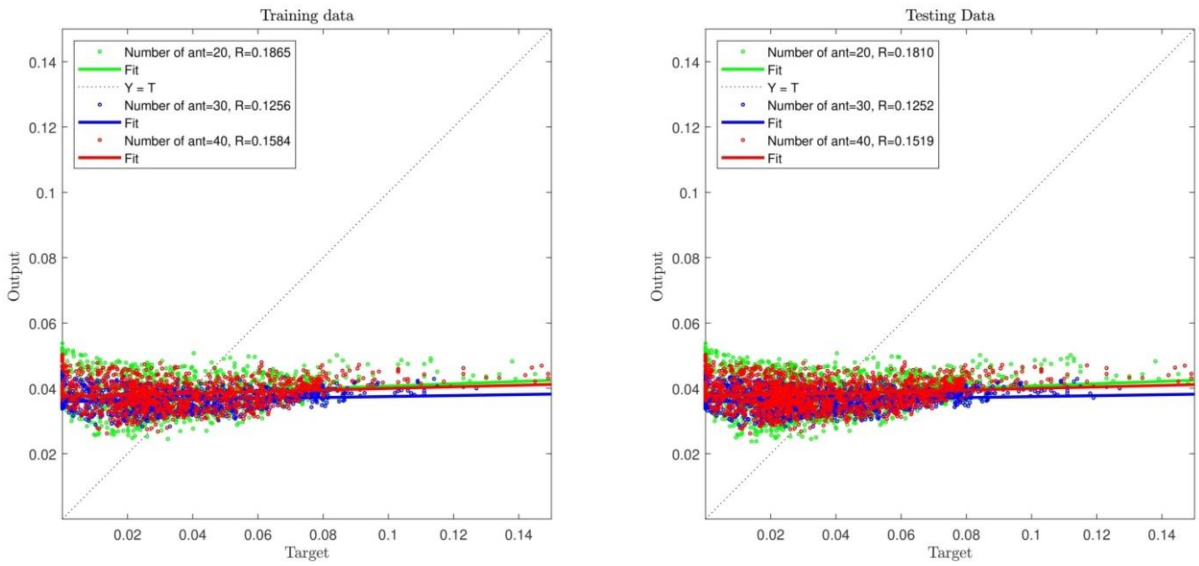

Figure 3: ant colony algorithm training and testing process with two inputs (number of ant =20, 30, 40; number of data=1500; max iteration=100; P=%70; FCM clustering).

To elevate the ant colony algorithm intelligence, the increase in the number of inputs from 2 to 3 was considered; also the x, y, and z coordinates were considered as inputs and the air volume fractions were considered as output. By conducting separate training and testing procedures for various numbers of ants, no significant changes are in observed in intelligence as shown in Fig. 4.

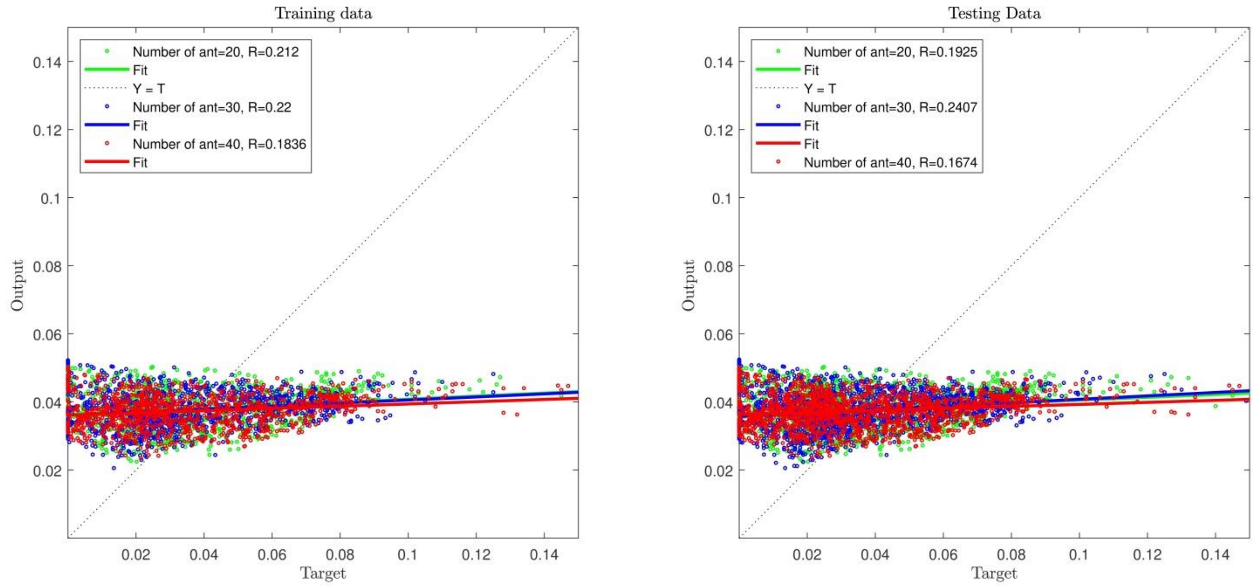

Figure 4: ant colony algorithm training and testing process with three inputs (number of ant =20, 30, 40; number of data=1500; max iteration=100; P=%70; FCM clustering).

In this stage of the study, one of the characteristics of the fluid inside the BCR i.e. pressure was added to the system as the fourth input. The learning processes (training and testing) for 20, 30, and 40 ants were done separately, but unfortunately, there was still no significant effect on elevating the system intelligence. (See fig. 5)

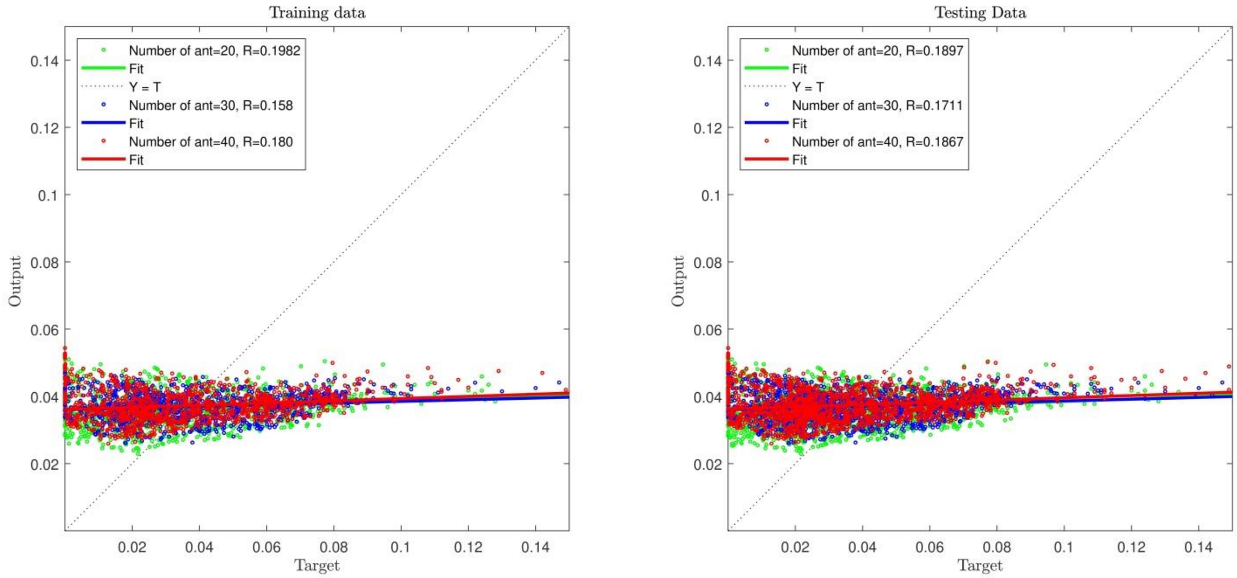

Figure 5: ant colony algorithm training and testing process with four inputs (number of ant =20, 30, 40; number of data=1500; max iteration=100; P=%70; FCM clustering).

Afterward, in order to attain favorable system intelligence, another characteristic of the fluid inside BCR i.e. air superficial velocity was considered as the fifth input, and the learning processes were carried out for 20 ants. As presented in fig.6, the value of R for the training process has increased from about 0.20 to 0.96 and for the testing process, it has increased to 0.95, which indicates a very favorable enhancement in the system intelligence and the achievement of complete intelligence for the system. Using this intelligence, various parts of the BCR can also be predicted. In Fig. 7, points of BCR that participated in the learning process are observed.

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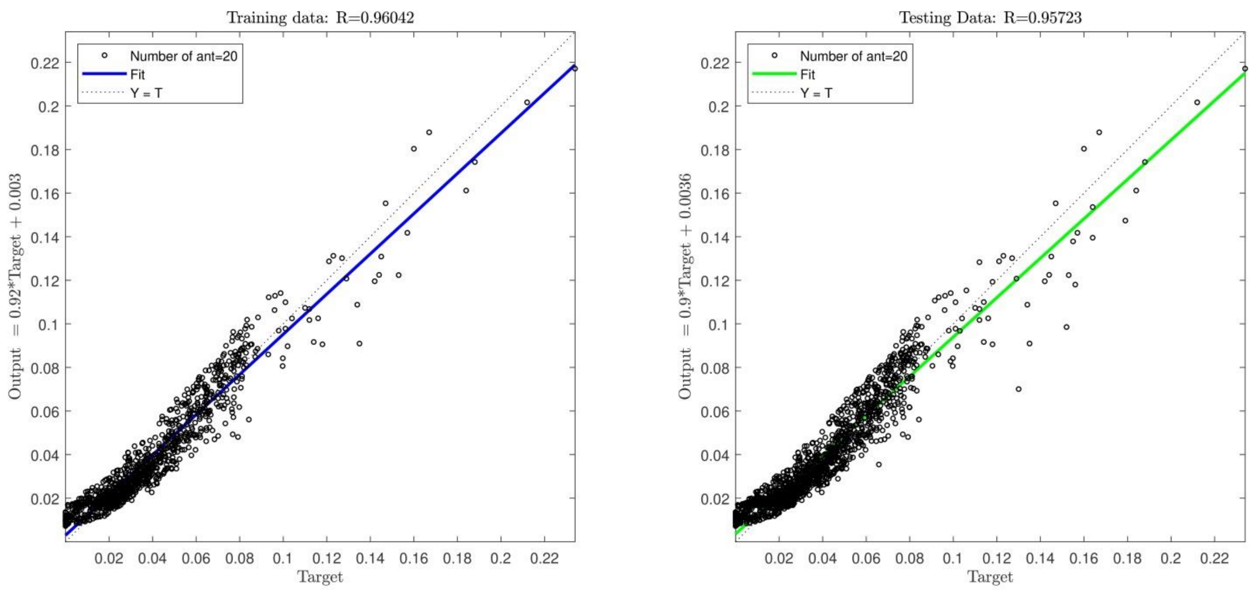

Figure 6: ant colony algorithm training and testing process with five inputs (number of ant =20; number of data=1500; max iteration=100; P=%70; FCM clustering).

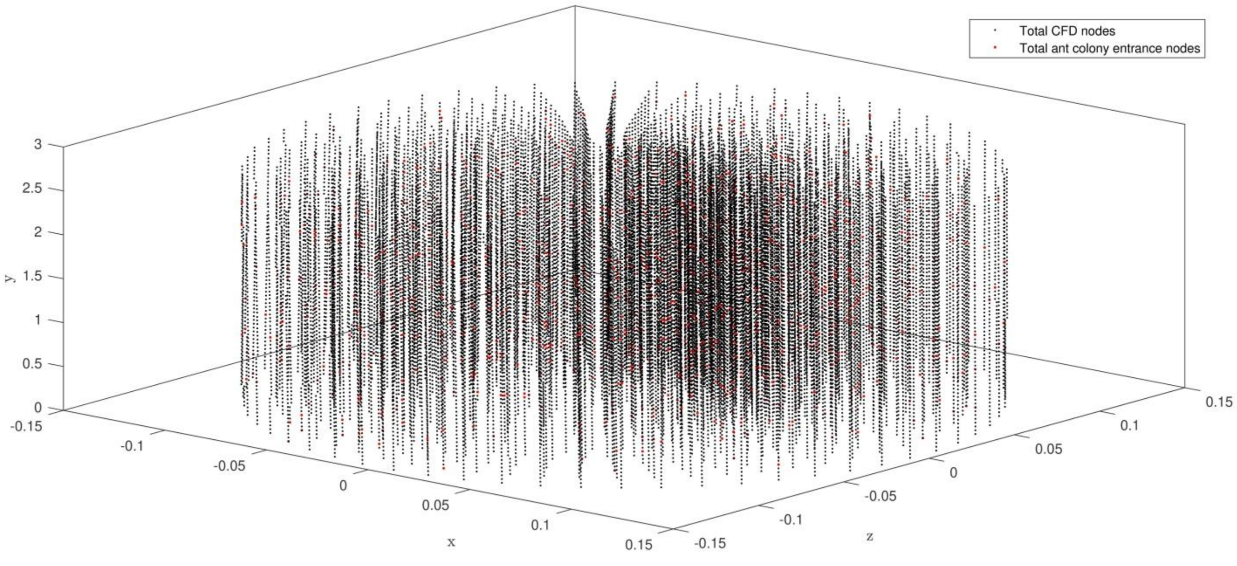

Figure 7: CFD method nodes that used in ant colony algorithm learning process.

The combination of artificial intelligence (ant colony algorithm) and the CFD method decreases the required time for calculations by the CFD method, it also leads to avoiding the solving of complex equations by the CFD method; moreover, by exploiting the created intelligence, much more information and result points can be acquired.

Comparison of the results of CFD and ant colony algorithm output demonstrates a very favorable agreement between the CFD results and the ant colony algorithm output (see Fig. 8(a, b)). Using this obtained intelligence, nodes that are not present in the learning process can be predicted and this shows the very favorable capacity of the artificial intelligence (ant colony algorithm), which is very advantageous and effective (see fig. 9).

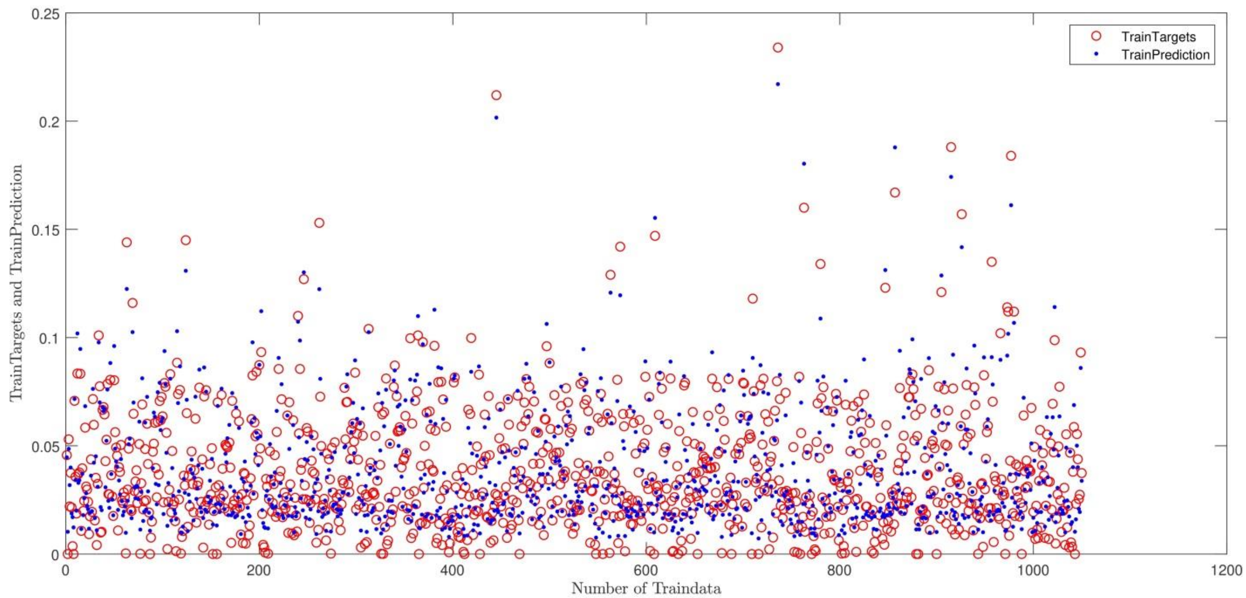

Figure 8(a): Training process target and prediction (number of ant =20; number of data=1500; max iteration=100; P=%70; FCM clustering).

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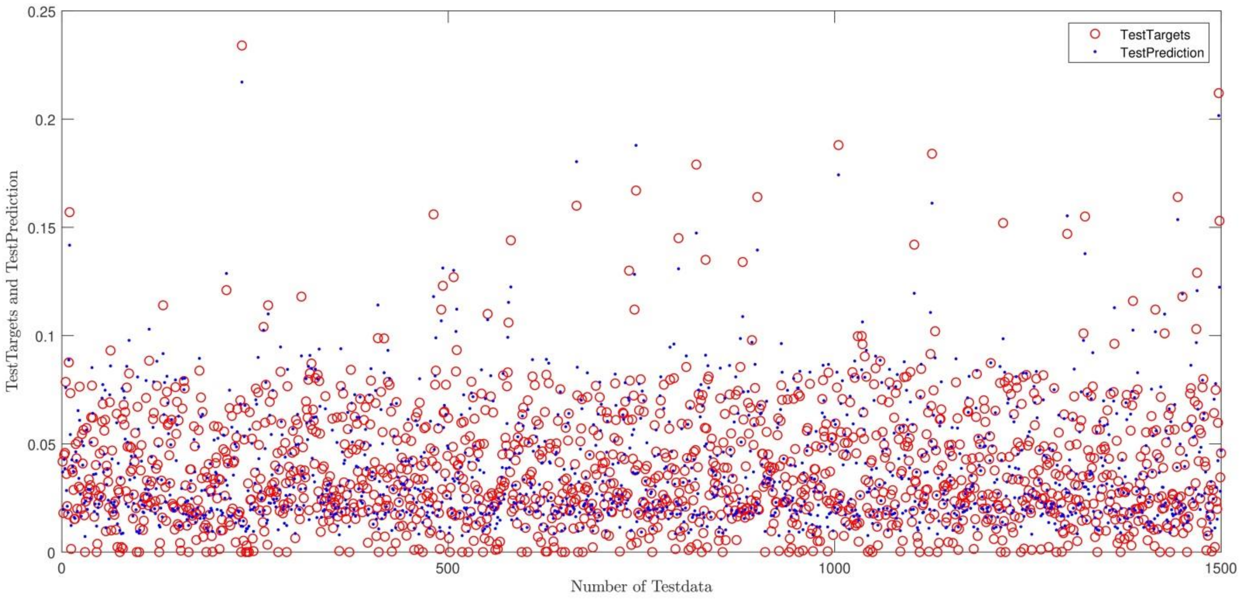

Figure 8(b): Testing process target and prediction (number of ant =20; number of data=1500; max iteration=100; P=%70; FCM clustering).

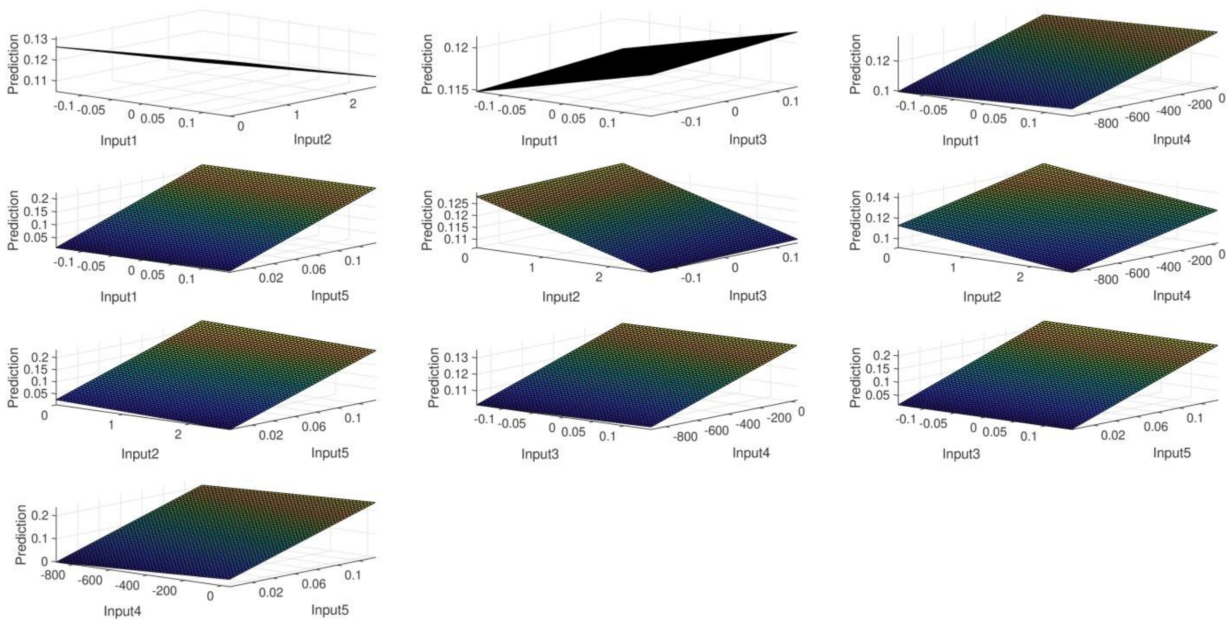

Figure 9: Ant colony algorithm Prediction (number of ant =20; number of data=1500; max iteration=100; P=%70; FCM clustering).

4 Conclusion

Current work describes the simulation of the gas fraction based on different bubble column characteristics with ant colony approach. In particular, the CFD data are considered as training inputs of ant colony method, and this method predict the behavior of the bubble column reactor. The simulation of the gas fraction is implemented in a 3D domain of fluid structure and it is compared with the results of CFD. In the training process, the reactor's top bottom and middle levels is chosen for computing the BCR hydrodynamics because of the gas holdup behavior at the mentioned levels. The Ant colony method model is an appropriate tool for prediction with almost 30 percent of data in the learning state. Nevertheless, the tuning parameters of this model significantly enhance the ant colony method's intelligence. Also, it is possible to train it in a highly short period of time (iteration), which provides a quick learning procedure having very small computational time and efforts. Moreover, as no obstacle of computational time is present, a higher amount of data can be generated in the input domain of data indicating novel reactor conditions with no experimental or numerical outcomes. This new perception of data analysis with artificial ants and local search algorithms is sophisticated process for post processing the data as other researchers started with other soft-computing methods.

1. Li, H. and A. Prakash, *Analysis of flow patterns in bubble and slurry bubble columns based on local heat transfer measurements.* Chemical Engineering Journal, 2002. **86**(3): p. 269-276.
2. Schäfer, R., C. Merten, and G. Eigenberger, *Bubble size distributions in a bubble column reactor under industrial conditions.* Experimental Thermal and Fluid Science, 2002. **26**(6-7): p. 595-604.
3. Kumar, A., et al., *Bubble swarm characteristics in bubble columns.* The Canadian Journal of Chemical Engineering, 1976. **54**(5): p. 503-508.
4. Dhotre, M., K. Ekambara, and J. Joshi, *CFD simulation of sparger design and height to diameter ratio on gas hold-up profiles in bubble column reactors.* Experimental thermal and fluid science, 2004. **28**(5): p. 407-421.
5. Lefebvre, S. and C. Guy, *Characterization of bubble column hydrodynamics with local measurements.* Chemical engineering science, 1999. **54**(21): p. 4895-4902.
6. Bouaifi, M., et al., *A comparative study of gas hold-up, bubble size, interfacial area and mass transfer coefficients in stirred gas–liquid reactors and bubble columns.* Chemical engineering and processing: Process intensification, 2001. **40**(2): p. 97-111.
7. Shah, Y., et al., *Design parameters estimations for bubble column reactors.* AIChE Journal, 1982. **28**(3): p. 353-379.
8. Pourtousi, M., J.N. Sahu, and P. Ganesan, *Effect of interfacial forces and turbulence models on predicting flow pattern inside the bubble column.* Chemical Engineering and Processing: Process Intensification, 2014. **75**: p. 38-47.
9. Kantarci, N., F. Borak, and K.O. Ulgen, *Bubble column reactors.* Process biochemistry, 2005. **40**(7): p. 2263-2283.
10. Cho, Y.J., et al., *Dynamic characteristics of heat transfer coefficient in pressurized bubble columns with viscous liquid medium.* Chemical Engineering and Processing: Process Intensification, 2002. **41**(8): p. 699-706.
11. Pino, L., et al., *Effect of operating conditions on gas holdup in slurry bubble columns with a foaming liquid.* Chemical Engineering Communications, 1992. **117**(1): p. 367-382.
12. Wang, S., et al., *Gas holdup, liquid circulating velocity and mass transfer properties in a mini-scale external loop airlift bubble column.* Chemical engineering science, 2003. **58**(15): p. 3353-3360.
13. Sokolichin, A. and G. Eigenberger, *Gas—liquid flow in bubble columns and loop reactors: Part I. Detailed modelling and numerical simulation.* Chemical Engineering Science, 1994. **49**(24): p. 5735-5746.
14. Chen, W., et al., *Generalized dynamic modeling of local heat transfer in bubble columns.* Chemical Engineering Journal, 2003. **96**(1-3): p. 37-44.
15. Ruzicka, M., et al., *Homogeneous–heterogeneous regime transition in bubble columns.* Chemical Engineering Science, 2001. **56**(15): p. 4609-4626.
16. Anabtawi, M., et al., *Hydrodynamic studies in both bi-dimensional and three-dimensional bubble columns with a single sparger.* Chemical Engineering and Processing: Process Intensification, 2003. **42**(5): p. 403-408.
17. Prakash, A., et al., *Hydrodynamics and local heat transfer measurements in a bubble column with suspension of yeast.* Biochemical Engineering Journal, 2001. **9**(2): p. 155-163.
18. Maalej, S., B. Benadda, and M. Otterbein, *Interfacial area and volumetric mass transfer coefficient in a bubble reactor at elevated pressures.* Chemical Engineering Science, 2003. **58**(11): p. 2365-2376.

19. Rabha, S., M. Schubert, and U. Hampel, *Intrinsic flow behavior in a slurry bubble column: a study on the effect of particle size.* Chemical Engineering Science, 2013. **93**: p. 401-411.
20. Dhotre, M.T., et al., *Large-eddy simulation (LES) of the large scale bubble plume.* Chemical Engineering Science, 2009. **64**(11): p. 2692-2704.
21. Michele, V. and D.C. Hempel, *Liquid flow and phase holdup—measurement and CFD modeling for two-and three-phase bubble columns.* Chemical engineering science, 2002. **57**(11): p. 1899-1908.
22. Behkish, A., et al., *Mass transfer characteristics in a large-scale slurry bubble column reactor with organic liquid mixtures.* Chemical Engineering Science, 2002. **57**(16): p. 3307-3324.
23. Leonard, C., et al., *Bubble column reactors for high pressures and high temperatures operation.* Chemical Engineering Research and Design, 2015. **100**: p. 391-421.
24. Krishna, R. and J. Van Baten, *Mass transfer in bubble columns.* Catalysis today, 2003. **79**: p. 67-75.
25. Luo, X., et al., *Maximum stable bubble size and gas holdup in high-pressure slurry bubble columns.* AIChE journal, 1999. **45**(4): p. 665-680.
26. Buwa, V.V. and V.V. Ranade, *Mixing in bubble column reactors: role of unsteady flow structures.* The Canadian Journal of Chemical Engineering, 2003. **81**(3-4): p. 402-411.
27. Masood, R. and A. Delgado, *Numerical investigation of the interphase forces and turbulence closure in 3D square bubble columns.* Chemical Engineering Science, 2014. **108**: p. 154-168.
28. Díaz, M.E., et al., *Numerical simulation of the gas–liquid flow in a laboratory scale bubble column: influence of bubble size distribution and non-drag forces.* Chemical Engineering Journal, 2008. **139**(2): p. 363-379.
29. Deen, N.G., T. Solberg, and B.H. Hjertager. *Numerical simulation of the gas-liquid flow in a square cross-sectioned bubble column*. in *Proceedings of 14th Int. Congress of Chemical and Process Engineering: CHISA (Praha, Czech Republic, 2000)*. 2000.
30. Shimizu, K., et al., *Phenomenological model for bubble column reactors: prediction of gas hold-ups and volumetric mass transfer coefficients.* Chemical Engineering Journal, 2000. **78**(1): p. 21-28.
31. Thorat, B. and J. Joshi, *Regime transition in bubble columns: experimental and predictions.* Experimental Thermal and Fluid Science, 2004. **28**(5): p. 423-430.
32. Krishna, R., J.v. Baten, and M. Urseanu, *Scale effects on the hydrodynamics of bubble columns operating in the homogeneous flow regime.* Chemical Engineering & Technology: Industrial Chemistry-Plant Equipment-Process Engineering-Biotechnology, 2001. **24**(5): p. 451-458.
33. Masood, R., Y. Khalid, and A. Delgado, *Scale adaptive simulation of bubble column flows.* Chemical Engineering Journal, 2015. **262**: p. 1126-1136.
34. Pourtousi, M., P. Ganesan, and J. Sahu, *Effect of bubble diameter size on prediction of flow pattern in Euler–Euler simulation of homogeneous bubble column regime.* Measurement, 2015. **76**: p. 255-270.
35. Razzaghian, M., M. Pourtousi, and A.N. Darus. *Simulation of flow in lid driven cavity by MRT and SRT*. in *Thailand: International Conference on Mechanical and Robotics Engineering*. 2012.
36. Verma, A. and S. Rai, *Studies on surface to bulk ionic mass transfer in bubble column.* Chemical Engineering Journal, 2003. **94**(1): p. 67-72.
37. Besagni, G., G.R. Guédon, and F. Inzoli, *Computational fluid-dynamic modeling of the mono-dispersed homogeneous flow regime in bubble columns.* Nuclear Engineering and Design, 2018. **331**: p. 222-237.
38. Silva, M.K., M.A. d'Ávila, and M. Mori, *Study of the interfacial forces and turbulence models in a bubble column.* Computers & Chemical Engineering, 2012. **44**: p. 34-44.

39. Li, H. and A. Prakash, *Survey of heat transfer mechanisms in a slurry bubble column.* The Canadian Journal of Chemical Engineering, 2001. **79**(5): p. 717-725.
40. Pourtousi, M., et al., *Prediction of multiphase flow pattern inside a 3D bubble column reactor using a combination of CFD and ANFIS.* RSC Advances, 2015. **5**(104): p. 85652-85672.
41. Besagni, G., G.R. Guédon, and F. Inzoli, *Annular Gap Bubble Column: Experimental Investigation and Computational Fluid Dynamics Modeling.* Journal of Fluids Engineering, 2016. **138**(1): p. 011302.
42. Clift, R., *Bubbles.* Drops and Particles, 1978.
43. Rzehak, R. and E. Krepper, *CFD modeling of bubble-induced turbulence.* International Journal of Multiphase Flow, 2013. **55**: p. 138-155.
44. Wang, H., et al., *CFD modeling of hydrodynamic characteristics of a gas–liquid two-phase stirred tank.* Applied Mathematical Modelling, 2014. **38**(1): p. 63-92.
45. Tabib, M.V., S.A. Roy, and J.B. Joshi, *CFD simulation of bubble column—an analysis of interphase forces and turbulence models.* Chemical Engineering Journal, 2008. **139**(3): p. 589-614.
46. Simonnet, M., et al., *CFD simulation of the flow field in a bubble column reactor: Importance of the drag force formulation to describe regime transitions.* Chemical Engineering and Processing: Process Intensification, 2008. **47**(9-10): p. 1726-1737.
47. Joshi, J., *Computational flow modelling and design of bubble column reactors.* Chemical engineering science, 2001. **56**(21-22): p. 5893-5933.
48. McClure, D.D., et al., *Development of a CFD model of bubble column bioreactors: part one–a detailed experimental study.* Chemical Engineering & Technology, 2013. **36**(12): p. 2065-2070.
49. McClure, D.D., et al., *Development of a CFD model of bubble column bioreactors: part two–comparison of experimental data and CFD predictions.* Chemical Engineering & Technology, 2014. **37**(1): p. 131-140.
50. Jamialahmadi, M. and H. Müller-Steinhagen, *Effect of alcohol, organic acid and potassium chloride concentration on bubble size, bubble rise velocity and gas hold-up in bubble columns.* The Chemical Engineering Journal, 1992. **50**(1): p. 47-56.
51. Pourtousi, M., *CFD modelling and anfis development for the hydrodynamics prediction of bubble column reactor ring sparger*. 2016, University of Malaya.
52. Buwa, V.V., D.S. Deo, and V.V. Ranade, *Eulerian–Lagrangian simulations of unsteady gas–liquid flows in bubble columns.* International journal of multiphase flow, 2006. **32**(7): p. 864-885.
53. Simonnet, M., et al., *Experimental determination of the drag coefficient in a swarm of bubbles.* Chemical Engineering Science, 2007. **62**(3): p. 858-866.
54. Xing, C., T. Wang, and J. Wang, *Experimental study and numerical simulation with a coupled CFD–PBM model of the effect of liquid viscosity in a bubble column.* Chemical engineering science, 2013. **95**: p. 313-322.
55. Burns, A.D., et al. *The Favre averaged drag model for turbulent dispersion in Eulerian multi-phase flows*. in *5th international conference on multiphase flow, ICMF*. 2004.
56. Mahmoud, M.A. and A.E. Ben-Nakhi, *Neural networks analysis of free laminar convection heat transfer in a partitioned enclosure.* Communications in Nonlinear Science and Numerical Simulation, 2007. **12**(7): p. 1265-1276.
57. Sudhakar, T., C. Balaji, and S. Venkateshan, *Optimal configuration of discrete heat sources in a vertical duct under conjugate mixed convection using artificial neural networks.* International Journal of Thermal Sciences, 2009. **48**(5): p. 881-890.
58. Ozsunar, A., E. Arcaklıoglu, and F.N. Dur, *The prediction of maximum temperature for single chips' cooling using artificial neural networks.* Heat and Mass Transfer, 2009. **45**(4): p. 443-450.

59. Saleem, M., G.A. Di Caro, and M. Farooq, *Swarm intelligence based routing protocol for wireless sensor networks: Survey and future directions.* Information Sciences, 2011. **181**(20): p. 4597-4624.
60. Rampure, M.R., A.A. Kulkarni, and V.V. Ranade, *Hydrodynamics of bubble column reactors at high gas velocity: experiments and computational fluid dynamics (CFD) simulations.* Industrial & Engineering Chemistry Research, 2007. **46**(25): p. 8431-8447.
61. Krishna, R., et al., *Influence of scale on the hydrodynamics of bubble columns operating in the churn-turbulent regime: experiments vs. Eulerian simulations.* Chemical Engineering Science, 1999. **54**(21): p. 4903-4911.
62. Berrichi, A., et al., *Bi-objective ant colony optimization approach to optimize production and maintenance scheduling.* Computers & Operations Research, 2010. **37**(9): p. 1584-1596.
63. Lu, H.-C. and H.-K. Liu, *Ant colony fuzzy neural network controller for cruising vessel on river.* Applied Ocean Research, 2013. **42**: p. 43-54.
64. Pourtousi, M., et al., *A combination of computational fluid dynamics (CFD) and adaptive neuro-fuzzy system (ANFIS) for prediction of the bubble column hydrodynamics.* Powder Technology, 2015. **274**: p. 466-481.
65. Xu, B., et al., *Ant estimator with application to target tracking.* Signal Processing, 2010. **90**(5): p. 1496-1509.
66. Dorigo, M. and L.M. Gambardella, *Ant colonies for the travelling salesman problem.* biosystems, 1997. **43**(2): p. 73-81.
67. Pfleger, D. and S. Becker, *Modelling and simulation of the dynamic flow behaviour in a bubble column.* Chemical Engineering Science, 2001. **56**(4): p. 1737-1747.
68. Dorigo, M. and C. Blum, *Ant colony optimization theory: A survey.* Theoretical computer science, 2005. **344**(2-3): p. 243-278.
69. Baker, B.M. and M. Ayechew, *A genetic algorithm for the vehicle routing problem.* Computers & Operations Research, 2003. **30**(5): p. 787-800.
70. Yu, B., Z.-Z. Yang, and B. Yao, *An improved ant colony optimization for vehicle routing problem.* European journal of operational research, 2009. **196**(1): p. 171-176.
71. McMullen, P.R., *An ant colony optimization approach to addressing a JIT sequencing problem with multiple objectives.* Artificial Intelligence in Engineering, 2001. **15**(3): p. 309-317.
72. Mullen, R.J., et al., *A review of ant algorithms.* Expert systems with Applications, 2009. **36**(6): p. 9608-9617.
73. Mocholi, J.A., et al., *An emotionally biased ant colony algorithm for pathfinding in games.* Expert Systems with Applications, 2010. **37**(7): p. 4921-4927.
74. Maroosi, A. and B. Amiri, *A new clustering algorithm based on hybrid global optimizationbased on a dynamical systems approach algorithm.* Expert Systems with Applications, 2010. **37**(8): p. 5645-5652.
75. Tian, J., L. Ma, and W. Yu, *Ant colony optimization for wavelet-based image interpolation using a three-component exponential mixture model.* Expert Systems with Applications, 2011. **38**(10): p. 12514-12520.
76. Mohan, B.C. and R. Baskaran, *A survey: Ant Colony Optimization based recent research and implementation on several engineering domain.* Expert Systems with Applications, 2012. **39**(4): p. 4618-4627.
77. Li, T., et al., *Fight sample degeneracy and impoverishment in particle filters: A review of intelligent approaches.* Expert Systems with applications, 2014. **41**(8): p. 3944-3954.
78. Rao, K.R., T. Srinivasan, and C. Venkateswarlu, *Mathematical and kinetic modeling of biofilm reactor based on ant colony optimization.* Process Biochemistry, 2010. **45**(6): p. 961-972.

79. Suganthi, L. and A.A. Samuel, *Energy models for demand forecasting—A review.* Renewable and sustainable energy reviews, 2012. **16**(2): p. 1223-1240.
80. Bell, J.E. and P.R. McMullen, *Ant colony optimization techniques for the vehicle routing problem.* Advanced engineering informatics, 2004. **18**(1): p. 41-48.
81. Blum, C., *Ant colony optimization: Introduction and recent trends.* Physics of Life reviews, 2005. **2**(4): p. 353-373.
82. Castillo, O., et al., *Dynamic fuzzy logic parameter tuning for ACO and its application in the fuzzy logic control of an autonomous mobile robot.* International Journal of Advanced Robotic Systems, 2013. **10**(1): p. 51.
83. Dorigo, M., M. Birattari, and T. Stützle, *Ant Colony Optimization-Artificial Ants as a Computational Intelligence Technique. 2006.* IEEE Computational Intelligence Magazine.
84. Valdez, F., P. Melin, and O. Castillo, *A survey on nature-inspired optimization algorithms with fuzzy logic for dynamic parameter adaptation.* Expert systems with applications, 2014. **41**(14): p. 6459-6466.
85. Khansari N, Farrokhi A, Mosavi A. Orthotropic mode II shear test fixture: Iosipesque modification. Engineering Solid Mechanics. 2019;7(2):93-108. 109.
86. Mosavi A, Salimi M, Faizollahzadeh Ardabili S, Rabczuk T, Shamshirband S, Varkonyi-Koczy AR. State of the Art of Machine Learning Models in Energy Systems, a Systematic Review. Energies. 2019 Jan;12(7):1301.
87. Dineva A, Mosavi A, Ardabili SF, Vajda I, Shamshirband S, Rabczuk T, Chau KW. Review of soft computing models in design and control of rotating electrical machines. Energies. 2019 Jan;12(6):1049.
88. Mohammadzadeh, D., et. al, Prediction of Compression Index of Fine-Grained Soils Using Gene Expression Programming Model Danial, infrastructures, 2019.
89. Rezakazemi M, Mosavi A, Shirazian S. ANFIS pattern for molecular membranes separation optimization. Journal of Molecular Liquids. 2019 Jan 15;274:470-6.
90. Fardad K, Najafi B, Ardabili SF, Mosavi A, Shamshirband S, Rabczuk T. Biodegradation of medicinal plants waste in an anaerobic digestion reactor for biogas production. Computers, Materials and Continua. 2018 Jul 6;55(3):318-92.