VI. CONCLUSION

The aim of this paper was to investigate the suitability of using artificial neural networks (ANN) for the prediction of biodiesel kinetic viscosity from its chemical composition. To train the network, experimental data was collected from more than 120 peer reviewed paper published in recognized journal, conferences and reports. Altogether, 352 data sets which included biodiesel chemical compositions and corresponding kinematic viscosity at 40 °C of biodiesel were collected. The collected data comprises biodiesels (fatty acid methyl esters) from 55 different feedstocks, 5 biodiesel-biodiesel blends and 59 pure methyl esters. In the training stage, to define the output accurately, the number of neurons in hidden layer and learning algorithm was optimized using trial and error methods. The best network for this study was a standard back propagation (BP) neural network model with LM algorithms and 45 neurons in hidden layer. The performance of the developed ANN prediction model was evaluated by prediction with the 25 data sets which were not used in the training process. The network produced the predicted results in good argument to the experimental ones. The overall results show that the networks can be used as an alternative way for predicting kinematic viscosity of biodiesel at different temperature conditions. The absolute fraction of variance (R2), Root-Mean-Squared (RMS) and maximum average error percentage (MAEP) was values were found 0.93, 0.18 cSt and 4.65% respectively which is within an acceptable range of accuracy. The results of this study also show that an ANN has the ability to learn and generalize a wide range of experimental conditions. Therefore, the usage of ANNs may be recommended to optimize the chemical composition of biodiesels to optimize fuel quality for internal combustion engine application. However the network should be further improved by including additional robust data set during the training process.

VII. ACKNOWLEDGMENTS

The authors wish to express their thanks to QUTPRA scholarship, Faculty of Science and Engineering (SEF), Queensland University of Technology (QUT) for proving fund for this study.

VIII. REFERENCE

[1]. A. Demirbas, “Relationships derived from physical properties of vegetable oil and biodiesel fuels” Fuel, 2008, Vol. 87, pp. 1743-1748.
[2]. S. Fernando, P. Karra, R. Hernande, and J. S. Kumar, “Effect of incompletely converted soybean oil on biodiesel quality” Energy, 2007, Vol. 32, pp. 844–851.
[3]. M. I. Jahirul, R. J. Brown, W. Senadeera, Z D Ristovski, and I. O'Hara, “Artificial neural network approach in identifying sustainable future generation biofuel feedstock” Energies. Special issue: Alternative Fuels for the Internal Combustion Engines (ICE), 2013, Vol. 6, pp. 3764-3806.
[4]. C. Y. Choi and R. D. Reitz, “A numerical analysis of the emissions characteristics of biodiesel blended fuels” J Eng Gas Turbines Power, 1999, Vol. 121, pp. 31–37.
[5]. S. Lee, D. Tanaka, J. Kusaka, and Y. Daisho, “Effects of diesel fuel characteristics on spray and combustion in a diesel engine” JSAE, 2002, Vol. 23, pp. 407–414.
[6]. M. E. Tat, and J.V. Gerpen, Biodiesel blend detection with a fuel composition sensor. Trans ASAE 2002, Vol. 19, pp. 30–36.
[7]. G. Knothe, and K. R. Steidle, “Kinematic viscosity of biodiesel fuel components and related compounds Influence of compound structure and comparison to petrodiesel fuel components” Fuel, 2005, Vol. 84(9), pp. 1059-1065.
[8]. D. P. Geller, and J, W. Goodrum, “Effects of specific fatty acid methyl esters on diesel fuel lubricity” Fuel 2004, Vol. 83, pp. 2351–56.
[9]. A. A. Refaat, Correlation between the chemical structure of biodiesel and its physical properties. Int J Environ Sci Technol 2009, Vol. 6, pp. 677–694.
[10]. E. Alkim, E. Gürbüz, and E. Kılıç, “A fast and adaptive automated disease diagnosis method with an innovative neural network model” Neural Networks, 2012 Vol. 330, pp. 88-96.
[11]. M. A. Costa, A. P. Braga, and B. R. Menezes, “Convergence analysis of sliding mode trajectories in multi-objective neural networks learning” Neural Networks, 2012, Vol. 330 pp.21-31.
[12]. S. Carrillo, J. Harkin, L. McDaid, S. Pande, S. Cawley, B. McGinley, and F. Morgan. “Advancing interconnects density for spiking neural network hardware implementations using traffic-aware adaptive network-on-chip routers” Neural Networks 2012, Vol. 330, pp. 42-57.
[13]. T. Samura, and H. Hayashi, “Directional spike propagation in a recurrent network: Dynamical firewall as anisotropic recurrent inhibition” Neural Networks, 2012, Vol. 330, 236-246.
[14]. D. Gao, Z. Yang, C. Cai, and F. Liu, “Performance evaluation of multilayer perceptrons for discriminating and quantifying multiple kinds of odors with an electronic nose” Neural Networks 2012, Vol. 330 pp. 204-215.
[15]. R. C. J. Minnett, A. T. Smith, W. C. Lennon, R. Hecht-Nielsen, “Neural network tomography: Network replication from output surface geometry” Neural Networks 2011, Vol. 245, pp. 484-492
[16]. S. Baroutian, and M. K. Aroua, “Estimation of Vegetable Oil-Based Ethyl Esters Biodiesel Densities using Artificial Neural Networks” J Appl Sci, 2008, Vol. 8 pp. 3005-3011
[17]. A. S. Ramadhas, S, Jayaraj, C. Muraleedharan, and K. Padmakumari, Artificial neural networks used for the prediction of the cetane number of biodiesel. Renewable Energy 2006, Vol. 3115 pp. 2524-2533.
[18]. J. Kumar, Bansal A, and M. K. Jha, “Comparison of Statistical and Neural Network Techniques in Predicting Physical Properties of Various Mixtures of Diesel and Biodiesel” Proceedings of the World Congress on Engineering and Computer Science. San Francisco, USA. October 24-26, 2000.