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Review article

Artificial intelligence models for refrigeration, air conditioning and heat pump systems

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ABSTRACT

Artificial intelligence (AI) models for refrigeration, heat pumps, and air conditioners have emerged in recent decades. The universal approximation accuracy and prediction performances of various AI structures like feedforward neural networks, radial basis function neural networks, adaptive neuro-fuzzy inference and recurrent neural networks are encouraging interest. This review discusses existing topographies of neural network models for RHVAC system modelling, energy prediction and fault(s), and detection and diagnosis. Studies show that AI structures require standardization and improvement for tuning hyperparameters (like weight, bias, activation functions, number of hidden layers and neurons). The selection of activation functions, validation, and learning algorithms depends on author's suitability for a particular application. Backpropagation, error trial selection of the number of hidden layer, and hidden layers' neurons, and Levenberg–Marquardt learning algorithms, remain prevalent methodologies for developing AI structures. The major limitations to the application of AI models in RHVAC systems include exploding or/and vanishing gradients, interpretability, and accuracy trade off, and training saturation and limited sensitivity. This review aims to give up-to-date applications of different AI architectures in RHVAC systems and to identify the associated limitations and prospects.

Contents

1. Introduction

Energy conservation, performance management, and technology enhancement of refrigeration, heating, ventilation, and air conditioning systems (RHVAC) are forefront challenges. It is almost impossible to develop an ideal RHVAC system with the capacity to address dynamic recommendations from United

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Nations Environmental Protection (UNEP) and consumers' regarding optimum safety, performance, and economy (Adelekan et al., 2021). The complexities arising from (i) phasing out and retrofitting conventional working fluids (refrigerants) like chlorofluorocarbons (CFCs), hydrochlorofluorocarbon (HCFCs), and hydrofluorocarbons (HFCs) categories, (ii) identification of ideal refrigerants compatible to emerging user pattern especially for stand-alone, centralized or decentralized RHVAC system, and (iii) compatibility clauses for renewable (like wind, solar, tidal, geothermal) sources as alternative energy are justifications for new RHVAC system development (Sarbu, 2014). Thus, complex multi-objective problems that require high precision solutions to optimize the cost and performance of ideal RHVAC are solved using artificial intelligence techniques (Mohanraj et al., 2012).

Comparing experimental and theoretical testing approaches with artificial intelligence-based models shows improved speed, accuracy, and shorter evaluation time (Aprea et al., 2017). Many cumbersome modelling and monitoring of engineering systems using AI models are available in recent literature (Aprea et al., 2017; Mohanraj et al., 2012). Observations of efficient computational speed, simplicity, and ability to solve multivariate linear and non-linear problems using AIs are common conclusions. AI models excellently map the relationship between input and output variables without requiring analytical equations (Mohanraj et al., 2012). AI is a branch of computer science that develops systems with reasoning and intelligence capacities closer to humans. The capacity of simplified biological neural networks inspires AI to apply to computational-based models of artificial neuron networks (Park and Lek, 2016).

Significance of artificial intelligence systems includes (i) ability to learn the functional relationship between data inputs and outputs, (ii) approximate accuracy of continuous functions, (iii) predict unseen linear/non-linear data, and (iv) use generalization and flexibility functions more accurately than traditional statistical methods (Gill et al., 2020). The primary goal of AI system development is to assure accuracy closer to humans in reasoning, action, perception, and uncertainty. AI systems model and forecast non-linear time series engineering applications, recognize patterns and classify and resolve clustered problems (See Hosoz and Ertunc (2016)). Studies on AI systems are rapidly evolving, and identifying variations in emerging classifications is increasingly difficult. The distinction between machine learning, artificial intelligence, and data science approaches is almost non-existent. AIs combine methodologies of machine learning algorithms (such as support vector, decision tree, k based neural network, Bayesian learning, deep learning), neurocomputing and data science techniques (including statistics, visualization, text mining, experimentation, time series forecasting, process mining, processing paradigms, data preparation) to enhance its ability to mimic required human cognitive functions. Many engineering systems, including refrigeration and air conditioning, adopt AI techniques of natural language processing, decision science, bias, vision, robotics, linguistics, and planning for monitoring energy consumption or evaluation of process and consumer behaviour, and prediction and modelling of performance and fault detection and correction (Hosoz and Ertunc, 2016; Esen et al., 2008; Mirnaghi and Haghighat, 2020) (See Fig. 1). These are due to AI's ability to extract useful information without requiring complex governing equations and assumptions through data mining and machine learning algorithms.

AI machine learning is classified into supervised, semi-supervised, unsupervised, deep and reinforced learning depending on the data type (continuous, discrete, qualitative, quantitative) and task requirement (Fig. 2). Supervised learning algorithms are better suited for classification and regression problems due to their prediction and modelling accuracies (Lizhi et al., 2021). In contrast, unsupervised learning algorithms are suitable for clustering problems. The need for superior advantages to supervised and unsupervised learning algorithms led to the development of semi-supervised learning. Thus, it enables the mapping of labelled and unlabelled data (See Gangadhar and Shanta (2018)). In reinforced learning, optimal steps towards the target goal depend on previous training environment consequences. Deep learning combines initialization of weights and biases using unsupervised learning and backpropagation tuning algorithms (Jelmer et al., 2020). Most AI learning algorithms can minimize error functions (or loss function, cost function) by accurately tracking the global optimal parameters through optimization techniques (like swarm particle optimization, simplex, support vector machines, and visualization monitoring of gradient descent, batch gradient descent, stochastic gradient descent, mini gradient descent).

AIs neurons estimate inputs and outputs data relationship models. These neurons in groupings called layers can be input, output and hidden layers, respectively. The number of input and output neurons accounts for input and output variables of interest. At the same time, the number of hidden layers affects overall performance. Neuron interconnections between these layers enable the reception and transmission of signals. The earliest artificial neuron network architecture is the multilayer Perceptron (MLP) arranged in a feedforward manner. Feedforward artificial neural network allows only forward signals processing using neurons equal to identified input and output variables. The simplified structure of neural networks NNs consists of at least one input, output and hidden layer. Reception, processing and transmission of information signals occur between these multiple interconnected computational block layers. These layers contain neurons equipped with pre-infused summation and transfer functions.

Neurons receive an accurate number of input signals and transmit a non-linear estimate of these input signals as output signals. The non-linear estimated outputs from nodes or neurons consist of the real value input signal, weights, biases, summation function and activation function (Fig. 3). Typically, summation functions sum all input signal assigned weights and bias. Computational outputs of a neuron squash to different ranges (such as 0 and 1, $+1$ and -1 etc.) as per their selected activation functions (like a sigmoid, hyperbolic tangent, binary, linear functions etc.). AI classification, forecasting, pattern recognition etc., attributes correlate directly to selected activation functions (Enrico et al., 2018). AI are mimics of the neuro-computing capacities of the human brain. Thus, diverse AI structures with unique functioning capacities and mechanism controls for information processing and decision-making exist. Various AI system classifications in accordance to structures (such as feedforward, radial based function, Kohonen self-organizing recurrent, convolutional, and modular neural networks (see Mulholland et al., 1995), type of functions (summation, activation, transfer), algorithms (learning or validation), cost function mapping approach (gradient descent, batch gradient descent etc.) and statistical performance gauging (RMSE, R^2, COV etc.).

This review aims to give up-to-date applications of different AI architectures in RHVAC systems and to identify the associated limitations and prospects. This work is structured as follows: Section 1 introduces the work; Section 2 reviews the efficient implementation of AI in RHVAC systems; Section 3 illustrates AI structures for refrigerators, air conditioners and heat pumps, and Section 4 discusses the limitations and prospects of artificial intelligence models in RHVAC system.

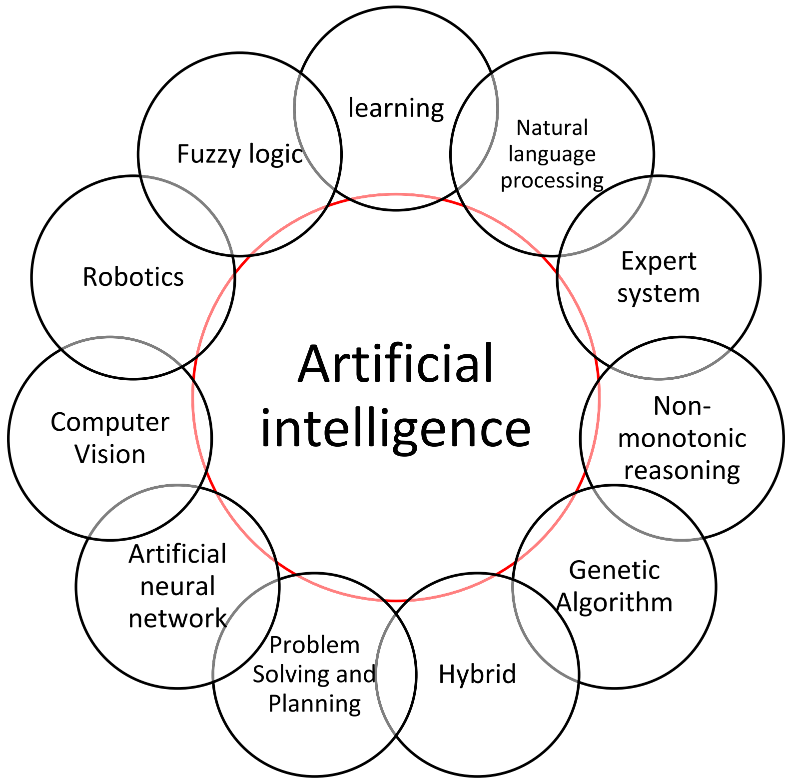

Fig. 1. Branches of artificial intelligence.

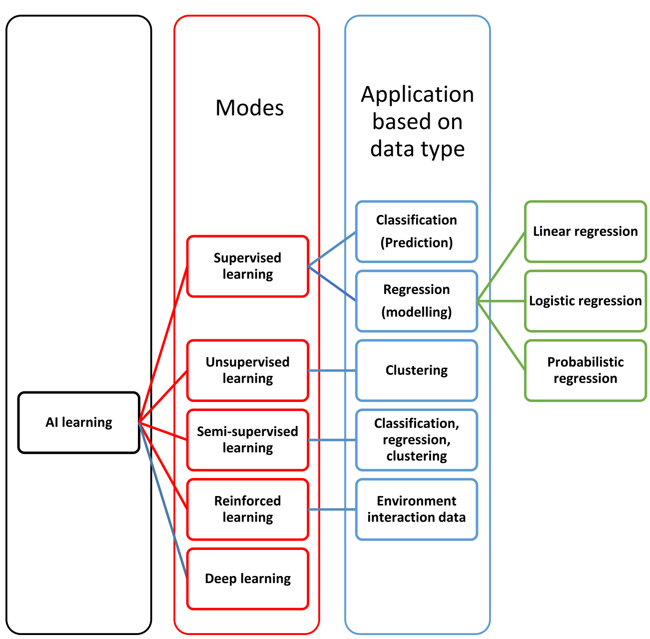

Fig. 2. AI learning algorithm classifications.

2. Recent application of AI in RHVAC system

Applications of AI structures like artificial neural networks, multi-feedforward neural networks, adaptive neuro-fuzzy inference systems, recurrent neural networks, radial biased neural networks, and convolutional neural network for different RHVAC applications is available in extant literature. Existing reviews detailed specialized AI applications for modelling, prediction, faults detection and monitoring refrigerators, air conditioners and heat pump systems. However, understanding the capacity of AI systems for future applications requires details of available varieties within existing AI structures. For instance, Mohanraj et al. (2012) reviewed the performance and characteristics of artificial neural networks structures radial biased neural network, adaptive neuro-fuzzy inference system, multilayer feedforward neural network, generalized regression neural network for predictive modelling of air conditioners, heat pump and refrigeration systems. The authors did not provide information on the characteristics of the AI structure capacities for modelling hybrids of these systems. Since the primary justification for adopting artificial neural networks is the ability to solve complex system processes, the complexities encountered with single and hybrid heating, cooling and power system integration energy and exergy analysis, building RHVAC load forecasting. RHVAC fault detection and diagnosis can be resolved with AI structures (Hadi et al., 2015; Gill et al., 2019a; Chen, 2020; Zhimin et al., 2014). Artificial intelligence neural networks can adequately model erratic or random systems (Haslinda et al., 2013). Other justifications for selecting artificial intelligent neural networks include (i) reasoning capacities (Gill et al., 2019b); and memory retention (Sendra-Arranz and Gutiérrez, 2020). Available modelling technologies for air conditioners are identified as ARIMA, backpropagation neural network and long short-term memory recurrent neural network by Chonggang et al. (2020). Although these models depend on regression models, ARIMA and backpropagation neural networks are not sensitive to randomness induced by the environment. Authors' identification of backpropagation neural network low sensitivity to environmental variations (random data) encouraged their development of an experience retaining long short-term memory neural network (also called recurrent neural network) for an air conditioner energy prediction. The selection requirements and justifications for adopting any AI architecture within RHVAC systems depend on the different application characteristics. Optimizing the safety, performance, and economy

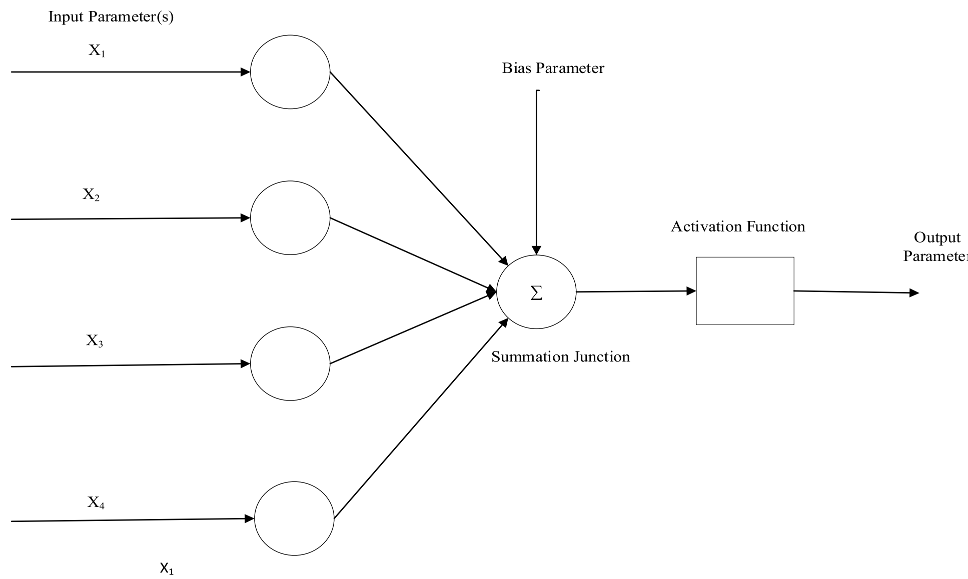

Fig. 3. Representation of activation neuron.

of refrigeration, air conditioning, and heating systems (RACHPs) has been a significantly complex challenge in recent decades. Abundant optimization studies on RACHPs subcomponents, primary/secondary working fluids (refrigerants) replacement, operating/ambient temperature etc., assert long computational time as justification for increasing AI modelling approach (Li et al., 2019; Tomczak and Kaminski, 2001). The use of neural networks is a state of the art trend for heat pump, refrigeration and air conditioning system development.

3. AI structures for refrigeration, air conditioning and heat pumps

This section describes applications of feedforward neural networks, adaptive neuro-fuzzy inference systems, radial basis function neural networks, and recurrent neural network models for RACHPs system. Inferences on the characteristics and selection justifications for these neural networks are also discussed.

3.1. ANN(s): Characteristics And application

Artificial neural networks (ANNs), also known as biological neural networks, are the most widely used AI models in RACHPs. ANNs process information using neuron relationship modelling of inputs to outputs (Gill and Singh, 2018a). ANNs behaves like black boxes equipped with interconnected processing units (that is, neurons). ANN neurons receive process, and send transformed signals between each other using mathematical functions that could be activation, summation or transfer functions. ANNs, like the human brain, memorize and learn from experience (Gill et al., 2020). Arrangement of neurons is according to layers, namely, input layer(s), output layer(s) and probably hidden layers. Artificial neural network (ANN) models deliver output(s) from input(s) through sets of computational processing units and predefined activation functions within neurons. ANN neurons identification depends on selected activation or transfer functions. Although the earliest applications of ANNs were suitable for learning, vision and conditioning, the development of ANN models has enhanced their widespread adoption. ANNs models can be linear mathematical or non-parametric and applied to linear and non-linear problems (Gill et al., 2018a). ANN models' performance depends on the number of hidden layers, number of hidden layer neurons, selection of training algorithms, activation function characteristics and error parameters (Mohanraj et al., 2012). The trial-and-error method of selecting the optimum number of hidden layers have been widely used in existing literature. Although a mathematical model to determine the number of hidden layers and hidden layer neurons is shown in the work of Wang et al. (2020). The observation of higher prediction accuracy with two hidden layer neural network model in comparison to single hidden layer model is shown in Thomas et al. (2017). In Gill et al. (2018a) study, activation functions were reported to be real, positive, limited, and continuous and have sigmoid shape. Activation functions simply correspond to calculation performed within artificial neurons of neural networks. A typical neural network neuron activation function consists of summation and transfer functions. The summation functions are a standard weighted sum of neural network inputs, bias and weights. In contrast, a linear or non-linear transformation of summation function solutions occurs in transfer functions of the activation function. Sigmoid, linear and Gaussian are popularly adopted forms of transfer functions (Kros et al., 2006). Sigmoid function also known as standard logistic function gives a simple differential equation solution ranging between 0 and 1. However, vanishing gradient problems occur in sigmoid or threshold activation function neural networks with three or more hidden layers. This limitation encouraged the development and adoption of rectified linear unit activation function. Neural network activation functions can be transcendental or algebraic groups. Algebraic activation functions are analytic functions having polynomial mathematical solutions, whereas transcendental activation functions (like sigmoid and tangent hyperbolic activation functions) do not have polynomial output solutions. Popular examples of algebraic activation functions are segmented linear function, step function, and algebraic sigmoid function. Other available activation functions include linear function, piecewise function, rectified exponential linear unit, partial rectified exponential linear units, leaky rectified exponential linear units, hyperbolic tangent, and logarithmic sigmoid function. Activation functions enable optimum performance of neural networks by controlling the speed of models during training and local minima determination processes. Since computations from activation layer are determined by activation functions, improving their performance is justifying development of new activation functions. Application of neurons with rectified activation functions as activation layers of neural networks are

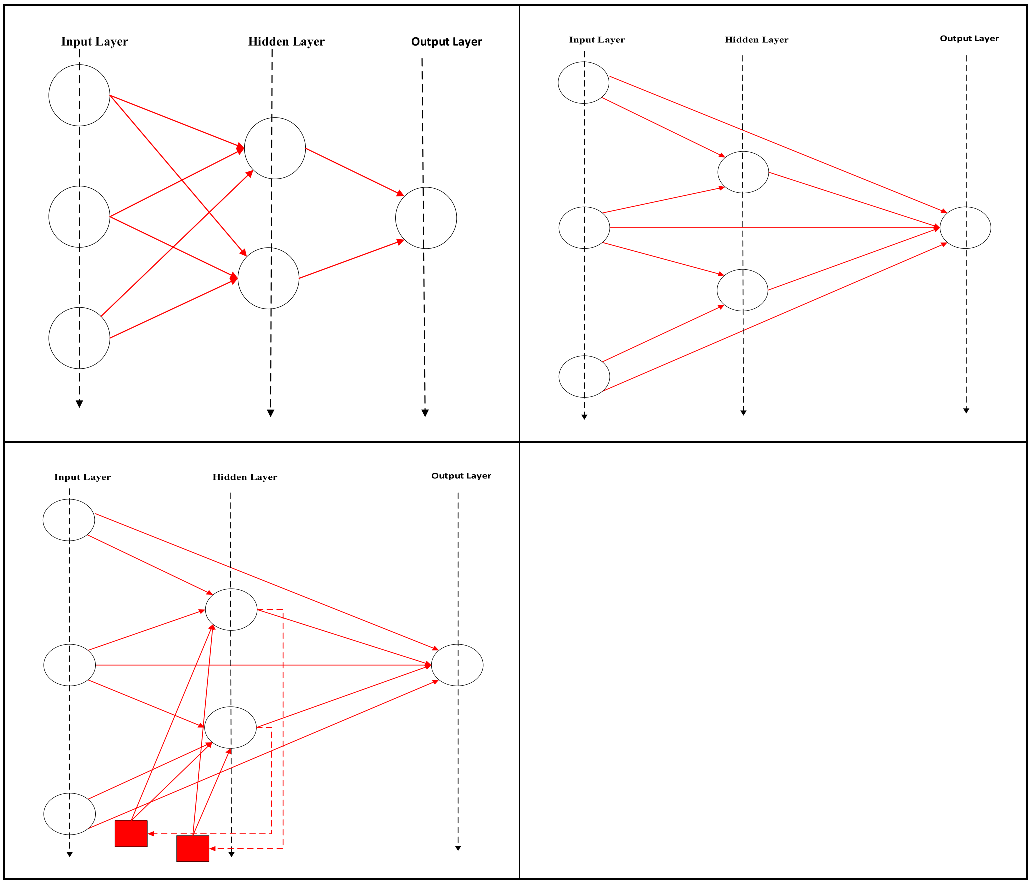

Fig. 4. (a) Feedforward backpropagation neural network; (b) Cascade forward backpropagation neural network; (c) Elman backpropagation neural network.

known as rectified linear units (RELU) (see Nair and Hinton, 2010). RELU activation functions have (i) easier and faster execution in comparison to sigmoid and tanh activation functions, (ii) better optimization of vanishing gradients, (iii) sparseness inducement and enforcement, and (iv) improve training speed for neural network with up to a thousand layers. However, RELU optimization performance is limited by their non-zero mean, unbounded outputs and negative missing characteristics (Zhou et al., 2021). RELU is compatible and efficiently adaptive with visual recognition-based feed forward neural networks (He et al., 2016).

Buchhop and Ranganathan (2019) successfully applied ELU, sigmoid and rectified ELU (RELU) based artificial neural networks for load profiling of residential dishwasher, furnace, refrigerator and stove. Gill et al. (2018a) adopted a sigmoid activation function for a domestic refrigerator energy parameter modelling, while Raghunatha Reddy et al. (2020) adopted log sigmoid activation function. Application of tangent sigmoid is available in Nasruddin et al. (2018), whereas log sigmoid was adopted by Faegh et al. (2021). It is important to note that the selection of the activation functions depends on the authors' requirements and preferences [see Ibham et al. (2022)].

The importance of training and validation algorithms in selecting optimum weights and biases for AI neurons cannot be overemphasized. It is arguably the toughest step required to improve the performances of AI models. Available validation techniques investigate prediction accuracy limits. Gill et al. (2018a) reported that setting the number of neurons in the hidden layer helped fit the experimental data accurately. The authors eliminated underfitting and overfitting of the experimental data using cross-validation and backpropagation algorithms.

3.2. Feedforward neural network and applications in RHVAC systems

Feedforward neural network allows unidirectional flow of signals from inputs to output without signal cycling or loop. These networks, like multilayer perceptron networks, are universal approximators for linear regression functions. Universal approximation functions give accurate gradient information between inputs and outputs. The outputs of neural networks are the summation of weights, biases and inputs. The primary characteristics of universal approximation feedforward neural networks are the application of non-polynomial activation functions and linear outputs (Leshno et al., 1993). Thus, besides traditional Bayesian classifier and linear discrimination model applications of feedforward neural networks, efforts to extend approximation capabilities of feedforward neural networks have been widely successful. Feedforward neural networks are better suited for either classification or regression problems. Feedforward neural networks train to set their weights and biases parameters using different backpropagation techniques (Feedforward backpropagation, Cascade backpropagation and Elman backpropagation). Nasruddin et al. (2018) reported that feedforward backpropagation neural networks differ from cascade backpropagation neural networks and Elman backpropagation neural networks by the uniqueness of their inputs–output correlations. There is no direct correlation between the input(s) and output(s) of feedforward backpropagation neural networks.

In contrast, cascade and Elman backpropagation neural networks directly correlate their input(s) and output(s). Elman backpropagation neural network, an extra layer called context layer, is included for weight adjustment without feeding the output(s) (Fig. 4a–c). Pure feedforward neural networks and their hybrid (like ANFIS) is widely adopted for predicting performances of refrigeration, air conditioner and heat pumps systems. Gill et al. (2018a) developed an artificial neural network based on feed-forward neural network for predicting irreversibility and second law efficiency of various LPG-TiO_2 nano lubricants in a refrigerator. The training and validation of the ANN models employed hybrid simulated and conjugate gradient method training algorithms and cross-validation techniques. The inputs neurons mapped inputs are condensing temperature, evaporating temperature, nanoparticle concentration and refrigerant mass charge. They obtained their signals through ten (10) hidden layer neurons to give desired outputs (second law efficiency and irreversibility). The ANN model prediction is permissibly accurate in comparison to the experimental results. Some authors used a similar approach to predict the power consumption, refrigeration capacity and coefficient of performances of LPG-TiO_2 nano-refrigerant driven refrigerator in Gill et al. (2018b). An assessment of artificial neural network (ANN) and adaptive neuro-fuzzy inference system (ANFIS) in predicting the performance of a variable speed scroll compressor is shown in the work of Zendehboudi et al. (2017a,b). The artificial neural network is characterized by a back-propagation algorithm, Levenberg–Marquardt algorithm, trial by error approach, number of hidden layer selection, 6-8-5 neuron number input/hidden/output layer architecture, and sigmoid and purelin transfer functions. While the ANFIS system had Sugeno fuzzy inference system, five layers (where layer 1 is for fuzzification or mapping fuzzy set to membership functions; layer 2 multiplies input signals to produce output; layers 3 and 4 are for normalization, defuzzification and layer 5 for summation); and utilized genfis2 subtractive clustering configuration selection algorithm. The comparison of the ANFIS and ANN models showed that the ANFIS model has the best prediction accuracy. Recently, applications of hybrid feedforward neural networks and fuzzy inference systems called ANFIS to RHVAC systems have grown. Tables 1 & 2 show other applications and characteristics of pure and hybrid feedforward neural networks applied in refrigeration, heat pumps and air conditioners. Comparative prediction performances of ANN and ANFIS models for a ground sourced heat pump studied by Esen and Inalli (2010) concluded that ANFIS model is better. The architecture of the best ANFIS model is triangular with two membership function. Similar affirmation is available in Sun et al. (2015);

3.3. Adaptive neuro-fuzzy inference system

Adaptive neural fuzzy inference system is a development introduced to fuzzy logic techniques for improved performance in engineering applications. In fuzzy systems, inputs are processed using predefined fuzzy arithmetic and rules to give output(s). Thus, Fuzzy systems have better reasoning capacity while neural networks have improved learning ability. Two types of adaptive inference systems based on fuzzy rules (Mamdani and Sugeno type) are adapted for engineering applications. In the Mamdani adaptive neuro-fuzzy system, the membership functions are fuzzy in nature, while Sugeno has linear or constant membership functions that enhance simplicity and accuracy. Mamdani ANFIS rules are more intuitive and interpretable than Sugeno ANFIS, especially where interpretability is absent and higher degree of freedom. Sugeno ANFIS are better suitable for multiple outputs based on computational analysis, whereas Mamdani ANFIS is more applicable to single output based functional analysis. ANFIS are simply the optimization of fuzzy inference systems using neural network. ANFIS combines if-then rules to membership functions to appropriately track inputs to outputs. Performance of ANFIS is dependent on minimization of prediction errors through modifications of if-then rules and membership functions. The earliest ANFIS development was developed in 1992 by Jyh-Shing Roger Jang. The Sugeno ANFIS had a multilayer feedforward neural network. Typical ANFIS model developments required specification of fuzzy rules (the rule 1 and 2), membership functions (A_1, A_2, B_1, and B_2) and design parameters (q_1, q_2, p_1, p_2, r_1, and r_2) acquired through training to function accurately (See Eqs. (1)–(2)).

$$Rule\,1 = if\ x\ is\ A_1\ and\ y\ is\ B_1,\ then\ f_1 = p_1x + q_1y + r_1 \tag{1}$$

$$Rule\,2 = if\ x\ is\ A_2\ and\ y\ is\ B_2,\ then\ f_2 = p_2x + q_2y + r_2 \tag{2}$$

Specification of predefined functions of ANFIS models is attained in hidden layers. For instance, Gill and Singh (2017a) selected triangular and bell shape membership functions to determine its hypothetical parameters in the first layer. In contrast, the strength of multiplication rules, normalized strength rule, linear combination rule and summation rule were determined in the second, third, fourth and fifth layers. The authors developed an ANFIS model to predict the coefficient of performance, total exergy destruction and exergy efficiency of a domestic refrigerator using a 28–72 mass fraction of R134a/LPG refrigerant blend (see Gill and Singh (2017a)). The selection of multi-feedforward neural network, 2-5-1 neurons input, hidden and output layers, circular and square membership function and two fuzzy rules gave the least error in the refrigeration system performance predictions compared to experimental test results. In another work by previous authors, a Sugeno ANFIS was developed to predict the coefficient of performance from refrigerant mass charge, evaporating temperature and capillary tube length variations of R134a/LPG driven refrigerator. The ANFIS model fuzzy inference system was based on grid partitioning development within MATLAB fuzzy logic toolbox. The two fuzzy rules, five hidden layers, three input layers and one output layer gave the best prediction. Details of the system backpropagated neural network training algorithm revealed authors used gradient descent tracking of the error functions between the predicted and target values and least square error methodology. In addition, the selection of the best ANFIS model was based on the absolute fraction of variance, root mean square error, mean absolute percentage error of predictions. Different ANFIS has been successfully applied for complex modelling and predicting heat transfer characteristics and energy and exergy performances of refrigerators Gill and Singh (2017b). Features like the coefficient of performance, exergy destruction, mass flow rate, total irreversibility, heat transfer coefficient, second law efficiency; were evaluated using ANFIS in recent literature (see Table 1b). Gill et al. (2020) applied triangular and bell shaped membership functions within a Sugeno ANFIS model. Minimization of prediction errors was through backpropagation gradient descent algorithms. The ANFIS model contained a six-layer multi feedforward neural networks and a grid partition fuzzy inference system developed using MATLAB fuzzy logic toolbox. Yuliang et al. (2020) developed an ANFIS based predictive system for a liquid desiccant air conditioner. The five-layer ANFIS model used to predict the humidity ratio and air temperature of the system consists of Takagi–Sugeno fuzzy inference system, backpropagation and least square algorithms. The primary Takagi–Sugeno fuzzy inference system maps the correlation between the input and outputs while the backpropagation and least square algorithms set the parameters of the neurons. The relative errors in terms of root mean square error and mean absolute error of the ANFIS predictive model compared to experimental values were 2% and 4% for the outlet air temperature and humidity ratio, respectively. Innovations to improve the performances of ANFIS models have emerged in recent times. Elimination of slow training speed and development encountered with hybrid gradient descent and simulated annealing ANFIS algorithms used for large scale univariate and multivariate time series problems

Table 1
Applications of FeedForward neural network in refrigerator, air conditioner and heat pumps.

S/N	Application	Author(s)	AI types	Specification	Input/Output parameter(s)	Conclusion
1	Refrigerator ($LPG-TiO_2$ nanorefrigerant)	Gill et al. (2018a)	Multilayer feedforward 10 hidden layer neurons ANN and ANFIS	– Hybrid training algorithm of simulated annealing and conjugate gradient training method – Leave one out cross validation technique – One hidden layer	Nanoparticle concentration, Refrigerant mass, Evaporating and Condensing temperature/ second law efficiency, total irreversibility	The ANN models and experimental results correlated perfectly
2	Refrigerator ($LPG-TiO_2$ nanorefrigerant)	Gill et al. (2019a)	Multilayer feedforward with 9 hidden layer neurons ANN	– Hybrid training algorithm containing simulated annealing and conjugate gradient training method. – Leave one out cross validation technique – One hidden layer	Nanoparticle concentration, Refrigerant mass charge, Evaporating and Condensing temperatures/ Power consumption, refrigeration capacity, coefficient of performance	ANN modelled the experimental results with high precision
3	Refrigerator (28/72) R134a/LPG	Gill et al. (2019b)	Multilayer feedforward with 1 hidden layer with 10 neurons	– Hybrid training algorithm containing simulated annealing and conjugate gradient training method. – Leave one out cross validation technique/ – One hidden layer	Evaporating and Condensing temperatures/ second law efficiency, total irreversibility	Comparison of the AI models showed ANN models predict the experimental results with higher accuracy than ANFIS models
4	Refrigerator (28/72) R134a/LPG	Gill and Singh (2018b)		– Levenberg and Marquardt training algorithm – Linear transfer function – Tangent sigmoid function –	Cumulative of refrigerant properties and subcooling, inlet pressure, effect of coiled capillary tube, capillary tube geometry/ Reynolds number	Comparison of ANN and dimensionless modelling showed the ANN model was better with higher R^2 and lower RMSE and MAPE values
5	Thermo-acoustic refrigerator (Helium refrigerant, $\lambda/4$ resonator tube)	Anas and Xiaoqing (2017)	Multilayer feedforward with 10 hidden layer neuron	– Backpropagation – Summation and activation functions – Undefined validation technique	Pressure, frequency/ cooling load	Observation of minimum prediction error was observed with the use of one hidden layer having ten (10) neurons
6	Ejector absorption heat pump (methanol/LiCl)	Adnan et al. (2004)	Multilayer feedforward with 7 hidden layer neuron	– Backpropagation – Levenberg and Marquardt – Gradient descent – Scaled conjugate gradient – Single hidden layer – Logistic sigmoid function – Polak–Ribiere conjugate gradient	Temperature, Pressure and Concentration of salts/ Specific volume	ANN models were considered to faster and simpler than other mathematical models
7	Refrigerator	Hasan et al. (2016)	Multilayer feedforward with 5 hidden layer neuron	– Backpropagation – Levenberg and Marquardt – Tangent sigmoid – Trial and error	Evaporator surface temperature, Gap between evaporator and glass shelf, fan velocity, Evaporator height/ evaporator heat rate, evaporator temperatures	The performance of the ANN and CFD models are comparable

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prompted the development of fast Fourier transform embedded with recursive least square ANFIS algorithms by Molbanin and Scott (2019). Mohammed et al. (2020) reported that integration of the firefly algorithm within ANFIS improves the prediction accuracies 1, 2 and 3 hourly energies consumed within different buildings. There are records in literature where another artificial intelligent model outperforms ANFIS. For instance, a comparison for selecting the most suitable model for different nanorefrigerant mixtures of R113, R114. Cu, Al, Al_2O_3 and CuO, respectively, was accessed by Zendehboudi et al. (2017b) using predictive models, namely multiple linear regression, multilayer perceptron-artificial neural network, adaptive neuro-fuzzy inference system (ANFIS), and least-square support vector machine. The authors concluded that a multilayer perceptron-artificial neural network

Table 1 (*continued*).

S/N	Application	Author(s)	AI types	Specification	Input/Output parameter(s)	Conclusion
8	Magnetic refrigerator	Aprea et al. (2017)	Multilayer feedforward with 11 hidden layer neuron	– Levenberg and Marquardt – Cross validation – Sigmoid function – Trial and error	Rotation of magnetic, volumetric flow rate, heat rejection temperature, temperature span/ electric motor power, pump electric power, cooling capacity, coefficient of performance	The system can be accurately modelled
9	Vapour compression refrigerator	Raghunatha Reddy et al. (2020)	Multilayer feedforward with 22 hidden layer neuron	– Log sigmoid – Backpropagation – Levenberg and Marquardt – One hidden layer	Capillary length, refrigerant charge, evaporator temperature/ refrigeration effect, coefficient of performance, power consumption	The multilayer neural network predicted with higher accuracy the multiple regression model
10	Absorption chiller ($LiBr-H_2O$)	Nasruddin et al. (2018)	Feedback propagation, Cascade forward backpropagation, Elman Backpropagation	– Tangent Sigmoid – Bayesian regularization – Two hidden layer – Backpropagation – Elman backpropagation – Cascade forward backpropagation	Radiation, ambient temperature, dry bulb temperature/ hot water temperature	Elman backpropagation had the least training error and poor validation error. Feedforward backpropagation gave the best validation error
11	Electric vehicle air conditioning system	Tian et al. (2015)	Multilayer feedforward with one hidden layer	– Levenberg–Marquardt – Logarithmic sigmoid – Tangent sigmoid – 0.1–0.9 normalization range – 0.01 learning rate – 1000 number of epochs – Trial by error method for selecting the best number of hidden layer neurons	Compressor speed, electronic expansion valve opening, condenser inlet air temperature, evaporator inlet air temperature/ mass flow rate, condenser heat rejection, refrigeration capacity, energy consumption	Application 4-13-4 ANN architecture model successfully predicted the performance of the electric vehicle air conditioning system with least error.
12	Automotive air conditioning system	Jani et al. (2016)	Feedforward with 2 hidden layers	– Trainlm, – learngdm, – Tansig – Backpropagation	Temperature, relative humidity, mass flow rate/ coefficient of performance, cooling capacity and input power	12-12-3-3 neuron per layer network gave the best modelling performance
13	Solar hybrid liquid desiccant air conditioning system	Abdulrahman et al. (2013)	Multilayer feedforward with 2-11 hidden layer neurons	– Backpropagation – Trial and error – Tan-sigmoid – 0 and 1 normalization range –	Air flow rate, desiccant flow rate, air inlet humidity ratio, air inlet temperature, desiccant inlet temperature/humidity ratio, temperature, moisture removal rate, effectiveness	5-5-1 ANN structure gave the best prediction for moisture removal rate while 5-11-11-1 ANN structure gave the best effectiveness prediction

(*continued on next page*)

obtained the best model parameter in terms of R^2, MSE, RMSE and AARD. Inference from these results is that the performance of models depends on the process characteristics. Saee et al. (2018) optimized the prediction performance of an ANFIS model using five optimization algorithms (namely genetic algorithm, particle swarm optimization, ant colony optimization, differential evolution, and backpropagation) for modelling pool boiling heat transfer of nanofluids containing ester oil (VG68), R113 with either diamond or copper nanoparticle. The authors concluded that particle swarm optimization with the ANFIS model is the best compared to other developed models.

3.4. Radial basis function networks

RBF network is a variation of feedforward neural network driven by radial basis transfer functions within its hidden layer. Different radial functions (like multi-quadratic and Gaussian radial functions) applied in radial neural networks originate from

Table 1 (*continued*).

S/N	Application	Author(s)	AI types	Specification	Input/Output parameter(s)	Conclusion
14	Automotive air conditioner	Haslinda et al. (2013)	Feedforward neural network with one hidden layer	– Tangent sigmoid – Backpropagation – Levenberg–Marquardt	Compressor speed, evaporator inlet temperature, evaporator inlet air velocity, condenser inlet air temperature/ cooling effect, compressor input power, coefficient of performance	The use of 4-3-3 neuron ratio gave the best ANN prediction accuracy in modelling the automotive air conditioner performance
15	Ground coupled heat pump	Esen et al. (2008)	Multilayer Feedforward neural network based on 3 algorithms for 7, 10, 13 and 15 hidden layer neurons	– Levenberg–Marquardt – Scaled and Polak–Ribiere conjugate gradients, tangent sigmoid	Ground, discharge and condensing temperatures/ coefficient of performance	Levenberg–Marquardt based neural network gave the least prediction errors
16	Ground coupled heat pump	Esen and Mustafa (2009)	Multilayer Feedforward neural network based on 3 algorithms for 6, 8 and 10 hidden layer neurons	– Levenberg–Marquardt – Scaled and Polak–Ribiere conjugate gradients, tangent sigmoid	Inlet and exit temperatures of evaporator and condenser, antifreeze solution inlet and exit temperatures/ coefficient of performance	Levenberg–Marquardt based neural network gave the least prediction errors
17	Vertical ground source heat pump	Esen and Inalli (2010)	Multilayer Perceptron and Back propagation	– Levenberg–Marquardt – Scaled Conjugate Gradient – Polak–Ribiere conjugate gradients for 6, 8 and 10 single hidden layer neurons	The input layers include air temperatures at the inlet and exit of the evaporator, condenser and water antifreeze solution. The output layers are the heating and cooling coefficient of performance	Levenberg–Marquardt based neural network gave the best convergence
18	Direct expansion air conditioner	Li et al. (2013)	ANN based on Inverse model	Online based adaptive controller	Input layer parameters include compressor speed and fan speed and the output layer parameters are the indoor air humidity and air temperature	High control accuracy was obtained with the online based controller for the dry and wet bulb temperatures
19	Automotive air conditioning system	Ng et al. (2014)	Online trained ANN	– Levenberg–Marquardt – Sliding stack window – 1 step-10 step prediction validation – Feed forward architecture – Back propagation	Parameters investigated include Evaporator air speed, inlet air temperature of condenser and evaporator and thermal load of cabin	The controllers had improved reference tracking, disturbance rejection and adaptation capacity

approximation theories. RBF has fast learning speed and universal approximation. While both RBF and multilayer perceptron neural networks are suitable for non-linear regression problems, RBF networks are examples of non-linear feedforward neural networks suitable for regression, classification, time series and pattern recognition. RBF neural networks have a high degree of tolerance to noise. RBF can be trained to firstly set the centres and widths of hidden layers using unsupervised learning algorithms like vector quantization, decision trees, and k means and lastly, the connecting weights using a least-squares algorithm, gradient descent algorithm, particle swarm optimization algorithm, genetic algorithm, ant colony algorithm, and differential evolution algorithm.

Simplified RBF has one hidden layer, unlike MLP that requires more than one. Hao et al. (2016) compared the predictive performances of multilayer perceptron neural network, radial basis function neural network and support vector machine for an ejector air conditioner. Comparison of the neural networks favoured the selection of MLP based on the best accuracy. The earliest development of radial basis function neural network came in 1987 through Powel that applied it for clustering and pattern recognition (Powell, 1987). RBF neural networks have a fast-learning rate, simple generalization estimation theory and good prediction performance compared to other neural networks (Seyed et al., 2016). The primary justifications for selecting RBF neural network by Seyed et al. (2016) include the ability to model non-linear

Table 2
Hybrid feedforward neural network (Adaptive neuro-fuzzy inference system).

S/N	Application	Author(s)	AI types	Specification	Input/Output parameter(s)	Error parameter
1	Refrigerator (28/72) R134a/LPG	Gill and Singh (2017a)	ANFIS (MLFFNN & Sugeno Fuzzy)	Gradient descent Backpropagation Least square 5 fuzzy rules	Refrigerant mass, Evaporating and Condensing temperatures/ Coefficient of performance, Exergy efficiency, Total exergy destruction	R^2, MAPE and RMSE
2	Refrigerator (28/72) R134a/LPG	Gill and Singh (2018a)	ANFIS (MLFFNN & Sugeno Fuzzy)	Gradient Descent Backpropagation Least square 5 fuzzy rules	Refrigerant mass, Evaporating and Condensing temperatures/ Coefficient of performance, Power consumption, Refrigeration capacity	R^2, MAPE and RMSE
3	Refrigerator (28/72) R134a/LPG	Gill et al. (2018c)	ANFIS (MLFFNN & Sugeno Fuzzy)	2 fuzzy rules Leave one out cross validation Grid partitioning and subtractive training	Refrigerant mass, and evaporating and condensing temperatures/ exergy destruction in compressor, condenser, evaporator and capillary tube	MSE, R^2, MAPE and RMSE
4	Refrigerator (LPG-TiO_2)	Gill et al. (2020)	ANFIS (MLFFNN & Sugeno Fuzzy)	2 fuzzy rules Leave one out cross validation Grid partitioning and subtractive training	Refrigerant mass, nanoparticle concentration, and evaporating and condensing temperatures/ total irreversibility and second law efficiency	MSE, R^2, MAPE and RMSE
5	Refrigerator (28/72) R134a/LPG	Gill and Singh (2017b)	ANFIS (MLFFNN & Sugeno Fuzzy)	Gradient descent, Backpropagation Least square 2 fuzzy rules	Cumulative of refrigerant properties and subcooling, inlet pressure, effect of coiled capillary tube, capillary tube geometry/ Reynolds number	MSE, R^2, MAPE and RMSE
6	Refrigerator (28/72) R134a/LPG	Gill and Singh (2017c)	ANFIS (MLFFNN & Sugeno Fuzzy)	Gradient descent, Backpropagation Least square 2 fuzzy rules 5 hidden layers Grid partitioning 3-3-3 Gaussian input	Refrigerant mass, evaporating temperature, capillary tube length/ coefficient of performance	MSE, R^2, MAPE and RMSE

processes quickly and resist weighted sum convexity. The authors applied the RBF to select an optimum PID controller for regulating the temperature and humidity of a hybrid HVAC system. Faegh et al. (2021) identified a peculiar attribute of the RBF neural network to be the application of non-linear kernel activation functions. The authors explained that RBF neural networks use lesser weights between input and output layers, thus yielding better learning speed than MLP neural networks. The RBF neural network prediction performance better than ANFIS and lower than MLP neural network, respectively.

Similarly, Sina et al. (2016) modelled an HVAC system for improved humidity and thermal comforts using an RBF neural network. The authors evaluation of RBF and fuzzy systems based on statistical parameter comparison favoured the selected RBF neural network. Extant study of RBF neural network application shows limited adoption in RHVAC systems. Faegh et al. (2021) predicted the performance of heat pumps using ANN, RBF and ANFIS models. Swider et al. (2001) successfully adapted a generalized RBF neural network to model the coefficient of performance of a liquid chiller with a prediction accuracy of $\pm 5\%$. Enhancement in the load forecast accuracy of an air conditioning system is found with a RBF neural network aided with ternary forecast correction models (namely; multiple linear regression, autoregressive integrated moving average and grey model) when compared with ordinary RBF neural network, or RBF with single model correction by Yao et al. (2006). Similar conclusion on prediction accuracy of RBF applied on a liquid chiller to determine coefficient of performance and compressor work input is available in Bechtler et al. (2001). Inference observed studying the application of RBF neural networks for RHVAC system control show limited application.

3.5. Recurrent neural network in RAC

Recurrent neural network, also known as auto-associative neural network, has cyclic connections that enable interchanging back and forth signal loop processes. The development of recurrent neural networks by John Hopfield in 1982 was due to the need for high universal approximation estimation accuracy and quick memorization through feedback looping. Unlike feedforward network with no back-loop signals, recurrent neural network is proficient for time series and sequential data analysis. Literature suggests that Elman in 1993 and Jordan developed modified recurrent neural networks in 1996. Many non-linear and dynamic engineering systems can be adapted for identification (pattern and speech recognition), time series modelling and elimination of adaptive noise (Tatyana et al., 2019). The limitations of modelling dynamics non-linear system process using feedforward networks justified application of partial recurrent networks (Adorn et al., 2000). The study investigated the accuracies of modelling non-linear processes with two types of partial recurrent neural networks. The structures were equipped with local output feedback and four training algorithms. The training algorithms utilized backpropagation techniques in the training and testing of the networks. The networks modelled the simulated non-linear process accurately. In the work of Ramazan and Tung (1997), Elman based recurrent neural network gave better noise filtering capacity than feedforward network. According to Robert and Gregory (2020), gated recurrent units and long short-term memory architecture of recurrent neural networks are modified feedforward neural networks with the capacity to estimate variable or infinite length sequential data. Recurrent neural networks popular training algorithms include generalized delta rule or energy minimization function (Tarun and Khalid, 2019). Typically, recurrent neural networks analyze outputs from two inputs (that present and past time step data inputs). Recurrent neural networks keep information of immediate previous time step data and apply it in processing the next output (Fig. 4). Zhihong et al. (2020) compared prediction accuracies of artificial neural networks and recurrent neural network models developed from actual meteorological data of a weather station. The recurrent neural network gave the best prediction accuracy in comparison to the actual data. Scanty studies on recurrent neural network application in refrigerators exist. Habtom (1999) investigated the performance of a recurrent multilayer perceptron neural network trained using backpropagation for predicting the relative humidity and temperature of a mechanical refrigerator. The recurrent networks had one hidden and output layer and three input variables. Levenberg–Marquardt learning algorithm improves the performance of the recurrent neural network in predicting both relative humidity and temperature. However, recurrent neural network suits random data prediction (or time series processes). The search for recurrent neural networks applications in RHVAC systems showed surging applications of long-short memory units, and gated memory recurrent neural networks abound in building RHVAC systems. Recurrent neural networks are innovative ways to solve demand-side energy management of HVAC systems in buildings (Sendra-Arranz and Gutiérrez, 2020); faults identification and diagnosis (Hadi et al., 2019), thermal comfort automation (Zhengbo et al., 2020); predicting energy consumption in commercial and residential buildings (Ali et al., 2019). Compatibility of recurrent neural network with smart grid networks analysis of electricity use pattern and consumer behaviour enables peak-average ratio reduction, peak shaving and cost reduction estimation (Rogers et al., 2019). Long and short-term memory units and gated recurrent units' architectures of recurrent neural networks can accurately predict future energy demand in grid-connected systems and self-consumption of local energy generation systems (See Sendra-Arranz and Gutiérrez (2020)). Recurrent neural network design requires the selection of an algorithm capable of modelling the actual time series problem and setting the prediction limits for implementation. In the work of Sendra-Arranz and Gutiérrez (2020), the absence of neural network models for short and ultra-short periodic variations of HVAC energy consumption monitoring as demand management strategies justified the application of long-short memory recurrent artificial neural network for HVAC load predictions. Authors developed and verified three stacked long-short memory recurrent neural networks for a solar house called Magicbox. These recurrent neural networks were multilayer perceptron aided with through-time based backpropagation and backpropagation learning and training algorithms. Information processing between inputs, outputs and forget gates allowed memory retention in the long, short recurrent network. In contrast, neuron network system computations used tanh and hyperbolic sigmoid activation functions and Hadamard product. According to Hadi et al. (2019), the primary limitation of existing RHVAC fault detection and diagnosis methodologies is the need for historical data before implementation and accurate tracking of multiple faults and classification of faults. The unavailability of extensive historical data for modelling faults diagnosis led to the development of a generative adversarial network for fault detection diagnosis in chillers by Ke et al. (2020). Applications of feedforward artificial neural networks for fault diagnosis require extensive validation and testing data. The availability of memorization in recurrent neural networks increases their adoption for modelling and fault diagnosis of HVAC systems. The increasing applications of fault detection and diagnosis methodologies in recent times is driven by reasons not limited to; (i) energy conservation; (ii) improved economy; (iii) reduced maintenance cost; (iv) reduced peak load; (v) reduced peak load; (vi) efficient feedback on system performance and (vii) environmental protection (Rogers et al., 2019).

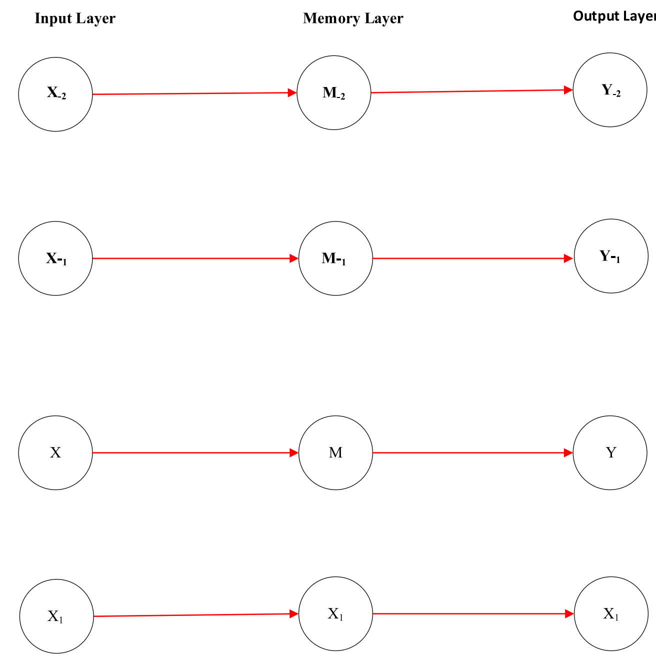

Fig. 5. Architecture of recurrent neural network.

Other available applications and architectures of existing recurrent neural networks for fault diagnosis and predicting energy consumption based on occupancy and performance parameter(s) RHVAC systems is depicted in Table 3 (see Fig. 5).

The complexity associated with developing accurate fault detection, monitoring and diagnosis (FDMD) system for RHVAC depend on accurate estimation of error signal transmission and classification. Resolving different faults with similar symptoms and different symptoms to a fault is a challenge widely researched. Incomplete information resulting from lack of data, faulty data, lack of sensors and physical scenario uniqueness; and uncertainty from measurements, symptom-fault probability and system process are issues limiting the development of improved physical FDMD systems (Zhao et al., 2019). Existing FDMD methods are data or knowledge-based approaches, while adopted artificial intelligence FDMD techniques include classification based, unsupervised learning-based and regression-based methods. Artificial intelligence models used for classification, association and prediction in FDMD technologies has increased considerably. These AI model applications (such as regression-based AI, association rule-based, clustering-based, support vector-based, probabilistic based, logarithmic based, principal component analysis based and classification based) were developed to enhance quantitative, qualitative and process history based physical FDMD methods (Katipamula and Brambley, 2005, 2011). In the work of Shiqiang et al. (2019), problems associated with a centralized model, databased sensor fault detection and diagnosis methods justified the development of microprocessor aid to a decentralized sensor fault network controller for RHVAC systems. The authors employed swarm particle algorithm in a decentralized RHVAC system to eradicate existing limitations and obtain equal-improved performance to conventional centralized sensor fault detection and diagnosis systems.

Huajing et al. (2019) reviewed applications of RHVAC system optimization designs. Three approaches, namely white box, black box and grey box approaches, were identified. The white box is based on traditional mathematical modelling of heat, mass, energy, and momentum transfer balances in building an RHVAC

Table 3
Application of recurrent neural network for RHVAC systems.

S/N	Application	Author(s)	Description	Specification	Input/Output parameter(s)	Error parameter
1	Sensor and actuator faults	Hadi (2020)	Generalized Elman neural network (layer recurrent neural network)	Bayesian regularization Backpropagation, prediction model based on 5 sub RNN models, hyperbolic tangent sigmoid function, 2 hidden layers with 5 neurons, linear transfer functions,	Intermediate product concentrations, cooling jacket temperature, / free radical concentrations (C_a, C_b), monomer concentration, temperature of reactor	Maximum absolute error
2	Multiple fault diagnosis of HVAC system	Hadi et al. (2019)	Layer recurrent network	Bayesian regularization Backpropagation, hyperbolic tangent sigmoid function, 3 hidden layers with 5 neurons and 1 delay, linear transfer functions, and subspace identification	Valve opening, inlet air and water temperatures/ supply air temperature, outlet water temperature	Maximum absolute error
3	HVAC system Sensor data validation	Mariam et al. (2020)	Auto associative neural network (optimal architecture 11-48-3-48-11)	3 hidden layers namely mapping, bottleneck and demapping layers, k fold validation, sigmoid and Tanh activation function, Adam backpropagation algorithm, grid search for selecting the best structure	Sensor parameter/ sensor correction, missing data replacement, noise reduction, inaccuracy reduction	Network reconstruction accuracy, and reduced noise level, mean squared error
4	Building energy forecast	Hanane et al. (2019)	Very short-term load and short-term load forecasting neural network models	Cross validation, fitness function, backpropagation, Levenberg–Marquardt, Bayesian regularization,	Humidity, dew point and dry bulb temperatures, occupancy index, previous energy demand data/	MAPE and RMSE
5	Occupancy prediction for building energy analysis	Wei et al. (2018)	Markov recurrent neural network aided with WiFi probe technology	Input, hidden, context and output layers, sigmoid function,	In-door air temperature, CO_2 concentration, humidity/ number of occupants	MAE, RMSE MAPE
6	Building energy analysis	Aowabin et al. (2018)	Comparison of Recurrent neural networks to multilayer perceptron neural network	ADAM gradient descent, gating function, long short-term activation function, weight decay regularization, early stopping generalization, six-layer recurrent models, 3-layer multi-perceptron model	Humidity, wind speed, solar irradiation, hourly, daily and monthly schedule plans/ aggregate electricity consumption	Relative error, RMSE, Pearson coefficient

system. In contrast, black box employs data-driven artificial intelligence to understand and model the behaviour of HVAC systems. Lastly, the grey box approach combines black and white box capabilities for improved performance. The use of genetic algorithm-based optimizations was found to be the most selected technique for RHVAC system optimization. Fault detection and diagnosis control mechanism for RHVAC system is a trend that improves aspects like energy conservation, reduction of energy cost, limitation of the maintenance cost, reduced peak load and demand, enhanced environmental efficiency and efficient system designs. Identified methodologies for fault detection and diagnosis have included the use of artificial intelligence to aid ease of fault detection and categorizing faults into soft or hard classifications. Notable faults that influence the performance of RHVAC systems includes filter blockage, fouled evaporator, bad filter, refrigerant undercharges, refrigerant overcharge, damage refrigerant duct or pipe, bad dryer or expansion valve, low pump power, valve leakage etc. Availability of modelling, classification,

Table 4
Artificial intelligence for fault and diagnosis in RHVAC systems.

S/N	Author(s)	Application	AI structure
1	Mavromatidis et al. (2013)	Supermarket RHVAC system energy and fault monitoring	Feedforward neural network (3-4-2 neuron per layer)
2	Dehestani et al. (2013)	HVAC air supply fan and damper faults tracking	Feedforward neural network integrated with support vector machine classification
3	Hou et al. (2006)	Development of sensor fault detection and diagnosis system using air handling unit temperature and humidity monitoring	Rough set approach and ANN
4	Zhimin et al. (2014)	Development of a detection system for soft sensor biases faults in HVAC system.	Backpropagation feedforward neural network with subtractive clustering classifier

imaging and prediction capacities within AI structures are some of the justifications that increase their selection. Traditional fault detection and diagnosis methodologies require tracking faults to performance. This raises two challenges (i) single faults may give multiple symptoms, and (ii) multiple faults may result in a single symptom. For instance, low cooling capacity can result from insufficient refrigerant driven by undercharging or leakage or low compressor pumping power. Whereas undercharging, refrigerant leakage and low pumping power may result in high energy consumption, low cooling capacity, and noisy compressor operation. AI structures for fault detection and diagnosis analysis rely on physical thermodynamic laws to model or track steady/transient performance variabilities. All thermodynamic models, including linear, non-linear, polynomial, and Bayesian functions, can be accurately solved by AI structures universal approximations. Evidence of AI capacity to accurately process electrical automation challenges like fault control, detection and diagnosis of process, equipment and operation is available in a mini performance review by Li (2020). The fundamental theories and methodologies of identifying the occurrence, locations of faults are extensive explained by Yaguo (2017). Selected applications of AI structures for fault detection and diagnosis is shown in Table 4.

3.6. Energy demand monitoring and prediction/forecasting of HVAC system

Overcoming the shortcomings of building HVAC system demand management technologies has increased the application of artificial intelligence for monitoring and predictive analysis. The precision and fitness accuracy of AI algorithms for time series forecasting is better than regression models. Thus, Sendra-Arranz and Gutiérrez (2020) developed several stacked long short-term memory artificial neural network models and verified their HVAC energy consumption forecasting accuracies within buildings. Three recurrent neural networks (RNN) architectures were developed to mathematically model the non-linear time series scenario. The backpropagation trained RNN accurately monitored six input variables (outdoor temperature, relative humidity, irradiance, user reference temperature, indoor temperature and carbon dioxide level) to predict the next day energy consumption of the building. Similarly, the energy demand of a building installed fan coil was accurately predicted using four input data (indoor air temperature, impulse air velocity, and the fan energy consumptions for samples one and two) radial based neural network by Yaser et al. (2018). The RBNN was trained using a gradient descent-based error minimization strategy (Levenberg–Marquardt training algorithm). The authors selected the best RBNN models using the least root mean square error and normalized root mean square error, respectively.

An assessment of significant input variables from 14 input data to predict energy use intensity in building HVAC systems was studied using multiple regression and artificial neural network by Chirab et al. (2018). The authors used Levenberg–Marquardt training algorithm with a backpropagation learning approach to determine the weight vector that gives the least error between the target and predicted output in the feedforward multilayer perceptron neural network. The study informed that selecting four input factors (including chiller plant efficiency, gross floor area, operational hour and energy consumption of air conditioners) gave the best energy use intensity prediction accuracies for the ANN model. Unlike the ANN model prediction, 5 inputs gave the best prediction accuracy with the regression model. Higher R^2 and lower MAPE values were observed for the ANN model when compared to the regression model. The best weights within the ANN architecture were based on gradient descent error minimization tracking of loss functions.

4. Limitations and prospects of artificial intelligent models in RHVAC system

The consensus on the performance of artificial intelligence dependent models to selected activation functions is popular. Thus, considerable efforts to improve the performance of traditional activation functions like sigmoid, rectified linear unit, partial RELU, tangent sigmoid, etc., are justifying the development of new activation functions like RELU swish, exponential swish, sinc-sigmoid, generalized swish, triple state swish and mean swish activation [See Kocak and Üstündağ Şiray, 2021].

Vanishing and exploding gradient problems, are dominant limitations to the performance of traditional activation functions in artificial intelligence networks. According to Alexander and Andreas (2020), the need to eliminate vanishing and exploding gradient problems of Elman recurrent neural networks, justified the development of gated units like long short-term memory and gated recurrent unit. Gated unit neural network such as long-short term memory network is easier to train than traditional recurrent neural network like Elman recurrent neural networks [See Goulas et al. (2021)]. The differences in the network topologies of Elman recurrent neural network and long-short term memory network in spite of their similar network architecture is responsible for long-short term memory network fast training capability.

Vanishing gradient problem in artificial neural networks especially feed forward neural networks with more than two hidden layers reduces approximation accuracies. The non-zero centre property of logistic sigmoid activation functions during training of artificial neural networks invariably lead to saturation and limited sensitivity (Brownlee, 2020). These limitation is resolved using rescaled logistic sigmoid activation functions by Xu et al. (2016). The application of accelerated Levenberg–Marquardt algorithm, equipped with error information filtering and width adjustment mechanisms also resolved vanishing gradient problem, memorization in training and increase learning performance of RBF neural networks as shown in the work of Miaoli et al. (2020).

Apart from the inability of feed forward artificial neural networks to account for interdependencies between its input variables in applications, other limitations of artificial neural networks shown in Ibham et al. (2022) include: (i) over fitting susceptibility, (ii) convergence uncertainty, (iii) big data requirement, (iv) undefined validation methodology, (v) trial and error for determining optimal network structure, (vi) limited regulation on amount and data training methods, (vii) complexity in the development of cause–effect correlations, (viii) absence of standard for determining the number of hidden layer neurons, (ix) insufficient information on criteria for selecting optimum training algorithm, and (x) absence of efficient training and validation algorithms in spite of their stability and accuracy.

ANFIS algorithm with reputable high generalization capabilities are costly to implement practically for increasing parameters. Complexities associated with ANFIS structure and gradient descent estimations, limit their practical implementation (see Salleh et al., 2017). Other identified limitations include: (i) selecting accurate membership function type and number, (ii) dimensionality problem, (iii) membership function location, and (iv) interpretability and accuracy trade off. The proposed solutions involve applying efficient training methods, and reducing rule-base or/and number of parameters. Reducing adaptive neurofuzzy inference system rule-base invariably reduces the computation time and number of parameters, and enhance accuracy (Salleh et al., 2017). Metaheuristic algorithms like particle swam algorithm (Kini et al., 2013), hierarchical hyperplane clustering synthesis (Panella, 2012), and Karnaugh map (Soh and Kean, 2012), are applicable solutions for addressing interpretability and accuracy trade-off limitations of ANFIS.

5. Conclusion

This work summarizes the applications of AI structures such as feed forward, radial basis function, adaptive neuro-fuzzy inference system and recurrent neural networks in refrigeration, heat pumps and air conditioners which focus on employed AI architectures and justifications for their selection. It was observed that feedforward neural work remains an excellent predictive model for RHVAC system approximation, while improvement in its performance depends on the accurate specification of training, testing and validation algorithms. The varieties of recurrent neural networks using Sigmoid activation function are improving modelling applications of AI in random or transient RHVAC process monitoring. Apart from predicting specific performance, improvement in the accuracy of fault detection and diagnosis, control, and monitoring of RHVAC systems has increased recently. However, the performance of the applications of these artificial intelligence models have been significantly impaired by vanishing and exploding gradient problems, costly computational/long training time during optimization of algorithms, and limitations in interpretability/accuracy trade-offs. The development and adoption of new and improved activation functions is being employed to address these application challenges.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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