5. PROPOSED SYSTEM

In this section, the investigation of HVAC and the refrigeration system are depending on the sensor models to detect the data of temperature, pressure, and the control units. The information sets have been downloaded from METEONORM. METEONORM utilizes the normal qualities from the period 1961-1990 for various climate stations as per the World Meteorological Institute (WMO) atmosphere typical (Remund 2005). The Forecasting model is designed by combining a two algorithm namely firefly optimisation algorithm, and LSTM techniques which are termed as Firefly based optimized Long Short-Term Memory Network (FOLSTM) model. Heretofore, firefly based heuristics used to find the time window size and architectural LSTM's hyperparameter factors. By using FOLSTM model, the prediction is improved efficiently which is compared with the conventional methods.

5.1 preliminaries

Firefly Optimization Algorithm (FOA)

A firefly optimization algorithm was a meta- heuristic algorithm which is motivated by a lifestyle of fireflies. The normal behavior of firefly was creating rhythmic and short blazes which is created by a process of bioluminescence according to inverse square law. The Fireflies are utilizing their flashes light for hunting, communication and cautioning their enemies. consider Light power (I) at a particular distance (r) where the light power diminishes with the increments of the distance between the fireflies. Also, the light and its power diminishes by air absorption and gets more vulnerable as distance increments. Hence, most fireflies communicate within a hundred meters distances which were its usual limit. Hence, the objective function is the blazing light which derived a population-based Firefly algorithm.

The light power I(r)) at r distance from a light source (ls) is can be determined using inverse square law which is given below.

$$I(r) = l_s/r^2 \tag{1}$$

The light is immersed in the air with a constant coefficient of light absorption ($\gamma \in (0,\infty)$. Therefore the Gaussian equation is formed and given in the following by Equation (2)

$$B(r) = B_0 e^{-\gamma r^2} \tag{2}$$

Where (r) is fireflies attractiveness at distance r and when r = 0, then B_0 is attractiveness.

Consider two fireflies i and j with its positions (, y_i) and $X_j(x_j$, y_j). r_{ij} is the two fireflies distance and the formulation is expressed by Euclidean which is shown in Equation (3)

$$r_{ij} = \|X_i - X_j\| = \sqrt{(x_i - x_j)^2 - (y_i - y_j)^2} \tag{3}$$

The new position ( ) of brighter firefly and its movement (j) is expressed in the following.

$$X_i = X_i + B_0 e^{-\gamma r^2}(X_j - X_i) + a \in_i \tag{4}$$

Where $\in_i$ is random vector variables and also the parameter of randomness (α) ∈ [0,1].

Long Short-Term Memory (LSTM)

Jürgen Schmid Huber proposed the LSTM dependent on the guideline of recurrent networks, the feedback connections stored the current info functions in the structure of the initiation (short-term) memory. Notwithstanding, error signals that were owing in reverse in time will in general explode or disappear. The cell state is the LSTM's key, which fills in as a transport line. The cell state directly runs the whole chain, with just some minor cooperations linearly. The gate structures are applied and used for regulations, LSTM can eliminate or add data to the phone state. Subsequently, LSTM was purposely designed to prevent dependency issues in long terms. There are three gates are presented in every cell such as input gate, output gate and forget gate. Assign an input of x(t) and h(t-1) and then every cell computation are expressed in the following.

$$f_t = \sigma(w_f.[h_{t-1}, x_t] + b_f) \tag{5}$$
$$i_t = \sigma(w_i.[h_{t-1}, x_t] + b_i) \tag{6}$$
$$g_t = tanh(w_g.[h_{t-1}, x_t] + b_g) \tag{7}$$
$$o_t = \sigma(w_o.[h_{t-1}, x_t] + b_o) \tag{8}$$
$$C_t = f_t.C_{t-1} + g_t.i_t) \tag{9}$$
$$Y_t = tanh(f_t.[C_{t-1} + g_t.i_t].o_t) \tag{10}$$

Where the t indicates the timestamp, C_t is the cell state and y_t is the output and it acts as a next timestamp input. The gates output are f_t, i_t, g_t, o_t and the coefficient matrixes are W_i, W_f, W_o, W_g, b_i, b_f, b_o and b_g respectively.

The data are corrupted by the error with the different cells interactions of input and output. Thus, the LSTM's loss function (L (t)) has two blocks namely loss at the time t, and the spread back loss from timestamp after the time t:

$$L(t) = \begin{cases} l(t) + L(t+1) & t < \tau \\ l(t) & t = \tau \end{cases} \tag{11}$$

Where τ is the last timestamp index.

5.2 Proposed methodology cc

FOLSTM TECHNIQUE

In general, LSTM utilizes previous data during the learning process, a proper selection of time window plays a significant role in an assured performance. The training model will omit important data when the window is too small.

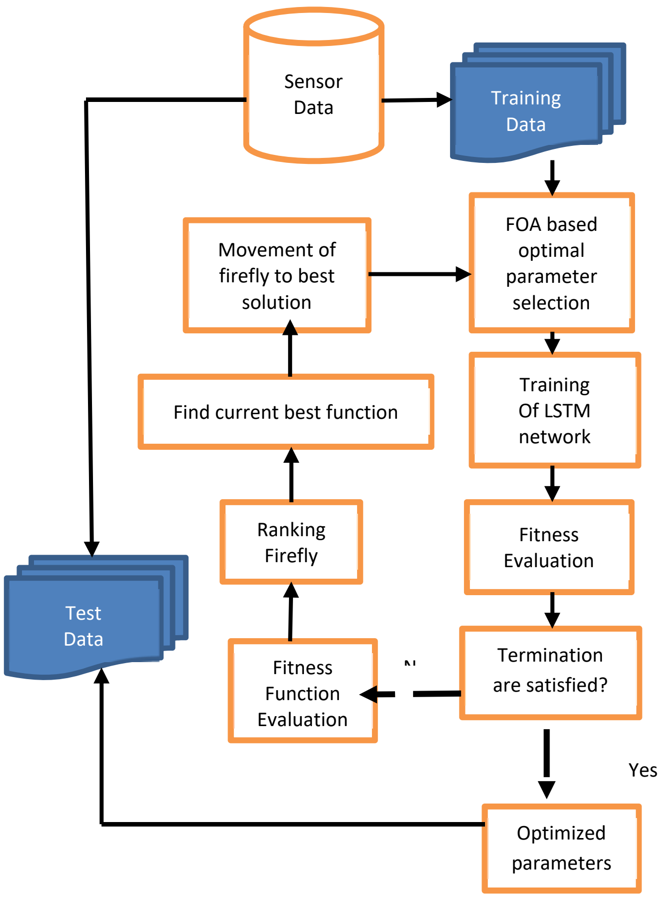

Fig. 2. Proposed prediction model.

Similarly, the model over fitted with training data when the window size is too big. The proposed prediction includes two stages, the proper selection of hyperparameters like time window size and architectural factors analysed by FOA.

The optimal number of hidden neurons in each hidden layer is examined by FOA. Primary weights of the network are set as random values, and the network weight is tuned by using a gradient-based "Adam" optimizer.
The figure 2 shows a flow chart of proposed work. Set m as LSTM's hyperparameters in attractiveness firefly and the exact prediction is done by LSTM as a criterion for calculating firefly positions. Next process is to search the flies iteratively.

Step1: Initialize the current position of fireflies and the hyperparameters LSTM to be optimized with the estimation of the upper and lower limit.
Step2: Substitute the LSTM hyperparameters corresponding to the every firefly position.
Step3: Divide dataset into train-set and test-set by updating recent data then predict the train-set next Sequence.
Step4: Compare the predicted value and test-set data
Step 5: Evaluate the error between the predicted value and test-set data using (11)
Step6: Evaluate the fitness function by brightening flashes of a firefly, and every firefly position changes using Equation (4).
Step7: Repeat Step 3-6 until satisfied.
Step 8: Result of optimized prediction is the hyperparameter position of firefly by LSTM

6. Result and Discussions

For the experiment, the data sets have been downloaded from METEONORM. METEONORM utilizes the normal qualities from the period 1961-1990 for various climate stations. The data set is separated into a training set and holdout sets. For prediction, pressure and temperature sensor values are used as input variables. The output of prediction models is detecting hazards or up normal event in HVAC systems

In this work the performance parameters of Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) used to find the error between actual and forecasted data. For air, comparison proposed prediction results compared with standard models of SVR (Support Vector Machine based Regression), and LSTM

RMSE characterizes the difference between the predicted value and the actual value. It is mostly used for finding the values at a different time interval. The prediction is more out of true when the value is high.

$$RMSE = \sqrt{\frac{\sum_{i=0}^{n-1}(y_i - f_i)^2}{n}} \tag{12}$$

The mean absolute error (MAE) is a quantity of errors between paired observations. The average error rate is,

$$MAE = \frac{\sum_{i=0}^{n-1}(y_i - f_i)}{n} \tag{13}$$

A statistical degree of the accurateness of a forecast model is the mean absolute percentage error (MAPE). It is estimated for each period by dividing the subtracted from the actual values to the actual values

$$MAPE = \frac{\sum_{i=0}^{n-1}(y_i - f_i)}{n\, y_i} X\ 100 \tag{14}$$

Table 2. Performance measure.

Method	**MSE**	**MAE**	**MAPE**
SVR	**198.5**	**13.3**	**1.30**
LSTM	**179**	**11**	**0.9**
FOLSTM	**174.99**	**10.18**	**0.86**

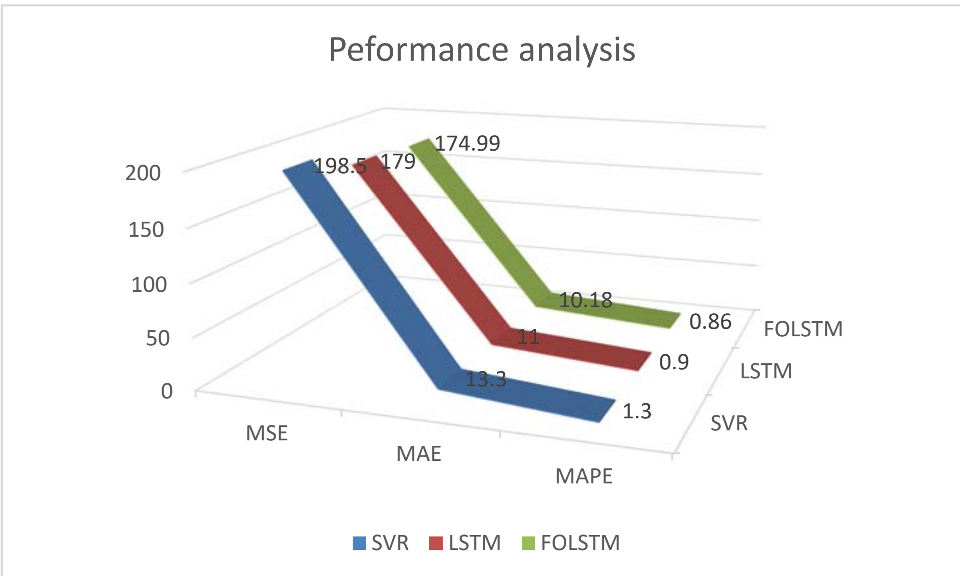

Figure 3 Performance analysis

The comparison result of proposed FOLSTM is shown in Table 1 and Figure 2, where the proposed FOLSTM is proved that it was much better than the Conventional method of SVR and LSTM respectively. In the MSE benchmark, the SVR has its value as 198.5 and LSTM has its value as 179 is 209.45, while the predicted MSE for proposed FOLSTM is 174.99 which enhances the performances by 13.11% than existing. Similarly the MAE and MAPE benchmark model of proposed FOLSTM is better than the SVR and LSTM respectively.

7. Conclusion:

In this paper, By IoT, enable the improvement of Predictive Maintenance. IoT based systems need to be enhanced with data science abilities, to attain the best objective of digitalization, which is supportive for decision making to optimally act on the physical systems. In this work, a hazard prediction model for Retail shops based on optimized LSTM networks was established. The experimental validation on data set shows that the proposed prediction model has better MAPE, MSE and MAE result performance. These entire outcomes show that optimized LSTM method can be an effective method for hazards and condition forecasting in retail shop systems.

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