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An energy efficient street lighting framework: ANN-based approach

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Abstract

An energy efficient street lighting framework is proposed in this paper to reduce energy consumption obtained from the street lights. It is determined for various possible inter-distances offered by International Commission on Illumination. An ANN model is approached to obtain such reduced energy consumption for various traffic volumes on the road with minimum mean square error. The results of the proposed approach show an improvement over existing works.

Keywords Street lighting · Energy consumption · Illuminance · Artificial neural network · Mean square error

1 Introduction

Street lighting system is an important component of a modern city that provides safety for the passersby and vehicles during night [19]. This lighting system is considered to be a major concern of the government for facilitating electricity. It is known that it consumes about 40% of the total electricity of a city [14] and about 114 TWh (TeraWatt Hour) annually [9]. In conventional street lighting system, lights are continuously on with 100% brightness for total operational hours that consumes an enormous amount of energy [10]. As a consequence, it results in huge CO_2 emission and also economic costs. Even an emission of over 150 millions tons of CO_2 is caused by the streetlights in USA also [5]. Therefore, this system needs to be utilized efficiently so that the energy consumption is reduced in case where lighting is unnecessarily kept ON. In order to resolve the issues in the field of street lighting, the International Commission on Illumination (CIE) [6] develops basic guidelines. Furthermore, improvements in lighting quality as per CIE can enhance safety conditions for both vehicles and pedestrians.

An energy efficient street lighting system is proposed in this paper that reduces the energy consumption of the streetlights by reducing unnecessary wastage of energy. In this work, the street lights are assumed to be controlled by the sensors so that an autonomous adjustment of brightness can be adopted by sensing the pedestrians and vehicles. Energy consumed by the streetlights is determined for various possible inter distance between two consecutive streetlights as per the recommendation of the CIE. In this context, an artificial neural network (ANN) [13] model is developed to predict the energy consumption for various traffic volumes and is trained several times for estimating the minimum mean square error (MSE) in connection to obtain reduced energy consumption. The results show an improvement over the existing work in terms of reduced energy consumption. Hence, the major contributions of the proposed work are highlighted as follows.

- An energy efficient street lighting system is proposed to reduce the energy consumption of the streetlights by reducing unnecessary wastage of energy.
- An ANN model is developed to predict the energy consumption for various traffic volumes.
- This ANN model is trained several times to assess the MSE related to obtain reduced energy consumption.
- Various simulation results show an improvement over the existing works in terms of reduced energy consumption.

The rest of this paper is organized as follows: Sect. 2 discusses a literature survey for completeness of the work. System model is presented in Sect. 3. Next, Sect. 4 describes the proposed approach. Various simulation results are shown in Sect. 5. The work is concluded in Sect. 6.

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2 Literature survey

In order to improve the energy efficiency of the street lights, various authors have contributed their research in different aspects. In [2], replacing traditional street lighting system by Light Emitting Diode (LED) lights have been studied in terms of energy consumption and the maintenance cost. Another lighting system is discussed in order to highlight the communication protocol for a group of wireless sensor nodes [21]. An adaptive lighting scheme presented in [9] adjusts the brightness of the streetlights in an energy efficient way. However, obtaining the energy consumption in this work was restricted for a predefined inter-distance. In another work [15], the energy-efficiency of the streetlights is approached in terms of various parameters related to the street conditions. In addition, various natural lighting scenarios and weather conditions have been considered for the dimming of streetlights [13]. Here, the output determines the luminance level after processing the information gathered from various nodes.

In [11], an algorithm has been used to analyze the data for street conditions and adapts the lighting level on the roads accordingly. The authors in [3] have developed a framework to support the decision making in selection of the efficient energy for a lighting system. Further, a procedure to enhance the energy efficiency for different lighting installation is used in [8]. Similarly, another algorithm has been applied in [16] for maximizing energy-efficiency by using illuminance of the light. In another research article [7], an ANN model was discussed with conventional training methodology with a manual setting of the number of neurons on hidden layers. However, the energy reduction is beyond scope of their work. Furthermore, a self-organizing map (SOM)-based model [17] has been developed to reduce the energy consumption of the lights as per user requirements.

In short, several procedures to obtain efficient energy for street lighting systems are discussed through various ways. However, minimizing error in order to obtain reduced energy consumption is beyond scope of their work. Hence, the work proposed in this paper introduces a predictive model for minimizing the error in order to obtain energy efficient street lighting system in accordance of traffic volume. This framework is comprehensively presented next.

3 System model

3.1 Network model

A sensor (S_i) is assumed to be associated with each streetlight (ST_i) as shown in Fig. 1, and the illumination of the lights is adjusted according to the Euclidean distance (d_{det}) from the pedestrian or vehicles. A total of $2m$ m (m meter front and m meter back) distance are considered to be lit for a single vehicle. Accordingly, each m meter is divided into different sub-regions (SR). Hence, the number of streetlights (N) required to cover such '$2m$' m distance can be determined as follows.

$$N = 2 \times \mathrm{SR} + 1 \tag{1}$$

Here, one light would be lit at the location of the pedestrian and SR number of lights would be lit at 'm' meter ahead as well as 'm' meter back of the pedestrian. Each sensor (S_i) determines the approximate distance (d_{approx}) of the streetlight with respect to the vehicles by using its detection

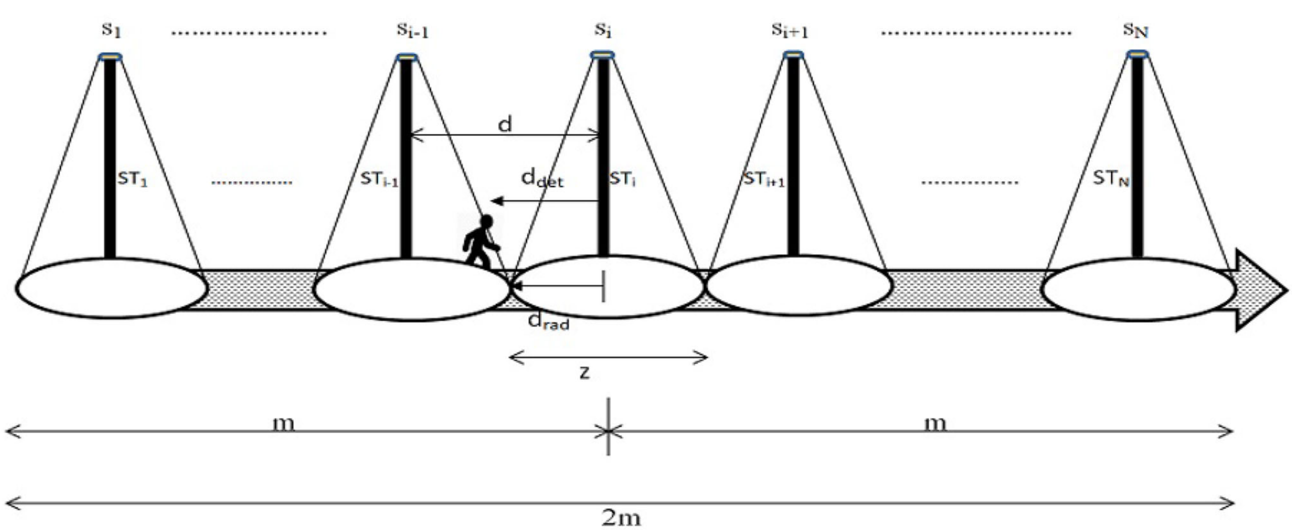

Fig. 1 Schematic background for the proposed work

range (d_{rad}). So, the value of such parameter (d_{approx}) can be obtained by the following.

$$d_{\text{approx}} = \begin{cases} 0 & d_{\text{det}} \leq d_{\text{rad}} \\ d_{\text{det}} - d_{\text{rad}} & \text{otherwise} \end{cases} \tag{2}$$

In (2), the approximate distance (d_{approx}) of the vehicles becomes zero if it appears in the detection range of the sensors. Further, the illumination level of the streetlights on each side of a pedestrian is adjusted according to the illumination zone $Z(d_{\text{approx}})$ of the streetlight with respect to d_{approx}. Here, $Z(d_{\text{approx}})$ can be determined as follows.

$$Z(d_{\text{approx}}) = \begin{cases} 0 & \lceil \frac{d_{\text{approx}}}{d} \rceil = 0 \\ \lceil \frac{d_{\text{approx}}}{d} \rceil - 1 & 0 \leq \lceil \frac{d_{\text{approx}}}{d} \rceil \leq \text{SR} \\ \text{SR} & \lceil \frac{d_{\text{approx}}}{d} \rceil \geq \text{SR} \end{cases} \tag{3}$$

The illumination zone of the nearest lights from the vehicles can be set as zero as per (3) and calculates the illumination zone of other lights to be lit accordingly.

3.2 Energy model

The energy consumption ($E(t)$) of the streetlights for t discrete timesteps, based on various inter-distance (d) between the streetlight, can be determined as.

$$E(t) = \sum_{n=0}^{t} P_{\max} \times \Phi \times T \tag{4}$$

where $P_{\max}$ is the maximum power rating from the source, Φ denotes the illumination level of the streetlight in % and T is the active time, i.e., the duration of the light being lit. The value of such $E(t)$ is determined for a particular vehicle/pedestrian passed by the specific street light. The procedure to determine these three parameters $P_{\max}$, Φ and T is discussed next.

At the very beginning, $P_{\max}$ is set as per the available power source. Next, for the safety purpose, the illumination level of the nearest lights would lit with full illumination level ($\Phi_{\max}$) and the rest of the lights would gradually decrease by a factor of $\frac{1}{\text{SR}}$. As the sub-regions SR depends on the value of 'd', so the illumination level of the streetlights is changed accordingly. Therefore, the illumination level (Φ) of a streetlight for a single vehicle can be expressed in terms of $Z(d_{\text{approx}})$ as.

$$\Phi = \Phi_{\max} + 2 \times \sum_{Z(d_{\text{approx}})=1}^{\text{SR}} Z(d_{\text{approx}}) \times \frac{1}{\text{SR}} \times \Phi_{\max} \tag{5}$$

Further, the parameter active time (T) is dependent on the speed of the vehicles. Less time is needed to cover a region, if the speed (S) of the vehicles is higher. Hence, T can be obtained as follows.

$$T = \frac{d}{S} \tag{6}$$

Remark 1 It is important to mention here that a set of traffic volume (TV) is considered in the proposed work as an additional parameter in order to determine the reduced value of energy consumption for different values of d.

4 Proposed approach

In order to minimize errors for obtaining an energy efficient street lighting system, an ANN-based approach is proposed in this work. For training purpose of the proposed ANN model, three input layers are taken as d, $E(t)$, and TV as shown in Fig. 2. The output layer of this model results the reduced energy consumption (E) obtained by the lighting system with minimum error value. The entire procedure is described as follows.

4.1 Input layer data collection

At first, the distance (m) to be lit before and after a pedestrian, the speed (S) of a pedestrian, the detection range (d_{rad}) of the sensors and maximum power rating ($P_{\max}$) are initialized with corresponding values provided by the system administrator. Further, the number of lights (N) to be lit is determined with the illumination level (Φ) for each pedestrian/vehicle according to the illumination zone $Z(d_{\text{approx}})$ on which a pedestrian belong to. Accordingly, the value of $E(t)$ is obtained at a specific time for every possible inter-distance

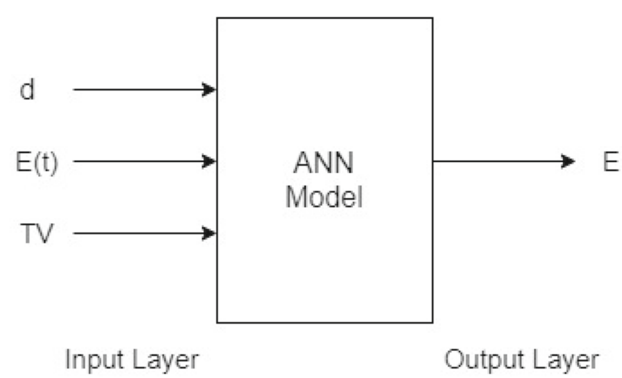

Fig. 2 Block diagram of the proposed ANN model

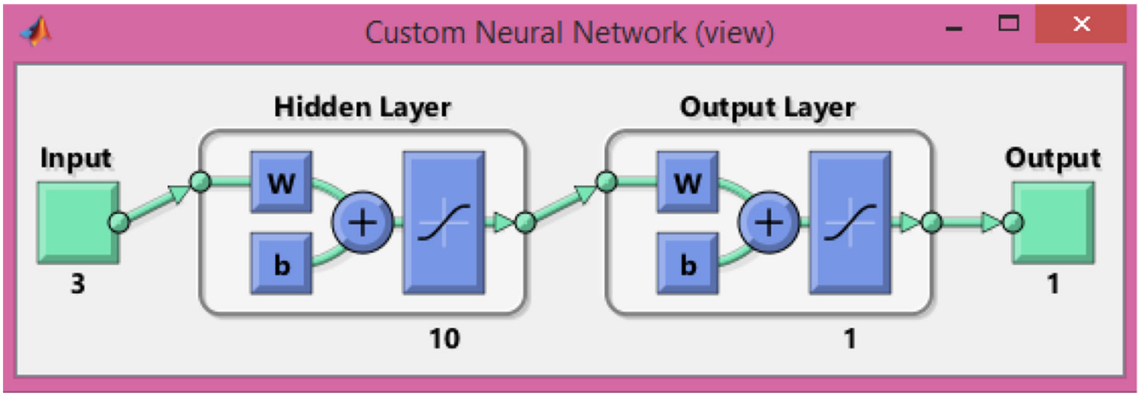

Fig. 3 Framework of the proposed ANN model

Table 1 Parameters used in simulation

Parameters	Value
Road segment to be lit (m)	150 m
Range of inter-distance (d)	10–50 m
Traffic volumes (TV)	180, 438, 1347, 3508, 6554 per day
Maximum illumination (Φ_{max})	100%
Input layer with number of neuron in ANN model	3 (d, $E(t)$, TV)
Output layer with number of neuron in ANN model	1
Number of Hidden layer in ANN model	1

Table 2 Various combinations of input values

d (m)	$E(t)$ (KWh)	TV (number of vehicles)
10	354.167	180
20	375.000	438
30	437.500	1347
40	500.000	3508
50	520.833	6554
10	354.167	438
20	375.000	3508
30	437.500	438
40	500.000	180
50	520.833	3508

Table 3 MSE for different training

Trial no.	MSE
1	6.4443e−05
2	2.4994e−08
3	5.7001e−07
4	1.5531e−05
5	6.8036e−05
6	1.0861e−04
7	8.1275e−05
8	7.9069e−05
9	8.2555e−04
10	9.2928e−06

(d) recommended by the CIE. This procedure is described by Algorithm 1.

Remark 2 The amount of traffic volume is set for different timing of a day including rush hours as well as an idle road. It also considers the traffic for weekends and weekdays also.

4.2 ANN model development

Algorithm 1 discussed earlier evaluates the energy consumption ($E(t)$) of the streetlights for different values of 'd''. Under such scenario, a neural network with feed-forward back-propagation approach is used to obtain the reduced value of E for varying the values of d and TV such that minimum error can be obtained. Here, variable learning rate (TRAINGDX) [20] is used as the training function so that the learning rate can be adapted accordingly in the training procedure to minimize the error. For the performance measurement in the proposed work, the error is computed as Mean Square Error (MSE) [1].

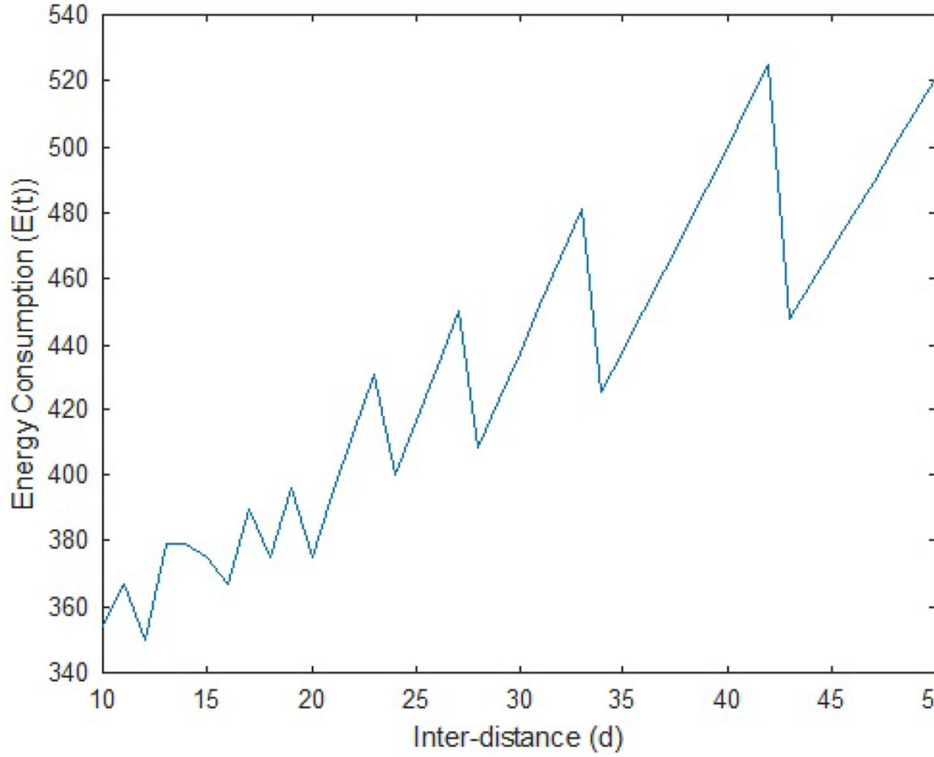

Fig. 4 Energy consumption $E(t)$ for a vehicle at time t

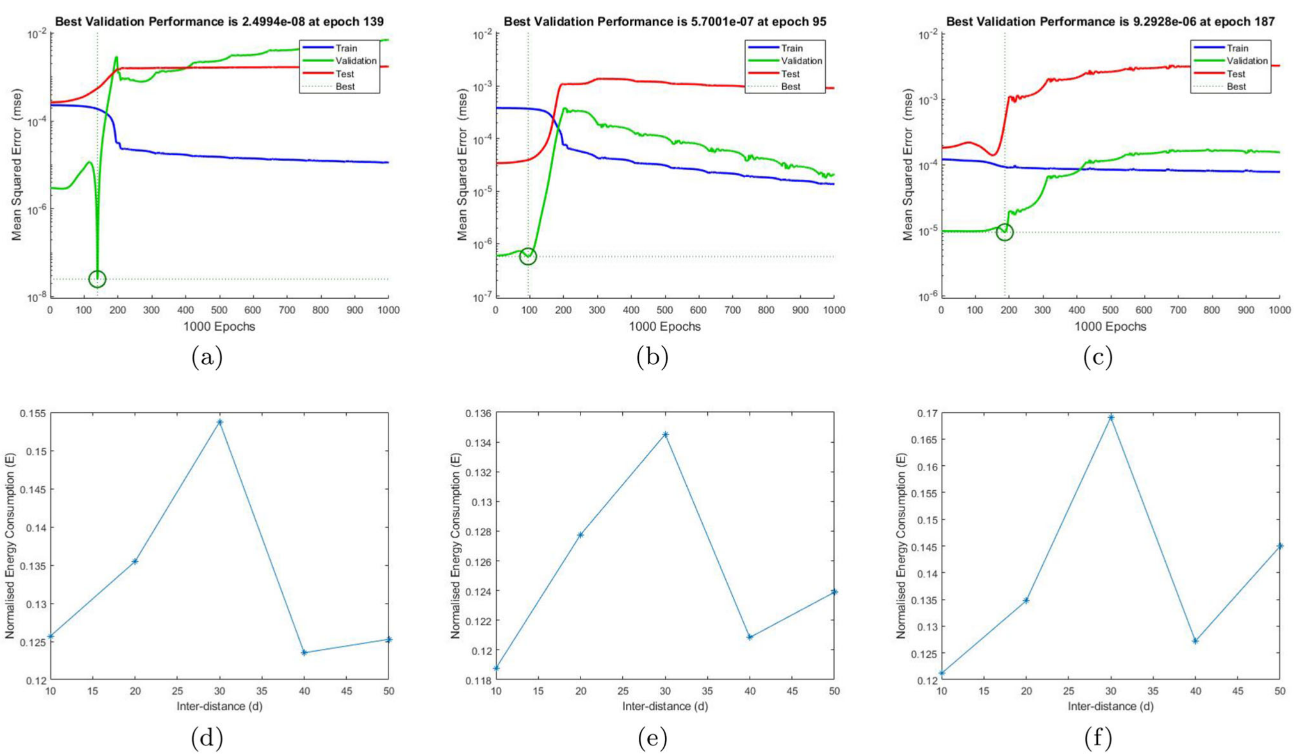

Fig. 5 **a**–**c** Performance plot of the ANN model, **d**–**f** Corresponding normalized energy consumption for different inter-distance and traffic volume = 438 vehicles

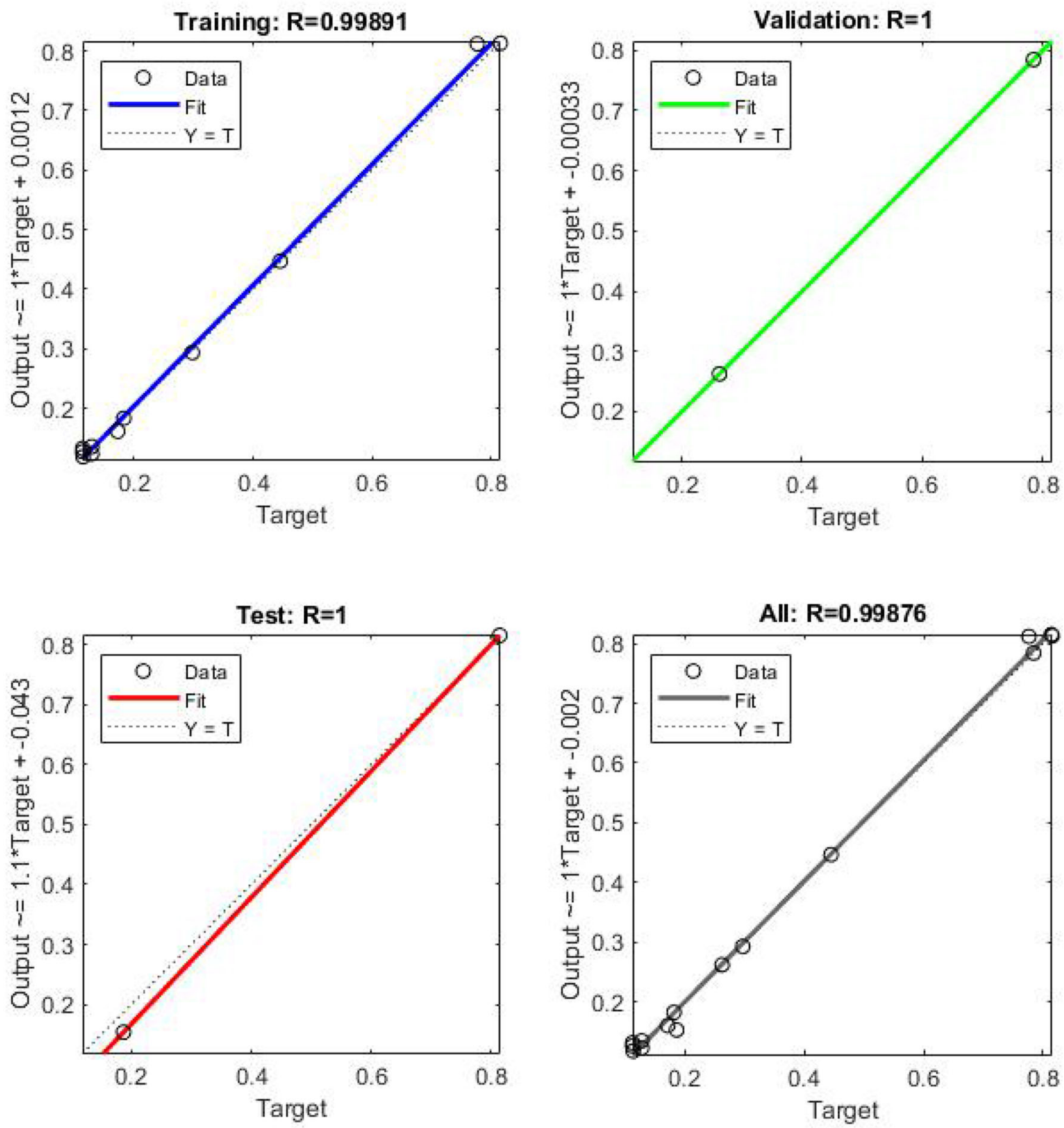

Fig. 6 Regression plot showing training, testing, validation, and overall performance of the ANN model

5 Simulation studies

5.1 Simulation setup

In the proposed work, a road segment of 150 m is considered for both before and after a vehicle to be lit when passing on the road. The proposed ANN is simulated by using the neural network toolbox in MATLAB (R2018a). Here, the input layer with three neurons is used to obtain the reduced value of E as the output layer with minimum error and, the corresponding model designed by this toolbox is shown in Fig. 3. The number of hidden layer in our proposed ANN model is considered as 1 to avoid the overfitting [12] of the network, and the corresponding number of neurons in the hidden layer is set as 10. The model is initially trained by considering the input–output pairs obtained from [18]. The following Table 1 summarizes the parameters with their values used for simulations.

5.2 Simulation results

5.2.1 Data collection

The training data of the proposed ANN are estimated for different inter-distances ranging from 10–50 m. The different traffic volumes for each of the inter-distance are considered

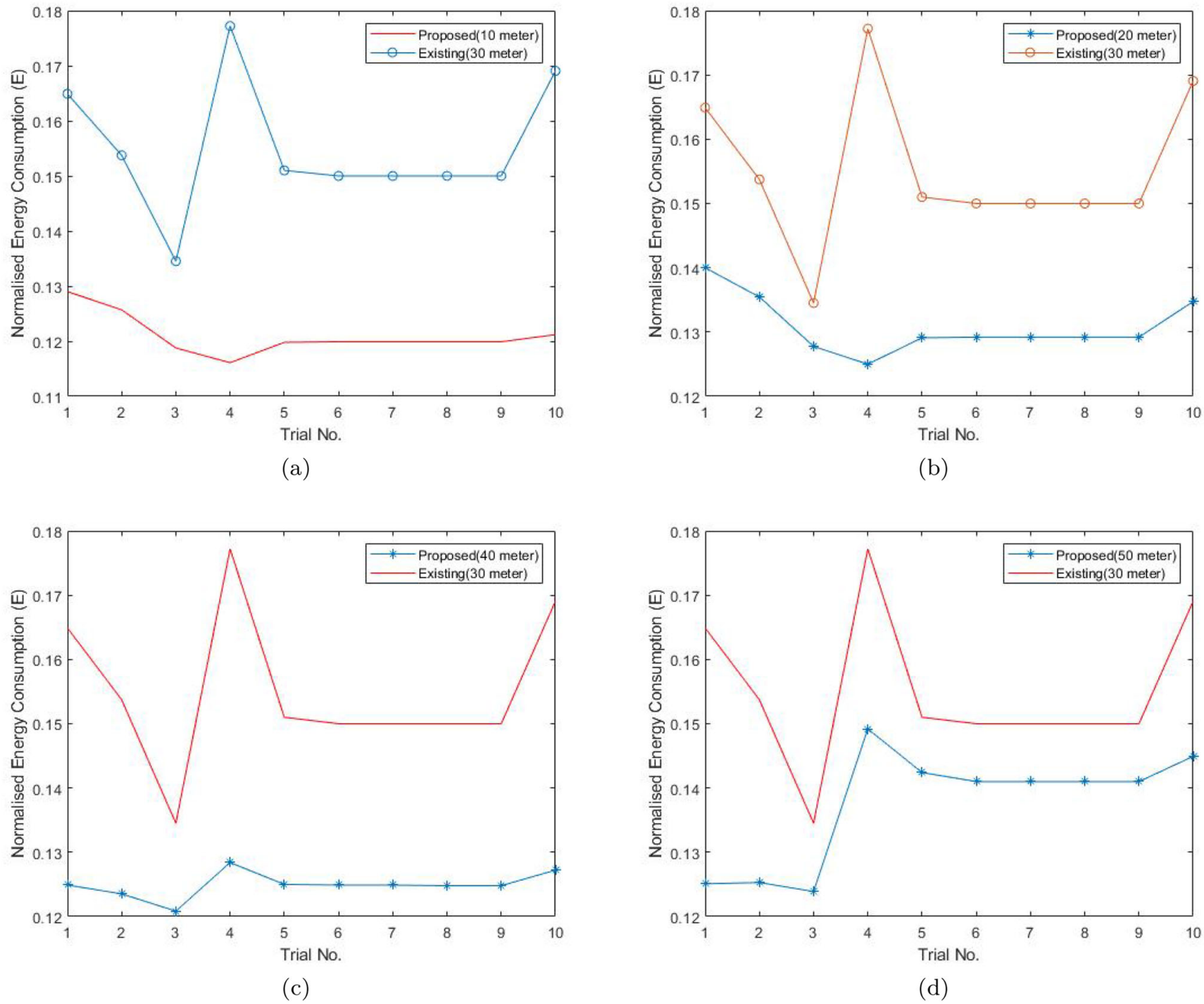

Fig. 7 **a**–**d** Improvement by the proposed work over existing work for various trial no

for this training purpose. Here, the sample data are collected by executing Algorithm 1. Among this entire dataset, 70%, 15%, and rest 15% are used for training, validation, and testing purposes, respectively.

In order to determine energy consumption of the streetlights, two important parameters are illumination level (Φ) and active time (T). According to the Algorithm 1, first the value of Φ for all the streetlights to cover $2m$ m distance and T is determined from (5) and (6), respectively. Accordingly, $E(t)$ is obtained from (4) for every inter-distance in the range of 10–50 m and the corresponding result is shown in Fig. 4.

The result shown in Fig. 4 is feed to the proposed ANN model as the second neuron of the input layer. Here, the main objective of the model becomes as finding the energy consumption of the streetlights for every combination of the inter-distance and traffic volumes. In order to present more clear view, some of the input combinations feed to the model are summarized in Table 2.

5.2.2 Performance evaluation

The ANN model, shown in Fig. 3, is trained for several times to enhance the accuracy in results. This performance is measured by reducing the value of MSE, and the corresponding MSE for each training is shown in following Table 3. Hence, minimum MSE value for this table is used for further analysis. It is observed that our proposed model can obtain significantly reduced MSE value as compared with the existing work [7].

From several training performed, the best three performances are shown in Fig. 5 along with their corresponding output values. By observing this figure, it can be stated that the proposed algorithm has less energy consumption than

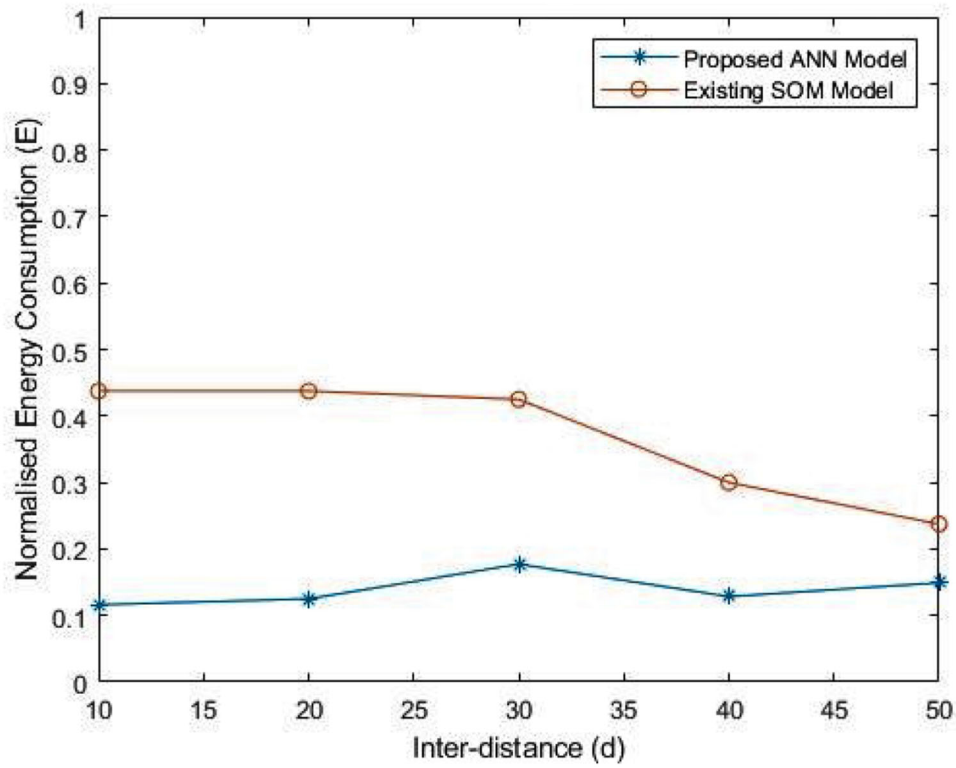

Fig. 8 Improvement obtained by the proposed work over SOM-based existing work for various values of 'd'

Algorithm 1: Input Layer Data Collection

Initialize $m, S, P_{\max}, d_{\text{rad}}, d_{\text{det}}$
Set $d_{\text{approx}} = 0$
for d = *10 to 50* **do**
  calculate $T = \frac{d}{S}$
  if $d_{\text{det}} \leq d_{\text{rad}}$ **then**
    $d_{\text{approx}} = 0$
  else
    $d_{\text{approx}} = d_{\text{det}} - d_{\text{rad}}$
  end
  set $z = d$
  calculate SR $= \lceil \frac{m}{z} - 0.5 \rceil$ and $N = 2 \times \text{SR} + 1$
  if $\lceil \frac{d_{\text{approx}}}{d} \rceil = 0$ **then**
    $Z(d_{\text{approx}}) = 0$
  else if $\lceil \frac{d_{\text{approx}}}{d} \rceil > 0$ *and* $\lceil \frac{d_{\text{approx}}}{d} \rceil \leq SR$ **then**
    $Z(d_{\text{approx}}) = \lceil \frac{d_{\text{approx}}}{d} \rceil - 1$
  else
    $Z(d_{\text{approx}}) = \text{SR}$
  end
  calculate
  $\Phi = \Phi_{\max} + 2 \times \sum_{Z(d_{\text{approx}})=1}^{\text{SR}} Z(d_{\text{approx}}) \times \frac{1}{\text{SR}} \times \Phi_{\max}$
  $E(t) = \sum_{n=0}^{t} P_{\max} \times \Phi \times T$
end

the existing one [9]. Figure 5 shows the value of E for inter-distance and the traffic volume as mentioned in Table 2.

To highlight the performance of the proposed model, a regression plot [4] for training, validation, and test data is generated. It shows the difference of the estimated output with respect to the actual target. The regression plot of the training, testing, and validation for the least MSE is shown in Fig. 6. In this figure, the target value of the model and the best fit obtained from the model are represented by the dashed line and solid line, respectively. Here, the value of R, shown in Fig. 6, for each sample indicates the relationship between the target value and the output. From Fig. 6, it can be said that there is a close relationship between the target and the output in case of testing and validation for the proposed model.

5.2.3 Performance comparisons

Energy consumption (E) of the streetlights can be reduced by varying the value of 'd' which in turn effects Φ and T [18]. In this context, some arbitrary values of d are considered for calculating energy consumption. In the proposed approach, the ANN model is trained to calculate E for several values of d. The results obtained from the ANN model for all the training performed are shown in Fig. 7a–d with respect to inter-distance (d). From these figures, it can be stated that the proposed algorithm shows an improvement in terms of energy consumption (E) over the existing work [9] having a standard inter-distance of 30 m.

In order to assess the efficiency of the proposed model over a SOM [17]-based existing work, the neural net clustering app in MATLAB is used. It facilitates a compatible model for highlighting the comparison with respect to our work.

Here, the proposed work obtains an improvement in terms of reduced energy consumption over the existing one [17]. The result related to such improvement is shown in Fig. 8. This reduced energy consumption is obtained by the proposed work for the range of 10–50 m of inter-distance.

6 Conclusion

In this paper, an energy efficient street lighting framework is proposed for minimizing the energy consumption of the street lights by using an ANN-based approach. Here, ANN model is developed to predict about the reduced energy consumption by the street lighting system with minimum MSE considering different traffic volumes. The effectiveness of the proposed approach is highlighted from different dimensions such as training, testing as well as validating the model introduced here. Thus, our proposed model has the capability of learning from the set of inputs and their relationships which is beneficial for obtaining reduced energy consumption by the street lighting system in accordance of traffic volume on the road. Furthermore, this energy efficient model can be utilized irrespective of the traffic way on the road. As a result, the installation of the street light following the CIE recommendation ensures the lit coverage area by the streetlights for any physical parameter of the road. The proposed approach outperforms the existing work. Furthermore, the lighting quality measurement in such a scenario is the future scope of our work.

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