# Detecting Occupancy of an Office Room by Recurrent Extreme Learning Machines

**Conference Paper** · September 2016

# Detecting Occupancy of an Office Room by Recurrent Extreme Learning Machines

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***Abstract*— Occupancy detection is a major task in building management systems in various perspectives, such as security and energy controlling. Occupancy detection has been done by utilizing passive infrared motion detectors, video cameras, smart meters, and sensors. Because of their small sizes, low energy requirements, and low costs, it becomes popular to employ them in occupancy detection. Therefore, determining the most relevant sensor types and the most suitable machine learning method for classification is an important task nowadays. Since the analyzed signals are time-varying, higher accuracy levels can be achieved by recurrent methods, but any recurrent method has not been employed in this subject yet. Based on this verity, the main purpose of this study was to validate the applicability and the success rate of recurrent extreme learning method (RELM), which was built to improve the learning methodology in training recurrent type single hidden neural network. Achieved accuracy levels by RELM were compared to the results obtained by ELM and other reported results found in the literature. RELM showed the highest success in terms of accuracy levels.**

***IndexTerms*—Occupancy detection, Recurrent Extreme Learning Machine, Sensor Signals.**

## I. Introductİon

Determining occupancy is a major task in building management (intelligent buildings) such as optimizing user comfort, security, and energy controlling [1]. It was reported that 30% to 42% of used energy can be saved by a successful occupancy detection [1-3]. This lower energy consumption is not only from minimizing energy wasted in lighting of unoccupied area [3-6] and switching of electric loads [3, 4], but also from minimizing energy wasted cooling or heating [4, 5] of these sections. This is also linked with smart grid networks [7, 8] in order to determine the amount of required electricity more accurately [9].

To achieve this purpose, in primary applications, passive infrared (PIR) motion detectors were employed [5, 10]. But because of obtained low accuracy by PIR detectors in determining occupancy of the subjects that remain relatively immobile [4, 10], video cameras [5, 10] and smart meters [5, 9, 11] have been used. Nowadays, to achieve cheaper and more accurate systems, and also because of the privacy concerns, using sensor groups (such as light, motion, temperature, sound, acoustics, humidity, power use, and CO2) becomes more popular [2, 4, 10, 12].

Due to its conceptual importance, there is a growing literature in determining the most relevant sensor types, and also the most accurate methods for their classification [4, 6], like artificial neural networks (ANN) [10, 13-17], support vector machines (SVM) [5, 10, 17], hidden Markov models, [10], k nearest neighbor models (kNN) [5, 16, 17], decision trees [2, 4, 17].

Occupation detection is done by time ordered datasets and therefore it can be said that it is a dynamic process. The recurrent type machine learning methods may show higher success in dynamic systems [18, 19] because they provide higher nonlinearity based on feedback neurons [20, 21]. But, from the best knowledge of the authors, any recurrent type method machine learning method has not been employed yet.

In this perspective this study was carried out to validate this idea by employing the recurrent extreme learning machines (RELM) that had been proposed by Ertuğrul [21]. RELM is an extreme learning machine [22] based recurrent training method developed for training single hidden layer neural networks. Occupancy detection dataset used in [2] was employed here for teststing the proposed method, and the achieved accuracy levels by RELM were compared with the reported results [2] and the obtained results by ELM for the same dataset, and also with the results found in current literature. The rest of the paper is organized as:. the employed dataset and the theory of RELM are presented in the next section. The obtained results and the related discussion in Section 3. Finally, in section 4 the study is concluded.

## II. MaterİalsandMethod

### A. Occupancy detection dataset

Occupancy detection dataset was generated by Candanedo and Feldheim [2] and published in UCI Machine Learning Repository [23]. This dataset contains 3 different datasets; one of them was employed for training and the others were employed in the validation of used machine learning method. These datasets consist of the following features

- Week status (WS): It was exacted from date raw (year-month-day) and it took 1 (if it is a weekday) or 0 (if it is a weekend).
- The number of seconds from midnight (NSM): It was exacted from time raw (hour:minute:second).
- Temperature in Celsius (T)

- Relative Humidity (φ)
- Humidity ratio (W)
- Light (Lux)
- CO2 (ppm)
- Occupancy: “0” was used for unoccupied; while “1” was used occupied status.

These features were detected by sensors and recorded. The occupation status was determined by taken pictures. Samples, which were recorded on February 5, 2015, were given in Fig. 1. More details about the employed dataset can be found in [2].

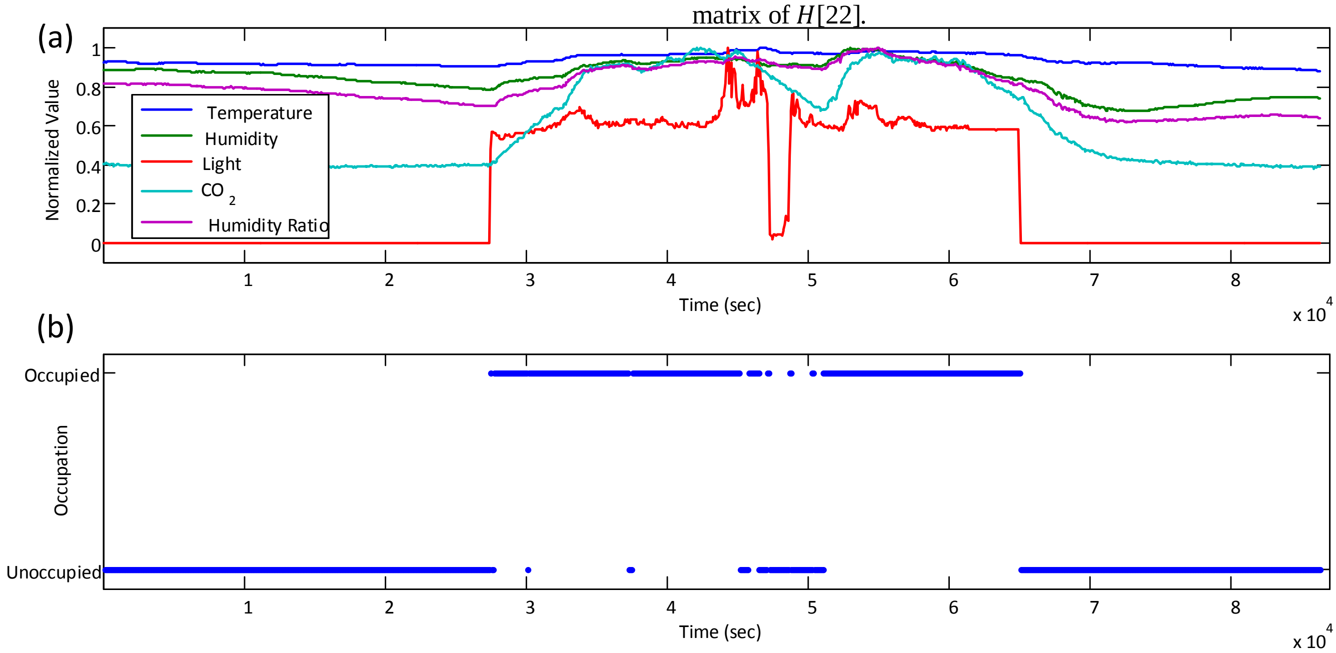


Fig. 2. (a). Sensor signals, (b) Occupation status

*B. Recurrent extreme learning machines*

RELM was based on ELM, which has been employed to train a single hidden layer artificial neural network by assigning weights in the input layer and biases in the hidden layer arbitrary and determining weights in the hidden layer analytically [22]. There is a large and growing literature that reports higher accuracies and faster training stages in ANNs trained by ELM with respect to ANNs trained by backpropagation [21, 24, 25, 26]. In RELM, the methodology of ELM was improved to train a single hidden layer recurrent artificial neural network, which is given in Fig. 2 [21], in order to increase its ability in modeling dynamic systems [27].

The output of this network can be calculated by:

$$y = \sum_{j=1}^{m} \beta_j \, g\left(\sum_{i=1}^{n} w_{i,j} x_i + \sum_{i=n+1}^{n+r} w_{i,j} \delta(t-i+n) + b_j\right) \quad (1)$$

where, $\delta$, $t$, and $r$ show delay, the instance order, and the number of employed context neurons, respectively. Output values were given as an extra input with delays by context neurons [21]. Later, the same learning procedure of ELM was evaluated; biases in the hidden layer, and weights in both input layer and feedback layer were assigned arbitrary.

$$H = \begin{bmatrix} g(w_{1,1}x_1 + b_1) & \cdots & g(w_{1,m}x_m + b_m) & g(w_{1,m+1}y^{-1} + b_{m+1}) & \cdots & g(w_{1,m+r}y^{-r} + b_{m+r}) \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ g(w_{n,1}x_1 + b_1) & \cdots & g(w_{n,m}x_m + b_m) & g(w_{n,m+1}y^{-1} + b_{m+1}) & \cdots & g(w_{n,m+r}y^{-r} + b_{m+r}) \end{bmatrix} \quad (2)$$

Finally, the output weights were calculated via new hidden (*H*) matrix:

where, $y^{-r}$ indicates the previous r[th] value of the output. By this way, the weights in the output weights ($\beta_{1\cdots m}$) can be determined by Moore–Penrose generalized inverse method, such as:

$$\hat{\beta} = H^{+} y \quad (3)$$

where $H^{+}$ is the generalized Moore–Penrose generalized inverse

matrix of $H$[22].

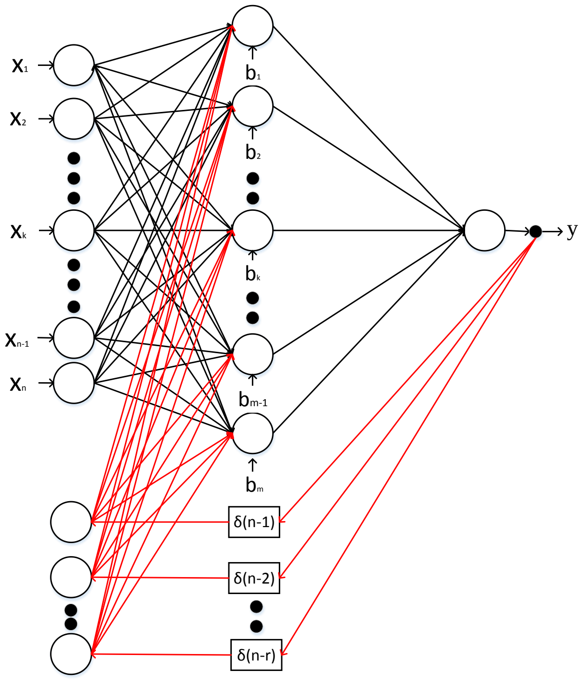


Fig. 2. Structure of Single Hidden Layer Recurrent ANN**[21]**

## III. RESULTS AND DISCUSSION

Similar to each machine learning methods, before implementing RELM; the optimal values of RELM parameters like number of neurons in the hidden layer, number of context neurons as well as the transfer function to be used in hidden neuronal nodes need to be determined. In this study, the optimal values of these parameters were simply determined based on the achieved accuracy levels in different trials. The accuracy was calculated by:

$$Accuracy\ (\%) = 100x \frac{\#\ correctly\ classified\ samples}{\#\ all\ samples} \quad (4)$$

### *A. Optimizing RELM parameters*

Firstly, the optimal number of context neurons, which show the total delay time via backward connections from the output layer to the input layer, was determined by trials. Achieved accuracies in separate trials were summarized in Table 1.

TABLE II. DETERMINING OPTIMUM NUMBER OF CONTEXT NEURONS

| **Number of Context Neurons** | **Obtained Accuracy (%)** | | |
|---|---|---|---|
| | **Train** | **Test#1** | **Test#2** |
| 1 | 99.85 | 99.10 | 99.56 |
| 2 | 99.89 | 99.14 | 99.53 |
| 3 | 99.90 | 99.10 | 99.55 |
| 4 | 99.90 | 99.02 | 99.54 |
| 5 | 99.89 | 99.10 | 99.52 |

Since similar accuracies were achieved in each case (see Table 1), the optimal number of context neurons was assigned as "1" in order to minimize the network complexity. This means, the output of the network was also used as an input by a delay. Later, the optimal transfer function and the number of neurons contained by hidden layer were determined by trials and obtained accuracies were summarized in Fig. 3.

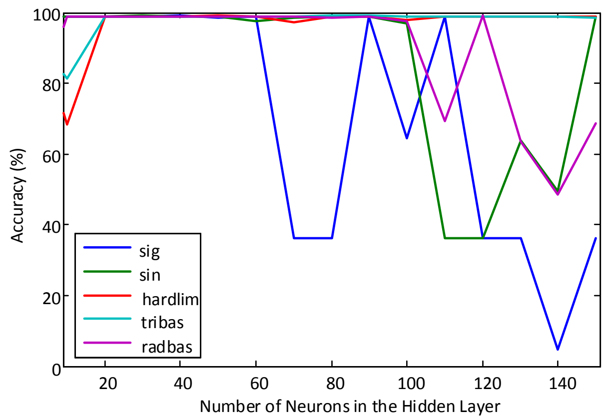


Fig. 3. Determining optimum number of neurons in the hidden layer and the activation function

As seen in Figure 3, the optimum transfer function and the number of neurons in the hidden layer were selected as triangular bases (tribas) and 80 neurons, respectively, because of having minimum network complexity.

### *B. Obtained results*

The same datasets (a training and two test datasets) were employed in classification by Linear Discriminant Analysis (LDA), Classification and Regression Trees (CART) and Random Forest (RF) methods [2] for some special cases. In order to have a fair comparison, RELM and ELM were employed for the same cases [2]. Obtained accuracies by RELM, ELM and achieved highest accuracies in [2] were summarized in Table 2.

It is obvious from Table 2 that, generally higher accuracy levels were achieved by ELM compared to the reported highest accuracy obtained by one of the LDA, CART and RF methods in [2]. The reasons behind this higher success may be because of high generalization capacity of ELM that was reported in many papers [22, 24-26]. Additionally, for each case higher accuracies were obtained by RELM compared to ELM, LDA [2], CART [2] and RF [2]. Since the training algorithm of both ELM and RELM are similar, the difference between obtained accuracies in RELM and ELM can be because of the delayed feedback context neuron. This result well suits with the findings available in the literature. The feedback loops boosted the network improves the train ability and adaptability of network [20] by providing higher nonlinear characteristics [18]. Furthermore, the obtained accuracy levels from this dataset by each method (RELM, ELM, LDA, CART and RF) were generally higher than those reported accuracy levels in the literature, which can be summarized as: 81-98.44% [4], 59-90% [5], 63.23-66.43% [13], 70.4-72.37% [14], 67-69% [15], and 55.26-98.2% [17].

## IV. CONCLUSION

In this study, the applicability of RELM, which is a recurrent type training method, in detecting occupancy was investigated. The superiority of this method can be appreciated by comparing the achieved accuracy levels to the ones reported in variety of studies found in literature. The main reason behind this success may be high generalization capacity of ELM and consequently RELM which has a capability of modeling networks suitable for nonlinear data structures through the delayed feedback connections.

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TABLE II. OBTAINED ACCURACIES

| Dataset | RELM | | | ELM | | | In [2] | | |
|---|---|---|---|---|---|---|---|---|---|
| | Train | Test#1 | Test#2 | Train | Test#1 | Test#2 | Train | Test#1 | Test#2 |
| T, φ, Light, $CO_2$, W, NSM, WS | 99.85 | 99.10 | 99.53 | 99.59 | 97.90 | 98.27 | 98.85 | 97.90 | 99.33 |
| T, φ, Light, $CO_2$, W | 99.68 | 99.10 | 99.56 | 99.66 | 97.90 | 99.18 | 98.78 | 97.90 | 98.76 |
| T, φ, $CO_2$, W, NSM, WS | 99.55 | 99.02 | 99.51 | 99.26 | 94.93 | 79.26 | 96.55 | 94.71 | 72.32 |
| T, φ, $CO_2$, W | 99.53 | 99.02 | 99.51 | 98.60 | 92.01 | 79.07 | 91.91 | 85.33 | 73.77 |
| T, φ, Light, W, NSM, WS | 99.68 | 99.10 | 99.57 | 99.67 | 97.97 | 99.24 | 98.77 | 97.90 | 98.96 |
| T, φ, Light, W | 99.71 | 99.10 | 99.58 | 99.39 | 97.90 | 99.30 | 98.55 | 97.90 | 98.24 |
| T, φ, W, NSM, WS | 99.55 | 99.02 | 99.51 | 99.24 | 94.52 | 81.63 | 99.98 | 95.50 | 92.49 |
| T, φ, W | 99.53 | 99.02 | 99.51 | 94.87 | 87.35 | 81.96 | 85.46 | 85.44 | 85.36 |
| T, Light, NSM, WS | 99.69 | 99.10 | 99.54 | 99.53 | 97.94 | 99.29 | 98.75 | 97.90 | 99.31 |
| T, Light | 99.61 | 99.10 | 99.56 | 99.01 | 97.94 | 99.21 | 96.56 | 97.90 | 98.62 |
| φ, Light, NSM, WS | 99.68 | 99.17 | 99.56 | 99.47 | 97.94 | 98.10 | 98.86 | 97.86 | 99.31 |
| φ, Light | 99.67 | 99.14 | 99.56 | 99.20 | 97.90 | 99.10 | 98.86 | 97.86 | 99.31 |
| Light, $CO_2$, NSM, WS | 99.71 | 99.14 | 99.56 | 99.62 | 97.90 | 98.16 | 99.98 | 96.14 | 77.71 |
| Light, $CO_2$ | 99.66 | 99.10 | 99.56 | 99.08 | 97.90 | 98.51 | 90.26 | 87.62 | 80.40 |
| T, $CO_2$, NSM, WS | 99.53 | 99.06 | 99.51 | 99.35 | 96.85 | 85.23 | 99.98 | 96.14 | 77.71 |
| T, $CO_2$ | 99.53 | 99.02 | 99.51 | 95.01 | 87.54 | 87.38 | 90.26 | 87.62 | 80.40 |
| Light, W, NSM, WS | 99.69 | 99.10 | 99.54 | 99.55 | 97.94 | 98.33 | 99.99 | 96.74 | 99.03 |
| Light, W | 99.66 | 99.17 | 99.58 | 99.10 | 97.90 | 99.18 | 99.52 | 96.10 | 98.98 |
| T, φ, NSM, WS | 99.53 | 99.02 | 99.51 | 99.21 | 90.28 | 83.86 | 99.95 | 95.61 | 92.85 |
| T, φ | 99.53 | 99.02 | 99.51 | 94.63 | 84.20 | 83.51 | 88.24 | 84.02 | 86.30 |
| T, NSM, WS | 99.53 | 99.02 | 99.51 | 99.01 | 92.76 | 84.30 | 99.75 | 95.91 | 92.57 |
| T | 99.51 | 99.02 | 99.51 | 86.69 | 83.00 | 80.75 | 83.38 | 85.33 | 83.64 |
| Light, NSM, WS | 99.68 | 99.10 | 99.55 | 99.23 | 97.97 | 99.15 | 98.93 | 97.22 | 99.26 |
| Light | 99.61 | 99.10 | 99.56 | 98.93 | 97.86 | 99.32 | 98.77 | 97.86 | 99.32 |
| $CO_2$, NSM, WS | 99.56 | 99.06 | 99.51 | 99.25 | 95.38 | 83.29 | 99.99 | 96.21 | 74.51 |
| $CO_2$ | 99.53 | 99.02 | 99.51 | 92.61 | 85.97 | 80.03 | 88.38 | 86.19 | 79.93 |

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