JURNAL INFOTEL
VOL. 16, NO. 1, FEBRUARY 2024, PP. 105–119.
DOI:10.20895/INFOTEL.V16I1.1025

RESEARCH ARTICLE

Temporal Sequential-Artificial Neural Network Enhancements for Improved Smart Lighting Control

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Received: August 23, 2023; Revised: November 5, 2023; Accepted: January 16, 2024.

Abstract: Several previous studies have proposed a temporal sequential-artificial neural network (TS-ANN) to convert passive infrared (PIR) Sensor movement data into presence data and improve the performance of smart lighting control. However, such a temporal-sequential forecasting concept has a curse of dimensionality problems. This study aims to propose the application of principal component analysis (PCA) with TS-ANN (PCA-TS-ANN) as an intelligent method for controlling smart lighting with low dimensions. We have primary data directly from a smart lighting implementation that utilizes PIR sensors. We apply cross-correlation to the original dataset to find the optimum time step. Then we discover the optimum TS-ANN based on selected tuning parameter values through the Pearson correlation coefficient (PCC). We then design and compare scenarios involving the combination of TS-ANN and PCA. Finally, we evaluate these scenarios using the metrics accuracy, precision, recall, F1-score, and delay. The results of this study are the PCA-TS-ANN model with accuracy, precision, recall, and F1-score values of 0.9993, 0.9997, 0.9994, and 0.9996, respectively. The PCA method reduces the TS-ANN features from 1,200 features to 36 features. The model size has also decreased from 3,534 kB to 807 kB. Our model has a simpler complexity with TS-ANN in that the $\mu \pm \sigma$ delay is 0.27 $\pm$ 0.06 ms versus 0.34 $\pm$ 0.11 ms.

Keywords: cross-correlation, passive infrared-sensor, principal component analysis, smart lighting, temporal-sequence artificial neural network

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1 Introduction

Several studies have proven that smart lighting can produce efficiencies of up to 20 % [1]. After achieving efficiency, user comfort has recently become an important aspect of smart lighting [2]. Several studies have applied methods to obtain user comfort, such as the hierarchical hidden Markov model (HHMM) for activity recognition to detect user habits. However, the performance has not been optimal [3]. Further research and literature review need to be conducted to search for potential solutions.

We conducted a literature review to describe some relevant research on smart lighting. Jin *et al.* [4] mentioned that the problem in smart lighting is that the PIR sensor used to detect human presence is a motion sensor, not a presence sensor. This study proposes a temporal sequential-artificial neural network (TS-ANN) to convert movement data into presence data, like time-series forecasting. Several studies have stated the problem of dimensionality in time-series forecasting [5]. In addition, models with high dimensions have exponentially increasing complexity [6]. Several papers applied principal component analysis (PCA) for dimension reduction in the forecasting model [7]. A PCA-TS-ANN model can be a proposal for time-series forecasting with low dimensions.

The time step is an important element in forecasting [8]. Several studies used autocorrelation analysis to get the optimal time step in forecasting methods such as autoregressive integrated moving averages (ARIMA) [9]. However, non-autoregressive cases such as smart lighting control cannot use autocorrelation. On the other hand, cross-correlation looks at the correlation between two signals that have a lag. The cross-correlation method can be a research opportunity in this case. In the case of ANN, many studies state that the main problem in using the ANN model is the tuning parameter. Several methods of swarm intelligence and evolutionary computing can be a solution in the ANN parameter tuning [10]. On the other hand, the Pearson correlation coefficient (PCC) is a score that explains the strength of the relationship between the two variables [11]. Using PCC to measure the relationship between tuning parameters and model performance can be a research opportunity.

This study proposes the application of PCA-TS-ANN as an intelligent method for controlling smart lighting with low dimensions. We have primary data directly from a smart lighting implementation that utilizes PIR sensors. We apply cross-correlation to the original dataset to find the optimum time step. Then we discover the optimum TS-ANN based on selected tuning parameter values through PCC. We then design and compare scenarios involving the combination of TS-ANN and PCA. Finally, we evaluate these scenarios using the metrics accuracy, precision, recall, F1-score, and delay.

To the best of our knowledge, there has never been a study that applies PCA-TS-ANN to smart lighting control. Some of the contributions of this research are as follows:

1. An optimum smart lighting control dataset resulting from the cross-correlation process.
2. An optimized TS-ANN model for smart lighting control based on motion sensors.
3. A smart lighting control that applies PCA to reduce the dimensions of forecasting using TS-ANN.

The structure of the remainder of this paper is in the following systematic way: Section 2 describes our research method. Section 3 shows the study results and discusses the results compared to state-of-the-art papers, followed by the discussion in section section 4. Finally, section 5 reports the important results of this study.

2 Research Method

We applied the onion research before conducting this research. This research is classified as positivist research, where the ontology is an objective reality, the epistemology is real knowledge, and the methodology is quantitative with an experimental strategy. Figure 1 explains the methodology of this research. First, we perform a time-step analysis based on the cross-correlation method from the smart lighting control dataset obtained from our system. Then the next step is the temporal sequence data transformation for TS-ANN. The fourth step is PCA implementation. From the two versions of the existing dataset, we compare the two models' performance and complexity.

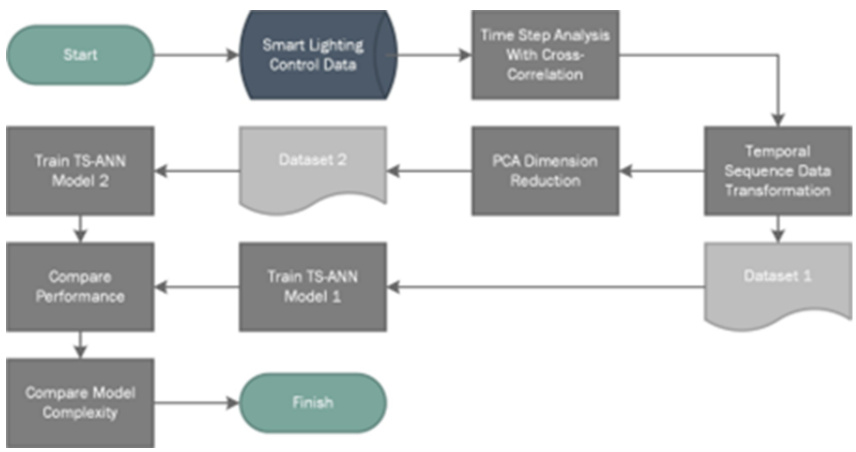


Figure 1: The research methodology.

2.1 Smart Lighting Control

Figure 2 describes the specifications involved in the smart lighting hardware we design. Each piece of hardware has a description explaining its use in the design system, which mainly contains an end device for smart lighting control and an IoT platform that runs the intelligent control mechanism [12]. The PIR sensor is the main sensor in this study. The value of the PIR sensor is twofold, namely 0 when there is no movement of people and 1 when there is a movement of people. NodeMCU has two main functions. The first is a microcontroller, which accepts sensor input and outputs output to the actuator. The second function of NodeMCU is to send and receive data from the server via Wi-Fi communication [13]. The message queue telemetry transport (MQTT) protocol is a middleware that connects lights with servers via the Internet of Things (IoT) [14]. The Raspberry Pi is a mini-PC that acts as a server on the platform layer [15]. Running on the Raspberry Pi is Node-Red. Node-Red is a back-end platform based on Node.js that can provide web services and collect data at the same time [16]. The Raspberry Pi collects and gathers the dataset we need in a comma-separated value (CSV) file.

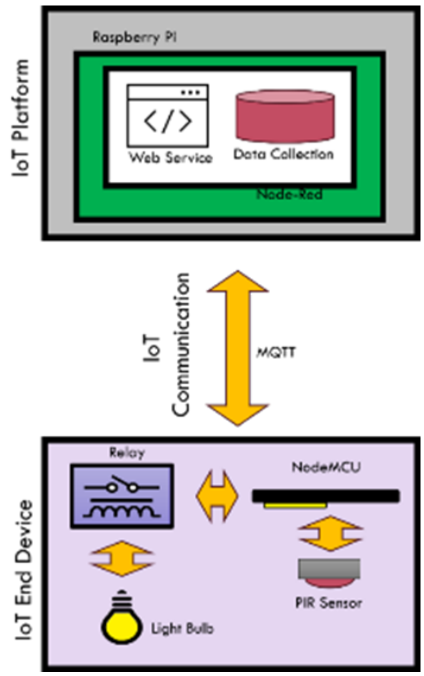


Figure 2: The IoT-based smart lighting control block diagram.

Hypothetically, the algorithm runs on the Raspberry Pi after implementing intelligent smart lighting control. The NodeMCU sends the PIR sensor data to the Raspberry Pi. The Raspberry Pi collects data and runs a Python program to generate intelligent control decisions. The Raspberry Pi sends the intelligent control decision back to the NodeMCU. Based on that decision, the NodeMCU controls the light emitting diode (LED) lights with the help of a relay [17].

2.2 Principal Component Analysis

PCA performs dimension reduction by utilizing the concept of standardization, calculating covariance, and applying eigenvalues [18]. The first step is standardization. After standardization, the next process is creating the covariance matrix [19]. From the covariance matrix, there is a formula for calculating eigenvalues. The formula is shown in (1).

$$(\mathbf{C} - \lambda \mathbf{I})\,\mathbf{V} = \mathbf{0} \tag{1}$$

where $\mathbf{C}$ is the covariance matrix of standardized data, λ is the eigenvalues, $\mathbf{I}$ is the identity matrix, and $\mathbf{V}$ is the eigenvectors. The equation can also have a matrix form as shown in (2).

$$\begin{bmatrix} (1-\lambda) & c_{12} & \dots & c_{1p} \\ c_{21} & (1-\lambda) & \dots & c_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ c_{p1} & c_{p2} & \dots & (1-\lambda) \end{bmatrix} \tag{2}$$

where p is the number of features in the dataset.

The final step in PCA is to map the old dataset to the new dataset based on the first selected n eigenvalues, where $n \in p$. Another name for eigenvalue is the explained variance. The larger the cumulative explained variance of the new dataset, the more representative the old dataset is in the new dataset.

2.3 TS-ANN

Temporal sequence refers to events that occur sequentially related to the time domain. Furthermore, ANN, as its name suggests, is decision-making that imitates the work of neurons in the brain [20]. ANN can be used for predictive cause, for example, to predict birth control in governance [21]. Because the predictive nature of smart lighting control is like forecasting, here we adopt an ANN with a useful model for forecasting [22]. TS-ANN is a type of ANN that uses the concept of autoregression [23]. Figure 3 shows the TS-ANN model architecture.

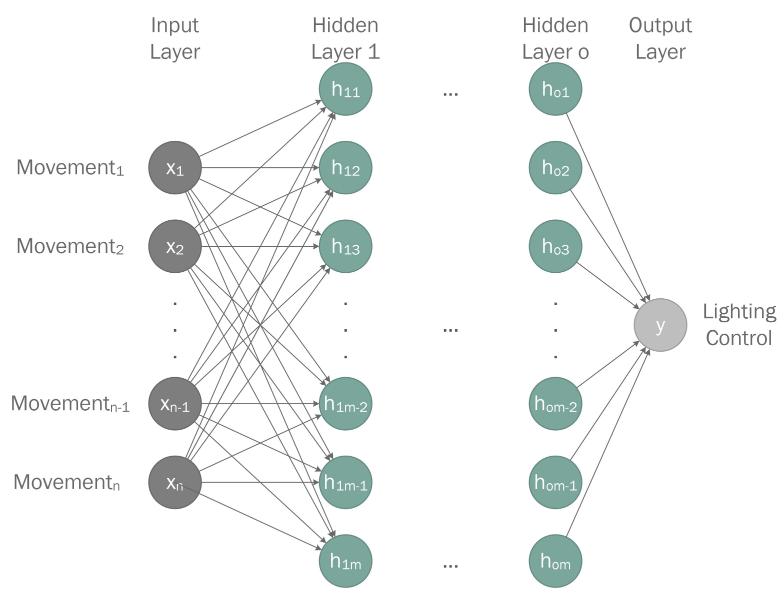


Figure 3: The TS-ANN model architecture.

The m variable describes the number of neurons in each hidden layer. The o variable describes the number of hidden layers. The value of $o > 1$ illustrates that the built neural network architecture is a deep neural network [23]. There is one neuron in the output layer. The model output is smart lighting control. There are two possible values, namely 0 (Off) or

1 (On). The input of the TS-ANN model is movement. The variable n describes the number of inputs and the length of historical data used to predict smart lighting control. The length of the historical data can be determined using the Pearson correlation for data with a low sampling rate of [24]. For high-sampling data, we propose using cross-correlation for two finite and discrete data [25]. The formula for the finite discrete cross-correlation between the two functions f_1 and f_2 is shown in (3).

$$(f_1 \star f_2)[n] \triangleq \sum_{m=0}^{N-1} \overline{f_1[m]} f_2[(m+n)_{modN}] \tag{3}$$

where x_1 is the first variable, x_2 is the second variable, i is the index data item in the dataset, x^1) is the average of the first variable, and x^2) is the average of the second variable.

In finding the optimum TS-ANN model, we create several cases, where each case consists of a combination of ANN tuning parameters [26]. These parameters include:

1. Dataset size = 10,000 and dataset size = 40,000.
2. Iterations = 60 and iterations = 300.
3. Neurons = 60 and neurons = 300.
4. Hidden Layers = 1 and hidden layers = 4.

There are four parameters with two different values, so there are $2^4 = 16$ cases. We name them Case I to Case XVI [27]. We also optimize the TS-ANN model by implementing PCA, which makes the model more lightweight [28].

We also use the PCC to analyze the relationship between tuning parameters and performance. PCC provides correlation scores between two variables [29]. The PCC (r) formula is shown in (4).

$$r = \frac{\sum(x_{1i} - \hat{x_1})(x_{2i} - \hat{x_2})}{\sum(x_{1i} - \hat{x_1})^2 \sum(x_{2i} - \hat{x_2})^2} \tag{4}$$

where x_1 is the first variable, x_2 is the second variable, i is the index data item in the dataset, x^1) is the average of the first variable, and x^2) is the average of the second variable.

We use accuracy, precision, recall, and F1-score to measure the performance of the 16 proposed models described previously, plus a comparison of the TS-ANN model with the low-dimensional PCA-TS-ANN. In addition to the latter comparison, we measure each model's delay distribution and size. The delay and size describe the complexity of the resulting model. The following are the equations for accuracy, precision, recall, and F1-score in (5), (6), (7), and (8), respectively.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \tag{5}$$

$$\text{Precision} = \frac{TP}{TP+FP} \tag{6}$$

$$\text{Recall} = \frac{TP}{TP+FN} \tag{7}$$

$$\text{F1-score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{8}$$

Each performance is an association between several variables from true positive (TP), true negative (TN), false positives (FP), and false negatives (FN). This is the explanation of each variable:

1. TP is when the lights are on while a person is present.
2. TN is when the lights are off while a person is not present.
3. FP is when the lights are on while a person is not present.
4. FN is when the lights are off while a person is present.

When comparing the delays of the two models, we execute the model on random input data 50 times. We show the significance of the difference in delay between the two methods by showing the two methods' delay probability density function (PDF). The PDF equation for a data set that has a normal distribution is shown in (9).

$$f(t) = \frac{1}{\sigma_t\sqrt{2\pi}} \exp\left\{ -0.5\left(\frac{t-\mu_t}{\sigma_t}\right)^2 \right\} \tag{9}$$

where $f(t)$ is the PDF value at t, t is the delay, μ_t is the average of the delays, and σ_t is the standard deviation of the delays.

3 Result

The following are the systematics of our tests: First, we do a time-step analysis with cross-correlation. Second, we performed temporal sequence data transformation. Third, we execute PCA dimension reduction. With the resulting dataset, we train our TS-ANN model. We compare the model with the initial dataset and the transformation dataset. Lastly, we compare the complexity.

We have a primary dataset from the smart lighting system we are building. Figure 4 shows a partial visualization of the dataset. There are two records: movement sensor and presence. The movement sensor data comes from the PIR sensor, where there are two values: "Off" when there is no movement, then "On" when there is movement. Then presence indicates the presence of someone in the room. We installed this device in a single-occupant room for 7×24 hours. This presence data is filled in manually by the occupants of the room. We aim to design a smart lighting control based on motion sensors for the smart lighting we have designed. When motion is detected, the light comes on. But not every time there is no movement, that means no one is present (movement sensor = "Off", presence = "Present"). That is what provides low user comfort. The hypothesis is that our proposed intelligent control plays a role in predicting presence (equivalent to smart lighting control) based on the movement sensor. Eventually increasing user comfort while maintaining energy efficiency. The Dataset Size is 56,729 data items.

We apply cross-correlation between the movement sensor with Presence data to find the optimum value of time step for data transformation before the TS-ANN process. Figure 5 shows the results of the cross-correlation analysis. The image is a snippet of the first 10,000 data from the cross-correlation results. Until the first 1,200 data, there is a gradual decrease in cross-correlation score. Then the optimum time step for transforming data into a temporal sequential form is 1,200.

The previous step produces 1,200 features for time steps in TS-ANN. The next step is the dimension reduction process to reduce the number of these features. Figure 6 shows the

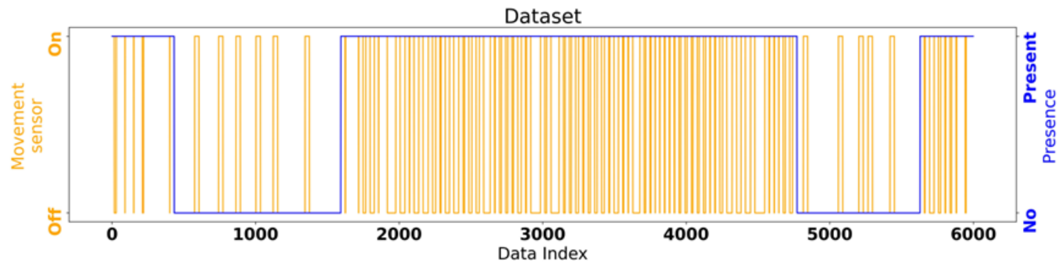


Figure 4: Visualization of the original smart lighting control dataset.

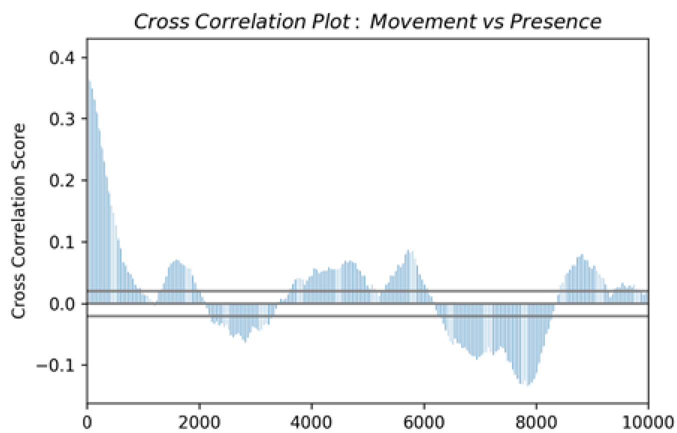


Figure 5: The cross-correlation analysis result.

explained variance of the first 200 principal components. The larger the reduced number of dimensions in the PCA process, the smaller the resulting complexity of the training model. On the other hand, there is a risk of losing the more explained variance.

Table 1 shows a comparison of our 16 TS-ANN model case based on a combination of four parameters, namely dataset size, iterations, neurons, and hidden layers. We highlight the metrics with the highest values. There are two Cases with the four highest measurement metrics, namely Case XII and Case XVI. The only parameter that distinguishes the two case is the iterations. We chose Case XII because it has fewer iterations, which means that Case XII has a shorter training time.

We deepen the discussion of the tuning parameters for the TS-ANN model using PCC. Figure 7 shows the PCC matrix between the measurement metrics and the TS-ANN tuning parameters. Dataset Size has the highest correlation with all four-measurement metrics. On the other hand, Iterations have a weak correlation, which explains that a low iteration value is optimal because it provides a shorter training time. The number of neurons correlates significantly with the measurement metrics except for recall. On the other hand, hidden layers have a strong negative correlation with only recall. Our optimum model has

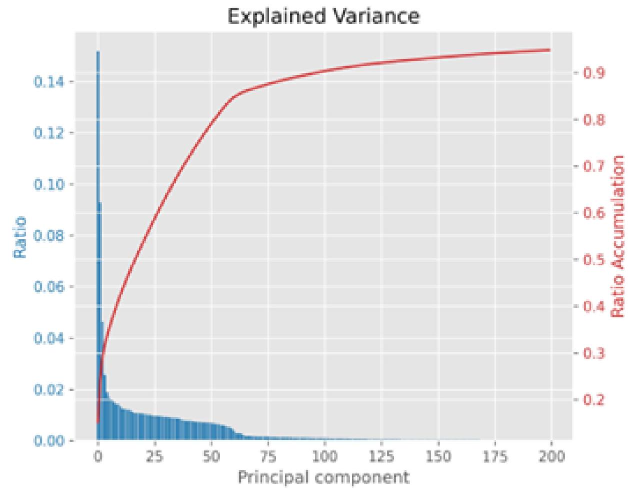


Figure 6: The PCA dimension reduction analysis result.

Table 1: TS-ANN model optimisation through parameter tuning

Case	Dataset Size	Iterations	Neurons	Hidden Layers	Accuracy	Precision	Recall	F1-score
I	10000	60	20	1	0.769	0.891	0.804	0.845
II	10000	60	20	4	0.815	0.898	0.862	0.880
III	10000	60	100	1	0.774	0.886	0.817	0.850
IV	10000	60	100	4	0.842	0.892	0.909	0.900
V	10000	300	20	1	0.773	0.893	0.807	0.848
VI	10000	300	20	4	0.792	0.890	0.839	0.864
VII	10000	300	100	1	0.778	0.890	0.817	0.852
VIII	10000	300	100	4	0.809	0.890	0.863	0.877
IX	50000	60	20	1	0.999	0.999	1.000	0.999
X	50000	60	20	4	0.999	0.999	0.999	0.999
XI	50000	60	100	1	1.000	0.999	1.000	1.000
XII	50000	60	100	4	1.000	1.000	1.000	1.000
XIII	50000	300	20	1	0.999	0.999	1.000	1.000
XIV	50000	300	20	4	0.999	0.999	0.999	0.999
XV	50000	300	100	1	1.000	0.999	1.000	1.000
XVI	50000	300	100	4	1.000	1.000	1.000	1.000

the most Neurons and Hidden layers. We observe that the lower value of recall does not significantly affect the F1-score, which is the accumulation value of precision and recall.

After obtaining the optimum TS-ANN model, we apply PCA. Since complexity increases with increasing dimensions and performance decreases with less explained variance, we look for an equilibrium number of principal components that gives the best performance. Figure 8 shows the relationship between the number of principal components, explained variance accumulation, and the accuracy of the resulting model. The higher the explained variance, the higher the accuracy. However, because the complexity of the

	Dataset Size	Iterations	Neurons	Hidden Layers
Accuracy	0.9863	-0.0289	0.8018	-0.4009
Precision	0.9992	-0.1600	0.8011	0.4794
Recall	0.9579	0.0793	0.5551	-0.7137
F1-Score	0.9823	0.0001	0.8016	-0.4011

Figure 7: The PCC matrix between measurement metrics and TS-ANN tuning parameters.

model also increases due to the higher dimensions, the accuracy gradually decreases. The best performance equilibrium of PCA-TS-ANN is when principal components = 36 with explained variance accumulation = 0.68 and model accuracy = 0.9993.

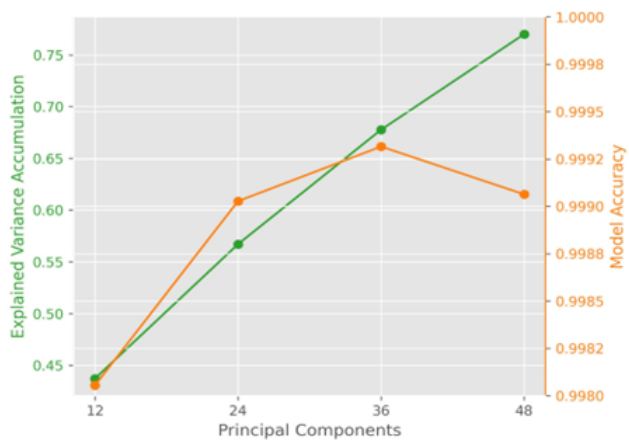


Figure 8: The relationship between principal component, explained variance accumulation, and accuracy.

We compare the performance of TS-ANN with PCA-TS-ANN. Figure 9 shows a comparison of both methods' accuracy, precision, recall, and F1-score. In these four parameters, the performance of PCA-TS-ANN is better than TS-ANN with a value of 0.9993, 0.9997, 0.9994, and 0.9996, respectively.

The next step is to prove that PCA-TS-ANN has a lower complexity model than TS-ANN. We prove this by measuring the delay required for both methods to make predictions. The program runs 50 times and results in these measurements' PDF. Figure 10 shows the PDF comparison-the $\mu \pm \sigma$ Delay of TS-ANN and PCA-TS-ANN are 0.34 ± 0.11 ms and 0.27 ± 0.06 ms, respectively. The μ delay of PCA-TS-ANN is lower than that of TS-ANN. Then the delay of the two methods significantly differs with P-Value < 0.001. The PCA method reduces the TS-ANN features from 1,200 features to 36 features. The model size also decreases from 3,534 kB to 807 kB.

Finally, we show the performance of TS-ANN and PCA-TS-ANN in improving the performance of smart lighting control based on PIR sensors. Figure 11 compares the performance of TS-ANN and PCA-TS-ANN in predicting smart lighting control. The TS-ANN has some mispredicted smart lighting control = Off states where the same case does not occur with PCA-TSANN.

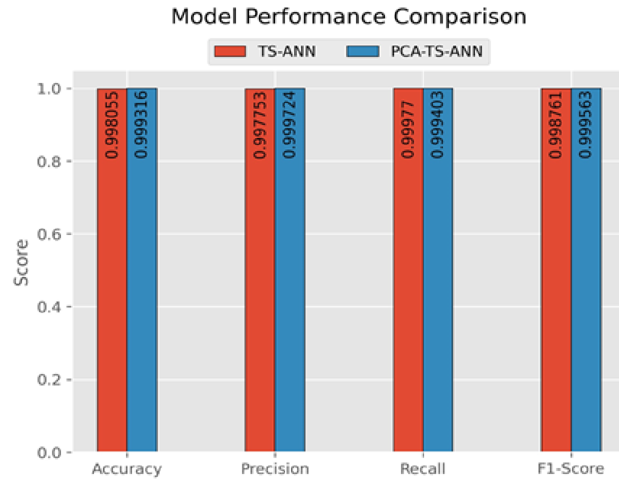


Figure 9: Performance comparison between TS-ANN and PCA-TS-ANN.

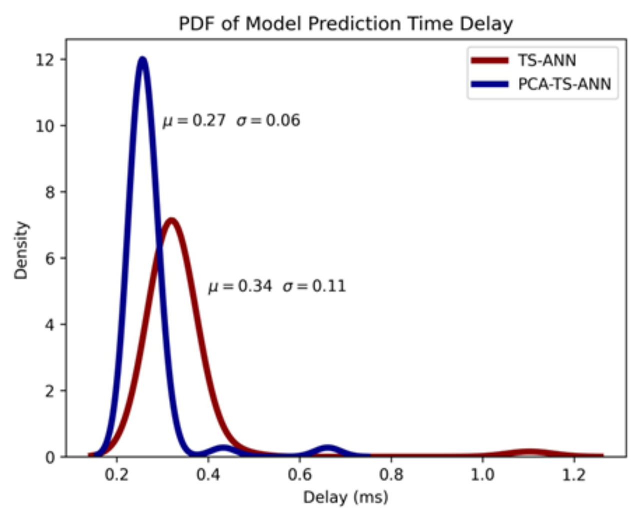
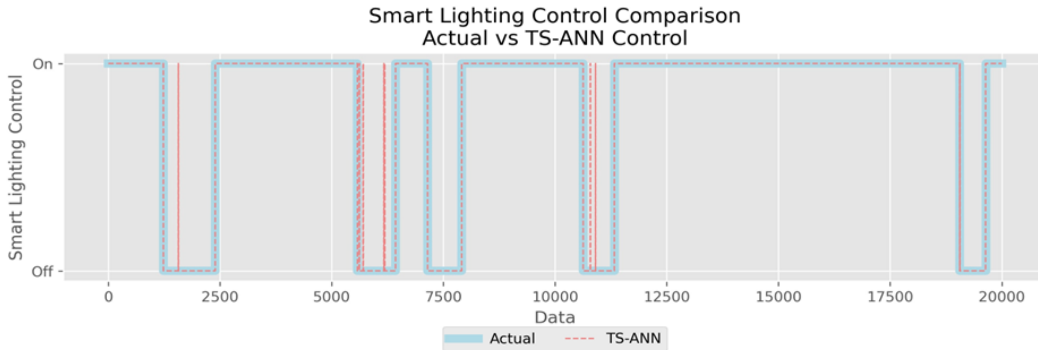


Figure 10: PDF comparison of machine learning models' delay on executing prediction.

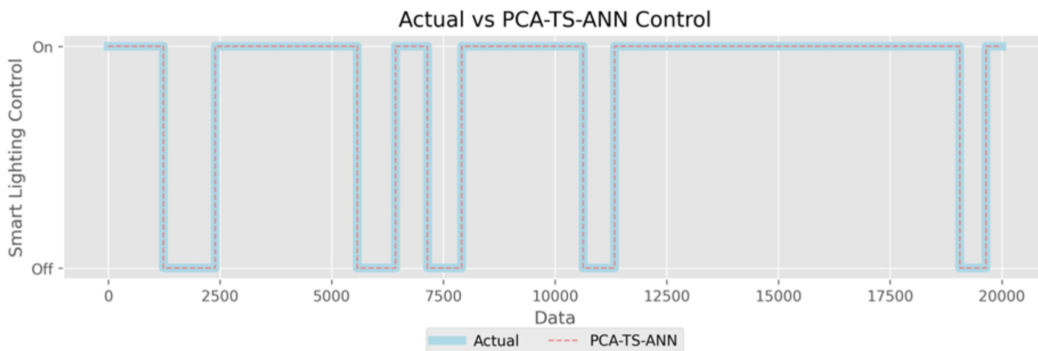
4 Discussion

We prove that by applying cross-correlation, we can find a time step to produce a TS-ANN model with optimal performance. It is as has been done in other studies [30]. This research contributes to a temporal-sequential dataset with the optimum time step result of the cross-correlation process.

We found the optimum TS-ANN model by tracing the tuning parameters. Several studies have done the same thing but without explaining which parameters are influen-



(a)



(b)

Figure 11: The visualization of the prediction of the four methods with comparison to the actual lighting control: (a) TS-ANN (b) PCA-TS-ANN

tial through the PCC calculation [31]. Our contribution is an optimal TS-ANN model with PCC-evaluated parameters.

Finally, a previous study has applied TS-ANN for smart lighting control [4]. A comparison of the accuracy of that study with our results is 0.97 versus 0.99. Our results have a significantly higher value. In addition, our research applies PCA so that the smart lighting control model has a low dimension. In machine learning, "low dimension" refers to the situation where the data or the feature space has a relatively small number of features [32]. This research contributes to the PCA-TS-ANN model, which can perform smart lighting control and has low dimensions.

5 Conclussion

Using our core dataset from a smart lighting prototype, we successfully created an intelligent and low-dimensional smart lighting control. By using cross-correlation and PCC for a more optimal model, we suggest PCA-TS-ANN. The PCA-TS-ANN model produced by this study had accuracy, precision, recall, and F1-scores of 0.9993, 0.9997, 0.9994, and

0.9996. The PCA technique reduces the 1200 TS-ANN features to 36 features. Additionally, the model's size has shrunk from 3534 kB to 807 kB. Compared to the other models, ours is simpler in complexity. Compared to 0.34 ± 0.11 ms, the delay with TS-ANN is 0.27 ± 0.06 ms. Our research's contribution is the more precise and smaller-dimensional TS-ANN for PIR-based smart lighting control. Future research should focus on developing an effective model that can be embedded in NodeMCU without causing a lag in the computer network.

Acknowledgments

We want to thank Telkom University and The Ministry of Education, Culture, Research, and Technology (Kemendikbudristek) for funding this research through the Doctoral Dissertation Research scheme.

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