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Research Article

Hybrid LSTM-PCA-Powered Renewable Energy-Based Battery Life Prediction and Management for IoT Applications

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To ensure self-sustainable and long-term requirement of Internet of Things (IoT) operation, energy harvesting (EH) is a promising technique. In this work, battery prediction problems and joint access control are studied in a IoT cell system with a base station (BS) and EH user equipment (UE) with limited uplink access channels. Every UE present holds a limited capacity rechargeable battery. In order to address this issue, we take into consideration the uplink wireless system with "N" EH user equipment (UE) along with the base station. To build the UE uplink access control, the first step involves the application of hybrid Q network (HQN) with long short-term memory (LSTM) to tackle the access control issue. This technique maximizes the uplink transmission sum rate. The LSTM DQN network designed has two layers with battery prediction and joint access control solution. The first layer is developed to predict battery levels, while the next layer generates the access control information based on channel information along with the predicted values. This network is trained to decrease the discounted prediction loss and increase long-term discounted sum rate, at the same time by training the two layers jointly. In recent years, IoT sensors have played a major role in collecting and monitoring data gathered from real-world applications such as environmental monitoring, transportation, urban security, smart energy management, agriculture, and health care. Several of these appliances function with batteries. Hence, the primary task would be to predict the batter's lifespan and provide a timeframe to replace or recharge the battery. The battery life used in an IoT network is predicted with the help of a hybrid random forest-principal component analysis (PCA) regression algorithm with machine learning.

1. Introduction

In recent years, the Internet of Things (IoT) has formed a crucial part of all technological advancements. However, there is one drawback when using IoT which is the need for self-sustainable or long-term operations with respect to its applications. Hence, energy harvesting (EH) has been identified as the optimal method that can be used to positively decrease the greenhouse gasses and improve the network lifetime. This methodology provides a convenient and plausible solution to the energy issues in IoT. EH is also a topic of interest in several areas like future cellular networks, wireless sensor networks, and D2D communications [1]. In general, it is not possible to predict the energy harvested amount because of the stochastic nature of the energy source. Hence, the most important aspect of tackling this would be to properly device a mechanism to deal with the dynamics of harvested energy in wireless communication systems with EH.

In order to address this issue, we take into consideration the uplink wireless system with "N" EH user equipment (UE) along with the base station. To build the UE uplink access control, the first step involves the application of hybrid Q network (HQN) with long short-term memory (LSTM) [2]. This is followed by the use of round-robin to create a battery prediction scheme based on a hybrid LSTM neural network to decrease prediction loss. This issue of battery prediction and access control of a two-layer LSTM-based neural network with DQN enhancements is proposed. The primary objectives of the work are as follows:

(i) A hybrid LSTM neural network-based battery prediction methodology that executes on the assumption that scheduled users use their true battery states information [3] while transmitting data is introduced in this work. This technique is incorporated by using round-robin access control policy and is known to decrease prediction loss

(ii) An algorithm based on LSTM DQN is proposed where the information on channel states of current time slot and user battery specifications are known at the base station. This algorithm enables maximization of long-term expected total discounted transmission data using the UE uplink access control scheme. The purpose of this work is to attain a more balanced and stable transmission along with addressing the traditional access control problems for a long time horizon

(iii) Assume a scenario with no statistical and noncausal knowledge about the system in which uplink transmission takes place with limited access channels and multiple EH UE present

(iv) The LSTM DQN network designed has two layers [4] with battery prediction and joint access control solution. The first layer is developed to predict battery levels, while the next layer generates the access control information based on channel information along with the predicted values. This network is trained to decrease the discounted prediction loss and increase long-term discounted sum rate, at the same time by training the two layers jointly

(v) There are several practical considerations taken into account in the proposed work. Here, the UE's energy arrival distribution is not known in priori by the BS. Moreover, it is assumed that the true battery states are embedded by the scheduled users only which transmitting data thereby decreases signaling overhead of the system

(vi) Simulation outputs based on varying scenarios indicate that the proposed work can attain higher network performance and effectiveness when compared with other similar methodologies

The battery life used in an IoT network is predicted with the help of an hybrid random forest-principal component analysis (PCA) regression algorithm [5]. The major features of this algorithm are as follows:

(i) Selection of optimal features using PCA and eradication of unnecessary features that affect the output

(ii) Dataset transformation using one-hot encoding scheme

(iii) Use of random forest regression algorithm to predict battery life of IoT network

(iv) A comparison [6] is drawn between the proposed model and similar other existing traditional methodologies

2. Literature Survey

In recent years, IoT sensors have played a major role in collecting and monitoring data gathered from real-world applications such as environmental monitoring [7], transportation, urban security, smart energy management, agriculture, and health care. Several of these appliances function with batteries [8]. Hence, the primary task would be to predict the battery's lifespan and provide a timeframe to replace or recharge the battery. Numerous research works have been initiated to develop an appropriate mechanism [9] to predict battery lifetime. However, there are several limitations that come into play in observing, analyzing, and finding a solution for predicting the battery lifetime, especially in places where an abnormal pattern of battery discharge is observed [10]. Recently, a survey was also carried out in the SPHERE [11] environment to test the discharge pattern of the battery and how the lifespan of the battery decreases/increases. The experiment was executed in a SPHERE sensing platform in which wearable sensor devices and environment sensors are used. To rectify the communication problems, a narrowband-based IoT has been introduced which makes use of low-energy appliances which require very less power and can run on the battery for a period of minimum 10 years without need for replacement.

In [12], the authors have proposed a methodology to predict the lifespan of a battery, and the output observed indicated that when compared with other traditional methods, the proposed work was able to decrease energy utilization by around 35% [13]. Several other investigations were carried out in many multiuser scenarios and the outputs were compared. In [14], a power utilization model is proposed using a tool to determine the lifetime of a battery in IoT devices by analyzing the information on feasible interference levels and expected network traffic. The work involved shows several techniques that can decrease the impact of the parts of the device which are responsible for high power consumption. One of the leading sources of energy in IoT devices is the solar energy which is used to power sensor nodes. It has been observed that due to excessive data transmission, the IoT sensor nodes will consume a large amount of energy. The amount of energy that is collected by a solar panel is measured using the algorithm proposed by the authors in [15] using the weighted average of light intensity. This has a 0.5% error rate prediction.

In today's scenario, a number of location tracking applications are used in the smartphones that hold WiFi, accelerometer, Global Positioning System, etc. Here, GPS is the most commonly used device that can be used to track the location of a person/device. However, it requires a large amount of energy and will eventually drain the battery dry, quickly. Hence, the authors in [16] introduced a novel application called SensTrack [17] to track the location in an efficient manner with optimal utilization of energy in the smart devices. However, the drawback with this application was that it was not able to provide high accuracy in tracking and the data processing for the accelerometer did not meet the expectation. There are two major classes to categorize the EH-based systems depending on the knowledge on energy arrivals.

(i) Class I involves the offline approaches carried out with information on noncausal data to determine the upper bounds of the system. Specifically, the authors in [18] investigated the optimal uplink resource allocation such that it used to send information collectively to the access point using the wireless signals with harvested energy. Moreover, the authors in [19] studied the optimal packet scheduling in multiple access channels based on the objective to decrease the time taken between the sender and the receiver of information

(ii) Class II is the online approach. Here, a partially observable Markov decision process (POMPP) is used to study the EH transmitters and multiaccess wireless system along with their issues are defined and studied by the authors. The authors in [20] considered EH nodes with optimal power control policies such that the EH dynamics is captured by a dam model

(iii) In these classes, the transmitter should be aware of some statistical knowledge of the system. However, in several cases, it is not possible to obtain the statistical knowledge of system dynamics or the noncausal knowledge. This is especially the case when EH processes originate from unknown distribution sources or are nonstationary. Based on these observations, there is much demand and need for learning-based model-free methodologies which do not require or are least dependent on priori information

(iv) On interacting, the learning agent will be able to observe some statistical information using learning-based methods in an unknown environment. In a related survey, the authors in [21, 22] studied the communication in an EH transmitter connected point to point. In particular, the authors in [23] introduced a Q-learning-based theoretic approach wherein a binary decision is made by the transmitter to decide on whether transmission should take place or not, based on the maximum utilization of transmitted data. Similarly, the authors in [24] have analyzed the transmission of power allocation using a reinforcement learning (RL) algorithm that improves the overall throughput function. Further, a nonlinear function approximation is combined with the RL algorithm to ensure the use of channel values and incoming energy that is determined within a particular range

3. Proposed Architecture

The application in which the IoT devices are deployed decides the amount of power required. Sensors transmit voluminous data and require more energy when they are in active mode, while they require lesser energy and send less data during sleep mode. However, certain sensors need more energy at all times. The overall power consumption of the device depends on the IoT application and the individual components used. In the IoT devices, the battery life estimation has to be done. The disposable batteries that are nonrechargeable and the rechargeable batteries coexist. Each of these batteries has specific advantages and disadvantages. Based on the battery used, the lifetime and power consumption of the system are estimated. The energy sources may exhibit nondeterministic or stochastic characteristics. For effective prediction, every facet of the energy system must be analyzed in an in-depth manner. A customized energy management module is required for every IoT device.

The sensor data is transmitted to one-hot encoding where the categorical data is converted into its corresponding numerical data. Battery prediction issues and joint access control are analyzed in an IoT cell system with BS and EH-UE with limited uplink access channels. Every UE has a limited capacity rechargeable battery. The uplink wireless system with "N" EH UE along with the base station is considered to overcome this issue. To build the UE uplink access control, the first step involves the application of HQN with LSTM and the access control issue is overcome. This technique maximizes the uplink transmission sum rate. The LSTM HQN network designed has two layers with battery prediction and joint access control solution. The first layer is developed to predict battery levels, while the next layer generates the access control information based on channel information along with the predicted values. This network is trained to decrease the discounted prediction loss and increase long-term discounted sum rate, at the same time by training the two layers jointly. The battery life used in an IoT network is predicted with the help of a hybrid random forest PCA regression algorithm with machine learning. Figure 1 provides an overview of the proposed system architecture.

All the elements in a group can be chosen equally in a specific rational order using the round-robin arrangement. The order is considered from the top to the bottom of the list

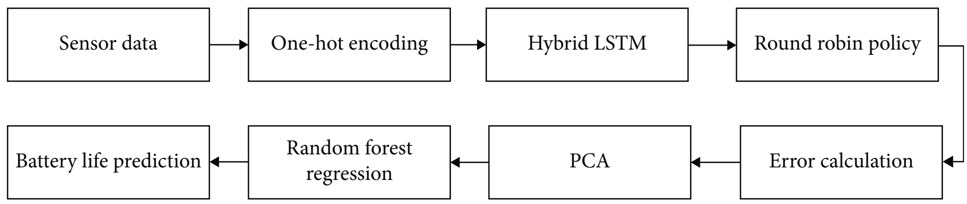


Figure 1: Block diagram of the proposed hybrid LSTM-PCA system.

Step 1: Initialization of experience memory D.
Step 2: Initialization of the prediction generator network parameters φ_Y
Step 3: Assign random weights θ_y to φ_Y
Step 4: Environment initialization at state S_1.
Step 5: Initialization of the total epochs E_p.
Step 6: When x=1, …. E_p
Step 7: Prediction output $o(S_x)=y_t$ given by current $\varphi_Y(\theta_y(t))$
Step 8: Provide the BS access control center with input y_t
Step 9: Apply round-robin policy to schedule UE
Step 10: Stop transmission if $P \leq Y_{ix}$
Step 11: Observe the new state S_{x+1}
Step 12: Store transition
Step 13: Sample random transitions
Step 14: Calculate error
Step 15: Update the network parameters using stochastic gradient descent.
Step 16: Stop

Algorithm 1: Hybrid LSTM algorithm for battery life prediction.

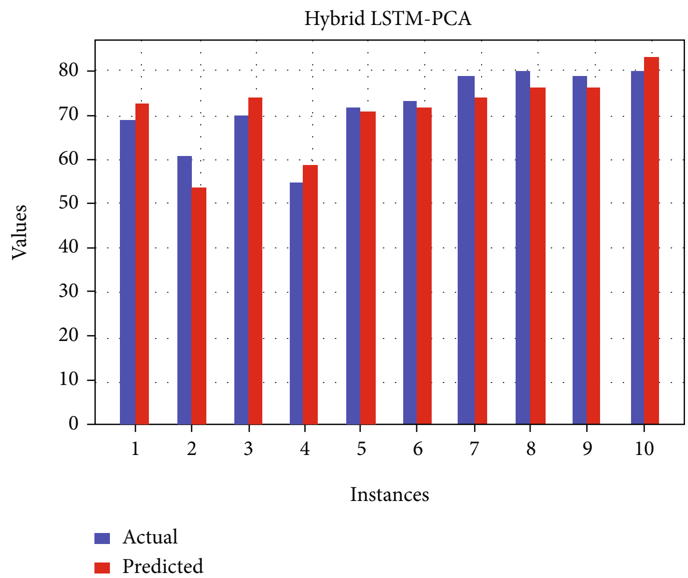
usually and then the process repeats as many times as required. Better prediction of data while converting it to prepare for the algorithm is achieved through the one-hot encoding scheme. Each categorical value can be converted into a new categorical column with on-hot encoding and the columns are assigned with binary values 0 or 1. A binary vector is used for representing each integer value.

3.1. Estimation of Power Consumption. In order to provide optimal results, both hardware and software are integrated into IoT as it is an embedded domain. Along with the hardware, the software also plays a major role in the battery life prediction of an IoT device. The software deployed on the hardware is used for measuring battery utilization and prediction. Various operating states of the deployed hardware are determined via software-based estimation (SBE). Different power is consumed by each operating state in order to be in that specific state and to move to another state. Customization is required for monitoring the different units deployed along with the acquisition of accurate information over a long duration from the SBE. A module is deployed by certain manufacturers of operating systems (OS) for monitoring the SBE's energy consumption.

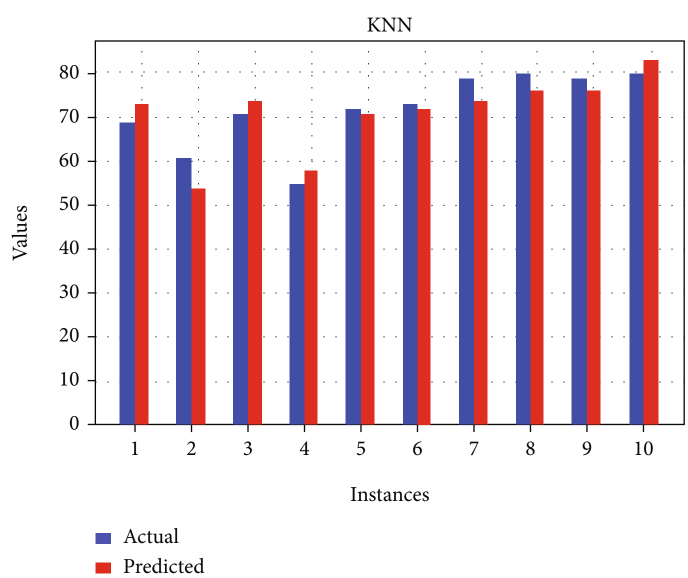
3.2. AI-Based Battery Prediction Algorithm. Various digital computing applications make use of artificial intelligence (AI). Machine learning (ML) is an application of AI where machines are trained to think and make decisions to behave like humans. The performance of these machines is tested. Better prediction of IoT is achieved with the help of ML. AI modules are incorporated in over 80% of IoT projects according to Gartner's report. Different battery lifetimes are predicted using a new ML model devised based on the real-time experimental data using the AI algorithms. Artificial neural network (ANN), convolution neural network (CNN), and deep learning techniques can be used for prediction of battery life. Most applications currently use the ML models; however, there are several limitations to these algorithms such as need for good featured and enormous data. In order to predict the battery life of IoT devices, the neural network models are often preferred.

In order to keep the energy neutral in the wireless energy harvest networks, the harvested energy and the expended energy must be maintained at equal values throughout the operation. In order to predict the future harvested energy in an accurate manner, an efficient energy-neutral policy is essential. The battery state of the user equipment may be predicted using the LSTM method. This prediction is completely data driven and the energy model of the user equipment is not necessary. New values can be calculated for the variables by using the gradients in the stochastic gradient descent technique for each variable in the model. The hybrid LSTM algorithm for battery prediction is described below.

3.3. AI-Based Battery Prediction Algorithm. The key features are determined and the data dimensionality is reduced largely

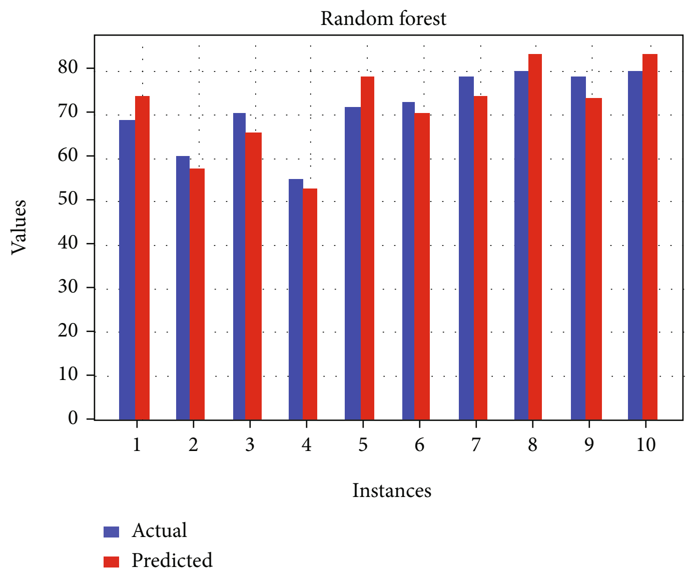


(a)

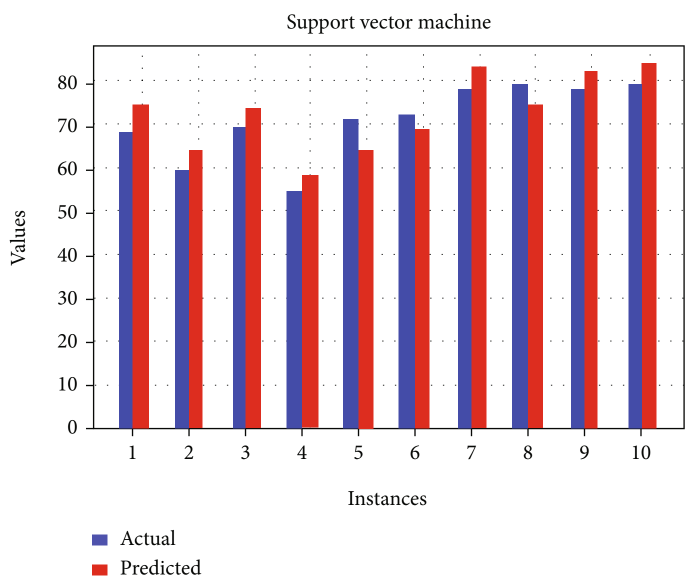


(b)

Figure 2: Continued.



(c)



(d)

Figure 2: Comparison of actual vs. predicted values for 10 random instances in (a) hybrid LSTM-PCA, (b) kNN, (c) random forest, and (d) support vector machine algorithms.

with the help of PCA in IoT applications. Data prediction, compression, elimination of duplication, and extraction functionalities can be executed with the help of PCA. Mean, standard deviation, covariance, and eigen values are estimated using

$$\bar{A} = \frac{1}{x}\sum_{i}^{x} A_a,$$
$$\mathrm{SD} = \sqrt{\frac{1}{x}\sum_{a=1}^{x}\left(A_i - \bar{A}\right)^2},$$
$$\mathrm{Cov}(A, B) = \frac{\sum_{a=1}^{x}\left(A_a - \bar{A}\right)\left(B_a - \bar{B}\right)}{x},$$
$$[U \| A] = \lambda X, \tag{1}$$

Table 1: Metrics estimated through the regression algorithm.

Sl. no.	Parameter	Value
1	Variance	σ
2	Determination coefficient	0.909
3	Root mean squared error	0.055
4	Mean absolute error	0.0474

where $A_1, A_2, A_3, \cdots A_x$ denotes the arbitrary variables for a sample of size x. U is an x × x matrix, λ is a scalar, $A \neq \underline{0}$ is an eigenvector of U, and $A \neq 0$.

A mobile application can be used to enable the user to view the current status of the battery and the percentage of energy utilization for each device. The user can also view the predicted battery status and optimize their usage accordingly.

4. Result and Discussion

Several IoT network sensor data such as array of things locations, beach water quality, connectivity traces, and outdoor temperature data are publicly available. The outdoor temperature data [25] collected by taxis in Rome, Italy, is used for analyzing the proposed model. A laptop with the following configuration is used for experimentation: Windows 10 OS, 500 GB HDD, and 8 GB RAM. Python programming language is used for this work. The dataset consists of several instances that are categorized based on their attributes. The attributes that do not contribute to the estimation of battery life are eliminated. Timestamp, temperature, battery life, and other such critical attributes are considered. Several preprocessing techniques are performed on the IoT network data before applying the random forest regression algorithm. The missing values are treated, data is normalized, dimensionality is reduced, and data is transformed. One-hot encoding technique is used for reducing the data complexity by converting the attributes into numerical values ranging from 0 to 1.

The unimportant and irrelevant attributes in the data are removed using PCA, which is a well-known dimensionality reduction algorithm. 90% of the components are retained after this process. Figure 2 shows the experimental results of the proposed model, kNN, random forest, and support vector machine algorithms with the same dataset. 10 random instances are considered for experimental purpose. Variance, determination coefficient, root mean squared error, and mean absolute error are the metrics evaluated by the regression algorithm as represented in Table 1. The following observations are made from the experimentation:

(a) The unimportant attributes are eliminated, thereby reducing the burden of the prediction and regression algorithm

(b) Optimal features are selected for enhancing the performance of the algorithm

(c) The proposed hybrid LSTM-PCA algorithm outperforms the kNN, RF, and SVM algorithms

5. Conclusions and Future Scope

Smart home surveillance, smart grids, smart cities, and several applications make use of IoT systems to enhance the quality of life of people. Several challenges have to be overcome to realize the actual potential of IoT networks. The battery prediction and user access control issues observed in IoT systems are overcome by the proposed work. The lifetime of the IoT network's battery is predicted using a PCA-based random forest regression algorithm. The LSTM HQN network with two layers offers a battery prediction and joint access control solution. Attribute mean technique is used for preprocessing. PCA algorithm is used for dimensionality reduction and feature selection. Random forest regression algorithm processes the reduced dimensions of the dataset. On comparison, it is found that the performance of the proposed model outperforms the conventional regression algorithms with an error minimization of about 92%. As a future dimension, a large dimensional dataset may be used for testing the proposed model.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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