Smart Grid Energy Management System for Industrial Applications

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Abstract— **Energy is one of the top operating expenses in industries. Following the increased adoption of smart grids in recent years, industries can leverage on its capabilities to design effective energy management schemes for competitive advantage. This paper addresses the challenge of energy management in industries by incorporating the aspects of a smart grid in designing an energy management system (EMS) where demand side management (DSM) is utilized to enable users control their energy usage and minimize costs. A forecasting model for electricity prices and demand is developed using Long Short Term Memory (LSTM) - Recurrent Neural Network (RNN). The predicted prices are used in load scheduling to realize potential energy cost savings. The non-priority loads are scheduled to leverage on low electricity prices during off peak times. The effectiveness of the designed energy management strategy is tested using an IEEE 30 bus system. A suitable operation schedule with committed units for each hour is given for one sample day. Using the test system with 20 loads yielded an annual energy cost saving of $2,961,169.20 and a payback period (PBP) of 4.39 years. Quantifying both the energy and non-energy benefits of investing in an EMS justifies its high investment cost. Long term use of an industrial EMS is likely to yield huge energy and cost savings.**

Keywords— Smart grid, Energy Management System, Long Short Term Memory, Recurrent Neural Network, Demand Side Management, Demand Response, Time of Use

I. Introduction

Various research works have explored energy management from different perspectives. Y. Nozaki et al. discussed EMSs for homes, buildings, communities, and data centers where energy is optimized jointly [1]. Tests run on each of these systems yielded either a reduction in carbon dioxide emission or a considerable saving in energy. Energy cost was minimized with shared use of the communication system. Automated demand response (DR), the role of consumers in energy management, and various smart grid technologies such as direct load control, storage, and cogeneration were explored by Samad and Kiliccote [2]. The importance of understanding the rate structures when performing peak scheduling was emphasized. The use of a standard information model that supports DSM activities was recommended. Collins et al. [3] came up with an energy monitoring and management system (EMMS) suitable for improving energy efficiency, cost savings, and ecological profile in industries. The model had a graphical user interface and operation scheduler (GUIOS) that generated feedback to the operator through the fuzzy inference system to ensure energy and cost savings. The scheduler was used to schedule machine operations assuming that all processes are schedulable.

According to Ogwumike et al. [4], scheduling of residential loads is done using dynamic prices determined from a day ahead variable pricing technique. A constrained linear programming problem for scheduling the appliances is solved using Mixed Integer Linear Programming optimization. It was noted that optimal scheduling of appliances can yield huge savings in energy. A generalized energy management scheme based on state task network was proposed in [5]. The scheduling of tasks and distributed energy resources was done based on the day-ahead hourly prices. The DR scheme enabled the users to shift electricty usage to off peak periods thus balancing the supply and demand, improving power reliability, and reducing the energy cost. In [6], a smart power management system based on hybrid energy storage is proposed. The authors created a smart EMS for a coal mine to boost energy efficiency, increase the utilization of renewable resources, and improve the reliability of the energy supplying system taking into consideration power quality aspects.

M. Acone et al [7] designed an EMS for smart houses that optimized energy consumption and electricity cost while ensuring the consumer's comfort. MATLAB, Simulink and Stateflow were used to simulate the EMS model whereas Monte Carlo Simulation was used to compare between the normal and economy scenarios. The importance of a smart grid in energy demand management was addressed in [8]. The authors introduced the smart home concept where smart appliances communicate with the smart meters using a Home Area Network to inform electricity usage decisions. Lastly, the idea of energy storage in prosumer based systems for both energy sharing and management was brought forth in [9]. The model was suitable in peak load management. Binary Integer Programming (BIP) was used for solving the objective function. This paper will therefore incorporate aspects of a smart grid in designing an EMS that will recommend suitable time of use (TOU) for industrial loads based on the predicted electricity prices.

A. Contribution

The capabilities of smart grids to process data, make informed decisions, and actively engage consumers in controlling their energy consumption are used in designing the EMS. LSTM machine learning technique is used in developing the prediction model. Load scheduling is performed based on the forecasted hourly electricity prices. A suitable operating schedule with committed units is generated to inform the user on effective ways of minimizing energy cost.

B. Paper Organization

The rest of the paper is organized as follows: Section II is the problem formulation, Section III is the proposed methodology, Section IV is a presentation of simulated results, while Section V is the work's conclusion and suggestions for further research. Lastly, the references used are listed.

II. PROBLEM FORMULATION

A multi-objective problem of not only seeking to minimize the energy consumption and cost but also to assess the economic viability of implementing an EMS is addressed. A forecasting model is developed using a machine learning technique rather than conventional time series modelling methods like Autoregressive Integrated Moving Average Model (ARIMA). Unlike other researches that use actual hourly electricity prices to do scheduling, predicted prices are used. This approach is highly recommended for long term planning in order to defer unnecessary energy costs. The economic viability of implementing the EMS is assessed using various economic tools.

A. Forecasting and Load Scheduling Model

The forecasting model is developed using LSTM RNN machine learning technique. The inputs to the model are historical data on hourly electricity prices and demand. LSTM networks are used to learn order dependence in the given sequence for accurate prediction. The main objective when training a machine learning model is to minimize the loss function. The mean squared error (MSE) loss estimator is chosen due to its suitability in determining the accuracy of the model when dealing with regression problems. MSE is selected over mean absolute error due to its ability to converge even with fixed learning rate and its sensitivity to outliers in the dataset. The magnitude of loss value is directly proportional to the gradient of MSE loss and this gradient reduces as the loss tends to zero. A good model should have MSE values closer to zero implying that the probability of the model to make accurate predictions is high. The number of epochs in the LSTM networks is increased until minimum MSE is obtained. The MSE is computed using the formula in equation 1:

$$MSE = \frac{1}{n}\sum_{t=1}^{n} e_t^2 = \frac{1}{n}\sum_{t=1}^{n}(y_t - f_t)^2 \qquad (1)$$

Where n is the size of the test set, e_t is the forecast error, y_t is the actual price, and f_t is the forecasted price.
The predicted prices are used to determine suitable load schedules.

B. Possible Load Combinations

Given n number of loads, the possible combinations is given by an array of binary groupings with a count from 0 to 2n-1 [3]. The viable load combinations must ensure that the supply meets the demand at all times and all priority loads are on. A unit commitment schedule is generated showing all the possible machine combinations and the resulting energy cost.

C. Objective Energy Cost Function

Upon scheduling of the loads, the known power consumption rates and operation times of the active machines are used to determine the energy cost using equation 2.

$$\boldsymbol{F(P_i)} = \sum_{\boldsymbol{i=1}}^{\boldsymbol{n}}(\boldsymbol{C_t} \times \boldsymbol{t} \times \boldsymbol{P_i}) \qquad (2)$$

Where $\mathbf{F(P_i)}$ is the total cost of electricity consumed by the ith active machine ($); $\mathbf{C_t}$ is the hourly electricity price ($/MWh), t is the running time of each machine (h), $\mathbf{P_i}$ is the power consumed by the ith active machine (MW), and n is the number of machines.

D. Power Balance Constraint

The maximum power consumption for all the machines need to balance the power supplied by the generators and/or utility grid at any given instant. Considering a region with hundreds of industries that lack EMSs and share a distribution grid, the losses in each company will result in a huge power demand hence a significant impact on the grid. However, taking the case of a single industry within this zone, the impact of losses on the grid can be considered negligible. Equation 3a gives the power balance constraint assuming such an industrial set up.

$$P_{KS} \geq \left(\sum_{i=1}^{n} P_i\right) \qquad (3a)$$

Where P_{KS} is the peak power supplied and P_i is the power consumed by the ith active machine (MW).
The non-priority loads are scheduled to take advantage of lower electricity prices ensuring that the constraint in equation 3b is met.

$$\sum_{j=1}^{8} P_{NL} \leq P_{KS} - \sum_{k=1}^{12} P_{PL} \qquad (3b)$$

Where P_{NL} is the power consumed by each non-priority load and P_{PL} is the power consumed by each priority load.

E. Economic Viability

The economic feasibility of investing in the industrial EMS is evaluated using cost benefit analysis (CBA). The costs which include the staff time utilized in setting up, implementing and conducting trainings on the use of the system are estimated. Others costs include that of purchasing additional metering tools and hiring experts to actualize the installation and use of the EMS. On the other hand, the energy and non-energy benefits of the EMS are also determined. The results of the CBA are evaluated using simple PBP and return on investment (ROI) computation using equations 4 and 5 respectively.

$$PBP = \frac{Initial\ investement\ cost\ in\ the\ EMS}{Annual\ energy\ cost\ saving} \qquad (4)$$

$$ROI = \frac{1}{PBP} \qquad (5)$$

III. LSTM – RNN TECHNIQUE

LSTM-RNN is proposed for forecasting the electricity prices and demand. The method is capable of learning long sequences with long time lags [10]. Unlike Feed Forward Networks that do not model memory, RNNs store activations from each time step in the internal state of the network to provide a temporal memory thereby remembering previous inputs. This capability makes RNNs better suited for capturing information from sequences and time series. A simple RNN learns using back propagation through time and experiences the vanishing gradient problem when tackling long term dependencies.

The pioneers of the use of LSTM were Hochreiter and Schmidhuber who devised the method to solve the problem of vanishing gradient by controlling the cell states using various gates [11]. The hidden layers in LSTM have memory blocks with four parts namely:

(i) Input gate which controls the activations that enter the memory cell.

(ii) Forget gate which assists the network in resetting the memory cells by forgetting past inputs.

(iii) Output gate which determines the output to pass on to successive networks and the ones to be filtered.

(iv) Self-connected memory cell.

The information at different states is regulated by the inputs and the hidden states generated from the previous steps after sigmoid or tanh activations within the neural network layers. Backpropagation through time (BPPT) is the training algorithm used in LSTM [10]. Equations 6 to 10 summarize the mathematical functions of the gates which perform the task of limiting the information passing through the memory cell.

$$i_t = sigmoid(W_{xi}x_t + W_{hi}h_{t-1} + b_i) \quad (6)$$

$$f_t = sigmoid(W_{xf}x_t + W_{hf}h_{t-1} + b_f) \quad (7)$$

$$o_t = sigmoid(W_{xo}x_t + W_{ho}h_{t-1} + b_o) \quad (8)$$

$$c_t = f_t.c_{t-1} + i_t.tanh(W_{xc}x_t + W_{hc}h_{t-1} + b_c) \quad (9)$$

$$h_t = o_t.tanh(c_t) \quad (10)$$

Where i_t is the input gate, f_t is the forget gate, o_t is the output gate, c_t denotes the cell state generated as an additional variable for the cell, x_t is the input, h_{t-1} is the hidden state in the previous step, W is the weight matrix and b is the biases to each layer. The symbol **.** stands for the operation of element-wise multiplication. Figure 1 shows the architecture of LSTM memory block.

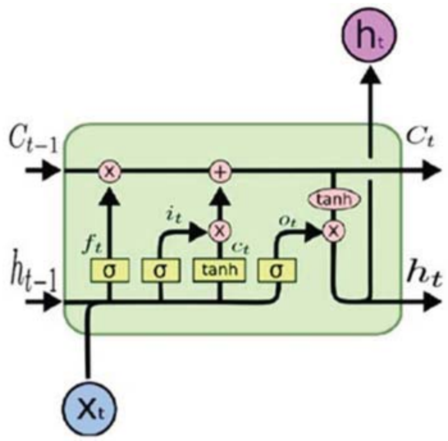

Figure 1: Architecture of LSTM memory block

Stacked LSTM with four layers is used in this paper where each hidden layer has 50 LSTM units. The model is fit using the efficient Adam version of stochastic gradient descent and optimized using the mean squared error loss function. Once the model is defined, it is fit on the training dataset before being used to make predictions. The key aspects of the LSTM forecasting model are highlighted below:

Layers: The number of layers influence the learning capacity of the model. It is important to use additional layers and have different numbers of neurons in each to improve hierarchical learning.

Features and time steps: These define the shape of the input by specifying what the model expects for each sample. The use of lag observations as input features and time steps can improve the predictive capability of the model.

Batch size: This is the number of training examples used in an iteration. The batch size determines the level of manipulation required for both the training and test datasets.

Optimization algorithm: There are several optimization algorithms that tend to either accelerate or decelerate the learning process to improve the configuration's efficiency.

Weight regularization: This is done to control the rate of learning and reduce overfitting of the networks.

Dropout: This is a regularization method that slows down learning within the recurrent LSTM networks.

Loss function: This is an evaluation method for performance of a specific algorithm in modelling the given data. Optimization is done to enable the loss function learn how to reduce the prediction error.

A summary of LSTM parameters mapping for the forecasting problem is given in Table 1.

Table 1: Parameter Mapping for the Forecasting Problem

LSTM Parameter	*Mapping to the Forecasting Problem*
Input	Historical values of electricity price and demand
Output	Predicted values of electricity price and demand
Bias	Error value being fed back to the input of the forecasting model
Gates	Factors that regulate the variation of electricity price and demand

The key steps involved in designing the EMS are:

(i) Analysis of historical data on electricity prices and demand.

(ii) Building a forecasting model.

(iii) Recommendation of possible operation hours.

(iv) User input to choose preferred TOU of available machines.

(v) Calculation of total energy consumed and energy cost.

(vi) Calculation of potential energy savings if the cost obtained in the previous step is less than that incurred during normal scheduling.

(vii) Determining viability of having an industrial EMS.

The effectiveness of the designed model is tested using an IEEE 6 generator 30 bus system with 20 loads. Figure 2 represents the IEEE 30 bus system.

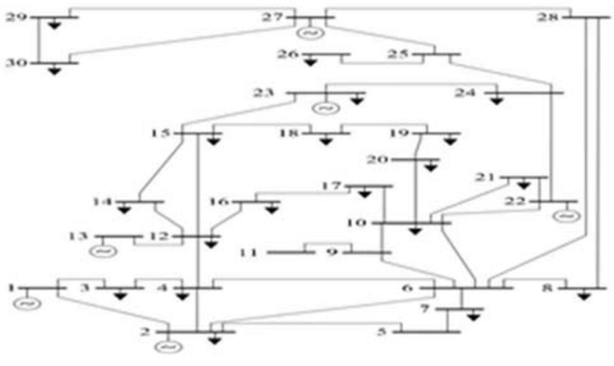

Figure 2: IEEE 6 generator 30 bus system

IV. RESULTS AND ANALYSIS

Forecasting: The historical data on electricity prices and demand was collected for 6 months beginning August 2019 for Texas. 80% of the data was used for training the LSTM model while the remaining 20% was used to test the model. For the demand, the percentage difference between the actual and forecasted values range from 0.06 to 3.08 while for the price, it ranges from 0.89 to 14.01. The results obtained for the entire test period are used to plot the graphs in Figures 3 and 4.

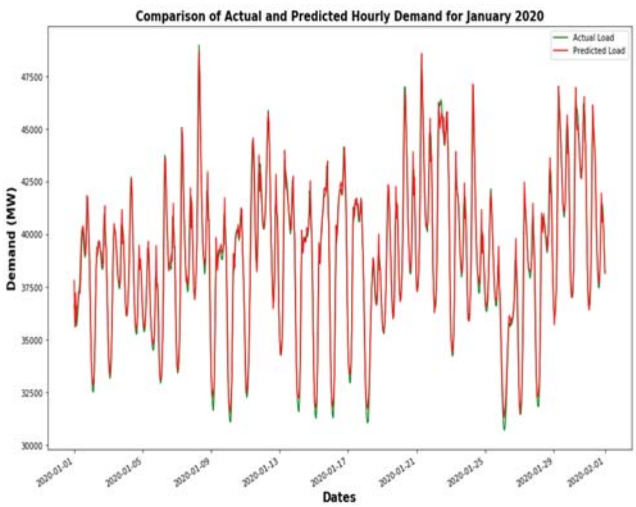

Figure 3: Comparison of Actual and Predicted Hourly Demand

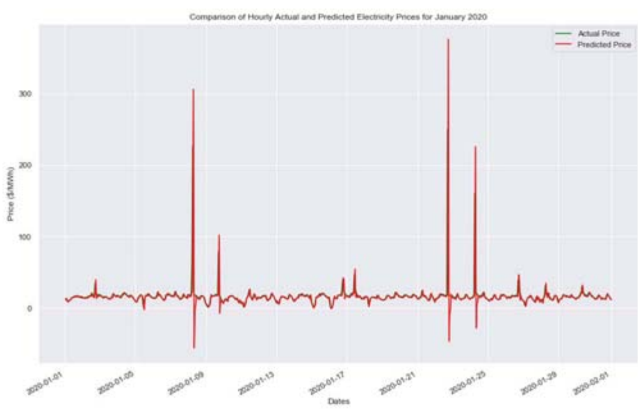

Figure 4: Comparison of Hourly Actual and Predicted Electricity Prices

Figures 3 and 4 indicate that the machine learned the pattern in the time series data given in the training set and used that pattern to predict the values in the test set. This was achieved by increasing the number of epochs in the training model thereby reducing the MSE loss.

Load scheduling using predicted prices: A chart is generated to show all the active loads during each hour and the energy cost incurred with and without an EMS.

The effectiveness of the operating schedule given is tested on an industrial system modeled based on IEEE 30 bus system. The system has a total supply of 435MW while the demand is 271MW for 12 priority loads and 214MW for 8 non-priority loads. Scheduling is done taking advantage of lower hourly electricity prices to operate non-priority loads that consume high power ensuring that the constraint in equation 3b is satisfied. Tables 2a and 2b give the original and recommended schedules respectively, with the committed units on the sample day.

Table 2a: Unit commitment original schedule for 20th January 2020

Time	Unit Commitment - Original Schedule																				Hourly Energy Cost using Actual Prices ($)	Hourly Energy Cost using Predicted Prices ($)
	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T		
12:00:00 AM	1	1	1	1	1	1	1	0	1	1	0	1	1	0	1	1	1	1	0	1	7273.8075	7091.01503
1:00:00 AM	1	0	1	1	1	1	1	0	1	1	1	1	1	0	1	1	1	1	1	1	6932.445	6467.42437
2:00:00 AM	1	1	1	1	0	1	1	1	1	1	0	1	1	1	1	1	1	1	0	1	6703.13	6328.09702
3:00:00 AM	1	0	1	1	0	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	6767.79	6180.76182
4:00:00 AM	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	0	1	0	1	6576.12	6381.81024
5:00:00 AM	1	0	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	7115.81	6118.72389
6:00:00 AM	1	0	1	1	0	1	1	1	1	0	0	1	1	1	1	1	0	1	0	1	7503.5	6939.60512
7:00:00 AM	1	0	1	1	0	1	1	0	1	0	0	1	1	0	1	1	1	1	0	1	7862.55	7264.51065
8:00:00 AM	1	0	1	1	1	1	1	0	1	0	0	1	1	0	1	1	0	1	0	1	7730.58	7551.15541
9:00:00 AM	1	1	1	1	1	1	1	0	1	0	0	1	1	0	1	1	0	1	0	1	7726.565	7161.63965
10:00:00 AM	1	0	1	1	0	1	1	0	1	0	1	1	1	0	1	1	0	1	0	1	7406.315	7221.86571
11:00:00 AM	1	1	1	1	1	1	1	0	1	0	1	1	1	1	1	1	0	1	0	1	6928.89	6751.10766
12:00:00 PM	1	1	1	1	1	1	1	1	1	0	1	1	1	0	1	1	1	1	0	1	6664.77	6269.7272
1:00:00 PM	1	1	1	1	1	1	1	0	1	1	0	1	1	1	1	1	1	1	1	1	6634.25	6098.3181
2:00:00 PM	1	1	1	1	1	1	1	1	1	0	0	1	1	0	1	1	1	1	1	1	6560.34	6210.79476
3:00:00 PM	1	1	1	1	0	1	1	1	1	1	0	1	1	1	1	1	0	1	1	1	6444.8	6169.42248
4:00:00 PM	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	0	1	1	1	6596.685	6031.46777
5:00:00 PM	1	0	1	1	1	1	1	1	1	0	0	1	1	1	1	1	1	1	0	1	7305.875	6293.85149
6:00:00 PM	1	1	1	1	0	1	1	0	1	0	0	1	1	0	1	1	0	1	0	1	8061.255	7221.02313
7:00:00 PM	1	0	1	1	0	1	1	0	1	0	0	1	1	0	1	1	0	1	0	1	7872.41	7942.19119
8:00:00 PM	1	0	1	1	0	1	1	0	1	1	0	1	1	0	1	1	0	1	0	1	7509.5875	7302.60927
9:00:00 PM	1	0	1	1	0	1	1	0	1	0	1	1	1	1	1	1	0	1	0	1	7251.3	6823.64296
10:00:00 PM	1	1	1	1	1	1	1	1	1	0	1	1	1	0	1	1	0	1	0	1	7190.4	6622.4469
11:00:00 PM	1	1	1	1	0	1	1	0	1	1	0	1	1	0	1	1	0	1	1	1	5909.995	6663.47962
Total Energy Cost																					170529.17	161106.691

Table 2b: Unit commitment proposed schedule for 20th January 2020

Time	Unit Commitment - Proposed Schedule																				Hourly Energy Cost using Actual Prices ($)	Hourly Energy Cost using Predicted Prices ($)
	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T		
12:00:00 AM	1	1	1	1	1	1	1	0	1	1	0	1	1	0	1	1	1	1	0	1	5841.8275	5695.02102
1:00:00 AM	1	0	1	1	1	1	1	0	1	1	1	1	1	0	1	1	1	1	1	1	6220.2075	5802.96296
2:00:00 AM	1	1	1	1	0	1	1	1	1	1	0	1	1	1	1	1	1	1	0	1	6378.785	6021.89878
3:00:00 AM	1	0	1	1	0	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	6642.75	6066.56761
4:00:00 AM	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	0	1	0	1	5891.1075	5717.03834
5:00:00 AM	1	0	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	7165.34	6161.31362
6:00:00 AM	1	0	1	1	0	1	1	1	1	0	0	1	1	1	1	1	0	1	0	1	5898.1	5454.8524
7:00:00 AM	1	0	1	1	0	1	1	0	1	0	0	1	1	0	1	1	1	1	0	1	5467.215	5051.36904
8:00:00 AM	1	0	1	1	1	1	1	0	1	0	0	1	1	0	1	1	0	1	0	1	5117.68	4998.90008
9:00:00 AM	1	1	1	1	1	1	1	0	1	0	0	1	1	0	1	1	0	1	0	1	5591.355	5182.54485
10:00:00 AM	1	0	1	1	0	1	1	0	1	0	1	1	1	0	1	1	0	1	0	1	5151.465	5023.17123
11:00:00 AM	1	1	1	1	1	1	1	0	1	0	1	1	1	1	1	1	0	1	0	1	5936.725	5784.39975
12:00:00 PM	1	1	1	1	1	1	1	1	1	0	1	1	1	0	1	1	1	1	0	1	6258	5887.0678
1:00:00 PM	1	1	1	1	1	1	1	0	1	1	0	1	1	1	1	1	1	1	1	1	6587.42	6055.27115
2:00:00 PM	1	1	1	1	1	1	1	1	1	0	0	1	1	0	1	1	1	1	1	1	6297.3075	5961.77705
3:00:00 PM	1	1	1	1	0	1	1	1	1	1	0	1	1	1	1	1	0	1	1	1	6353.6	6082.11933
4:00:00 PM	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	0	1	1	1	6659.065	6088.50293
5:00:00 PM	1	0	1	1	1	1	1	1	1	0	0	1	1	1	1	1	1	1	0	1	6561.4375	5652.53487
6:00:00 PM	1	1	1	1	0	1	1	0	1	0	0	1	1	0	1	1	0	1	0	1	5654.34	5064.98305
7:00:00 PM	1	0	1	1	0	1	1	0	1	0	0	1	1	0	1	1	0	1	0	1	5055.505	5100.31709
8:00:00 PM	1	0	1	1	0	1	1	0	1	1	0	1	1	0	1	1	0	1	0	1	5226.3875	5082.33852
9:00:00 PM	1	0	1	1	0	1	1	0	1	0	1	1	1	1	1	1	0	1	0	1	5645.655	5312.69345
10:00:00 PM	1	1	1	1	1	1	1	1	1	0	1	1	1	0	1	1	0	1	0	1	6368.64	5865.59582
11:00:00 PM	1	1	1	1	0	1	1	0	1	1	0	1	1	0	1	1	0	1	1	1	4950.855	5582.05572
Total Energy Cost																					142920.77	134695.296
Potential saving upon implementing EMS																					8225.473544	

Table 2c shows the comparison between the total energy cost using the original and the proposed schedules for the sample day.

Table 2c: Comparing energy cost incurred using the original and proposed schedules for 20th January 2020

	Total Energy Cost Using Actual Prices ($)	**Total Energy Cost Using Predicted Prices ($)**
Original schedule	170529.17	161106.6915
Proposed schedule	142920.77	134695.2965
Cost saving achieved using proposed schedule	27608.4	26411.395
% cost saving	16.18984013	16.39372937

Adopting the recommended schedule given in Table 2b yields a potential energy cost saving of $ 8225.47 on that sample day for 24 hours industrial operations. Considering 30 working days monthly and a similar energy cost saving per day, the annual energy cost savings is $2,961,169.20 which is a huge cost that industries can save on if they put in place an industrial EMS. Additionally, based on Table 2c, running the machines using the proposed schedule results in an energy cost saving of approximately 16% whether the actual or predicted hourly electricity prices are used in the cost estimation.

Economic viability of an industrial EMS: The economic analysis of investing in an industrial EMS is done using CBA, PBP, and ROI. Table 3 summarizes the total cost of setting up the EMS which includes internal costs incurred by the company, cost of hiring external experts, and cost of purchasing energy monitoring equipment.

Table 3: Cost of setting up the industrial EMS

Category	**Activity**	**Cost ($)**
Staff time	EMS training	200,000
	EMS set up	900,000
	EMS implementation	400,000
Expert support	International experts	1,000,000
	Local consultants	150,000
Other operational expenses	Extra energy monitoring equipment	10,000,000
	Other low cost expenses	350,000
Total		**13,000,000**

Using the capital investment of $13,000,000 and the annual energy cost saving for year 1 ($2,961,169.20), a PBP of 4.39 years and an ROI of 0.2278 are obtained. The non-energy benefits were overlooked in this case however quantifying them and considering the future value of energy cost savings would lead to the realization of a more reasonable cost to benefit ratio as well as ROI.

V. CONCLUSION AND RECOMMENDATIONS

Load scheduling which is a DSM technique is used in designing an EMS where suitable operation times are suggested to the consumer based on the predicted hourly electricity prices. The usage of non-priority loads with high consumption is shifted to time periods where electricity prices are low. A unit commitment schedule is generated to enable the consumer to easily make a choice on loads whose use can be shifted. This operation schedule ensures that all priority loads are on at all times and the power balance constraint is always satisfied. Using the recommended operation schedule results in potential energy cost savings since the TOU of non-priority loads is shifted to a more effective time period. With the proposed schedule, energy cost savings of 16.19% and 16.39% are obtained using the actual and predicted hourly electricity prices respectively.

The LSTM –RNN is used due to its effectiveness in time series forecasting especially when dealing with non-stationary and non-linear data compared to conventional techniques such as ARIMA. The use of a MSE loss function made it possible to track the error value and ensure that it's minimum by increasing the number of epochs. The predicted hourly electricity prices have been successfully used to schedule the available loads on one sample day. Testing the effectiveness of the designed model using an IEEE 30 bus system with 20 loads yielded an annual energy cost saving of $2,961,169.20. Long term use of an industrial EMS is likely to yield huge energy and cost savings.

The designed industrial energy management model enables users to actively manage their energy consumption by shifting the use of non-priority loads to off peak durations. The system generates automated unit commitment schedules daily based on the hourly predicted prices thereby improving energy performance and saving on cost. Taking into consideration the non-energy benefits of implementing an EMS as well as the future savings to be yielded by the EMS would help in obtaining a shorter PBP and a higher ROI to justify the investment.

Further research can consider other inputs that affect demand in the LSTM network when developing the forecasting model. Moreover, other DSM techniques can be taken into account when developing the EMS. It would be beneficial to also design an EMS that integrates the management of other forms of energy rather than electrical energy.

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