Research Article
Deep Learning–Based Soft Sensors for Improving the Flexibility for Automation of Industry

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Automation in industries offers the benefits of enhancing quality and productivity while minimizing waste and errors, raising safety and adds stability to the production process. Industrial automation offers high profitability, reliability, and safety. It is beneficial to employ machine learning in the field of industrial automation as it helps in monitoring and performing maintenance on industrial machinery. Rational industrial development is closely associated with efforts for automating industrial techniques in all existing ways. Latest improvements in the automation of industrial systems resulted in decrease in cost of energy consumption and hardware. The proposed system is dealt with deep learning–based soft sensors for automation of industrial processes. The eminent benefits of soft sensors are versatility, flexibility, and low cost. With deep learning, many number of features could be processed. Thus, deep learning–based soft sensor encapsulates the above benefits. Soft sensors offer another way for the measurement of process variables, which are measured offline. Deep learning techniques are famous in the design of soft sensors for tough nonlinear systems due to the robustness and accuracy. The work depicted here designs a soft sensor based on deep learning algorithm for automation of industry. In the proposed system, a soft sensor contemplated on deep learning such as the deep neural network (DNN) is presented. The application of deep learning–based soft sensors in the automation of some industrial processes is also discussed here. The proposed system is tested on automatic control on solar power plants and in the measurement of reactive energy in industries. It was found that the proposed system yielded better results with its application in the automated industrial processes.

1. Introduction

Soft sensor indicates software, which reflects about the output-input connection of a process, contemplated on known parameters of a particular process. These input parameters are referred to as secondary parameters, which are got utilizing physically available sensors [1]. Adding soft sensors are advantageous in various process industries with an objective for operating and maintaining the industrial processes at a stable budget. Soft sensor endeavors are observed in industrial processes like distillation columns and treatment plants, and these advantages are confirmed post addition of these sensors. A soft sensor should offer the correct information regarding the process variable, which any hardware sensor located in the same position for measurement. There are some commonly known reasons for deterioration of soft sensors. They are a variation in the characteristics of the process, which occurs due to deactivation or adhesion in a chemical process, faulty design input or soft sensor updating. For the past decade,
there has been a highly rigid trend of usage data-driven methods of artificial intelligence techniques for enhancing products or processes or machines across various domains of industries. This enhancement might fetch various forms from reducing consumption of raw material or energy across better usage machinery or higher automation levels for increasing the output quality [2]. In the current year, optimization of emissions because of stricter regulations of the environment is an eminent driver. But, collecting the essential data for such processes is faced with various challenges, where there exists a longevity of automation of industry. Even the lifetime of official service makes estimation for running depreciation from 6 to 30 years contemplated on industrial sector, machinery type, and country. Significantly, there is a demand among industrial firms for increased production efficiency, leading to effective control and measurement policies as a result of governments laws imposing severe limits on pollutant emissions and product requirements. On the perception of justifiable development of control of industrial process, the eminence of examining a huge set of processes and parameters with the aid of excess instruments for measurements is found as clear. However, the key challenge for executing a large-scale examining and policy of control is the large cost of online meters [2].

Mathematical techniques, which are contemplated on experimental data with the procedures for systematic identification, could assist greatly in minimizing the requirements for measuring instruments and for developing a strong management policy. The designed mathematical model for the previously mentioned tasks is referred to as soft sensors or virtual analyzers. Soft sensors are employed as a valuable tool in various industries such as industrial pollution monitoring, urban pollution monitoring, nuclear power plants, food processing, paper and pulp industries, power plants, cement kilns, chemical plants, and oil refineries. They are utilized for resolving a greater number of various challenges like backup system measurement, fault diagnosis strategies, sensor testing and installation, and examining with real-time forecasting [3–6].

Challenges are faced by the industries with the option of a suitable production policy that resulted in trade-offs among multiple constraints. Final quality and products of prices are two competing and relevant factors, which estimate the market success of an industry. Soft sensors provide a large number of advantages such as they act as an inexpensive option for hardware devices, which are expensive enabling for various comprehensive examining network; they have a parallel operation with the hardware sensors offering useful information for intervening tasks, thus enabling for more implementation of robust processes; they could be easily implemented on available and restorable hardware like microcontrollers, when there is a change in the settings of the system. They allow for the evaluation of the real-time data, by overcoming the delays in time by slow sensors, thus enhancing the control strategies’ effectiveness [7–9].

Deep learning techniques could assist the industrial machines in overcoming their drawbacks by introducing self-learning of a human being with the consistency and speed of a computerized system. Deep learning-based techniques are suitable for industrial processes, which seems complex. Deep learning techniques complement the approaches based on rules, and it minimizes the requirement for deep vision domain of expertise for constructing an efficient inspection. Deep learning converts the logical expressions into a trained system. Hence, the benefits of deep learning techniques and soft sensors are combined in this paper. The proposed system thus encompasses deep learning–based soft sensors for automation of industrial processes. The deep neural network (DNN) is the deep learning technique employed here [10–13].

2. Related Works

Ma et al. proposed a two-stage framework for identifying the subway stations’ functional stations. They are made of the smart card data (SCD) and point of interest (POI) data along with online to offline (OTO) data of the e-commerce platform, which is an endeavor that offers the customer with information regarding various businesses such as the comments, the score, and the location. In their paper, such data were combined for analyzing every subway station, taking into consideration, the data diversity, and gaining a feature map of passenger flow of various stations, the POIs and the OTO stores nearby. A two-stage framework was proposed in their paper. The outputs of these two stages were combined with a soft max function, which is utilized for the functional region’s final identification. The experimental results of their study indicated a good performance and possessed a reference value within the station’s planning and contribution to the smart city construction. Thus, they employed a soft sensor based on deep learning for detection of functional region in the urban environments [1].

An ensemble deep learning framework for semisupervised-based soft sensor modeling of processes in industries was presented in [2]. Their paper was aimed at high nonlinear and labeled data of soft sensors. The important features were identified with the SAE model for soft sensing. The prediction performance of their soft sensors was improved with an ensemble strategy. Their method eliminated the irrelevant weights and information for highlighting the relevant indications. Thus, the deep information is extracted by their approach. The reliability and performance of the soft sensors were enhanced by the ensemble strategy. The results of their study indicated an improved performance of prediction when compared with the traditional and state-of-the-art methods [2].

In [3], Yuan et al. proposed a novel variable-wise weighted stacked autoencoder (VW-SAE) for hierarchical feature representation related to output for representation of every layer. With the output variables’ correlation analysis, the eminent variables from other variables of the input layer in every auto-encoder are identified. Each variable was assigned with variable weights, respectively. Then, the deep networks were designed and ordered by the variable-wise weighted autoencoders. It was found that the proposed system provided a better prediction of performance when compared with SAE and the traditional neural networks.
The possibility of transferring the acquired knowledge in a soft sensor design for a particular purpose of a similar process is investigated [4]. In their study, they proposed two transfer learning methods with the evaluation of their suitability for designing soft sensors contemplated on nonlinear dynamic models. The results of their study indicated that the proposed two transfer learning methods provided suitability in the nonlinear dynamic model design for the industrial systems. Thus, their proposed model examined the dynamical model transferability problem in the development of soft sensors for the industrial endeavors. Their work failed to guarantee the possibility of employing transfer learning and provided an estimation of the expected performance [4].

Sun and Ge carried out a survey on the deep learning techniques based on the soft sensors that are data driven. The significance and necessity of deep learning based on the soft sensor endeavors were initially demonstrated by the analysis of the advantages of deep learning and the industrial processes' trends. Then, the deep learning models of the main stream, toolkits, frameworks, or tricks were summarized in their work, and suggestions were made for assisting the designers for propelling the upcoming progress of the soft sensors. Finally, the available works were analyzed and reviewed for discussing the problems and demands, which would be encountered in the practical endeavors. Finally, the conclusions and outlooks were given in their survey [5].

A soft sensor model, which is contemplated on enhanced Elman Neural Network having preprocessing of variable data and its endeavor, was proposed [6]. They proposed a newer soft sensor model, which is contemplated on variable data preprocessing method and Elman Neural Network to the model based on soft sensor. Feed forward network and local feedback mechanism were employed in the enhanced Elman Neural Network with the context layer for accurately reflecting the soft sensor model's dynamic characteristics that possess the superiority for approximating the delay systems and time varying characteristics adoption. The results of their proposed method indicated that it has excellent robustness and performance of generalization. The model has advanced anti-inference ability and prediction accuracy that are promising and effective.

Shao et al. carried out the soft sensor development for the multimode processes contemplated on semisupervised Gaussian mixture models [7]. For tackling the infrequency of technical or economic limitations, a semisupervised Gaussian mixture model was proposed, where both labeled and unlabeled samples were chosen, and regression coefficients and Gaussian parameters were simultaneously learned contemplated on the maximization-expectation algorithm. Their proposed system proved to be an effective one with the two case studies employed in their system. These case studies were implemented utilizing real-life dataset and simulated dataset gathered from the ammonia synthesis process involving a primary reformer.

The deep learning–based soft sensors for the industrial machinery were developed. They proposed a deep learning contemplated virtual sensor for the estimation of combustion parameters within a large gas engine utilizing the rotational speed as the developed input is then evaluated. The evaluation was contemplated on the data preprocessing influence when compared with the structure and type of network taking into consideration, the quality of estimation. The results of their analysis indicated that the data preprocessing method and the input possessed the most eminent impact on the accuracy of estimation. The output quality of the algorithm was lowered by a fast Fourier transformation, whereas best results were delivered by the rotational speed signal, which was measured. Their study recommends for future research on the data preprocessing effects [8].

In [9], Mahmoud et al. proposed an improved multilayer learning machine (MLLM) for the smart sensor endeavors contemplated on an extreme learning machine (ELM). Deep network based semisupervised autoencoders were utilized for extracting the unsupervised feature with respect to the samples of all process. The extreme learning machine (ELM) is employed during regression with the added quality variable. The simulation results of their proposal made a verification that the prediction accuracy and expectation of their approach showed an enhancement when compared with the existing methods. Also, the deep learning–based soft sensor model for the sour water striping plant was proposed [10]. To overcome the problem of various sampling intervals of quality and process variables, a deep learning–based soft sensor model was proposed. The data scarcity problem was also solved with the deep learning approach. For comparison, identification of traditional methods of MLP was made. The results of the report indicated that the proposed system enhances the neural network performance based on soft sensors.

### 3. Methodology

Contemplated on the prior research, there is a possibility that estimates the parameters of the signal generated by the deep neural networks (DNN) can be made. The related works all mentioned above vary significantly with their methods. The proposed system is designed for testing three eminent parameters such as neural network structure, neural network type, and the input data preprocessing. Because of the time constraints, the various approaches were examined in determining the first global parameters. Contemplated on the results generated, the promising results of the proposed system were generated for estimating the various parameters. Instead of seeking humans for programming tasks with the help of computer algorithms, the deep learning techniques are employed. Deep learning algorithms are an artificial intelligence subset for gaining prominence with the advancement in technology. With the leveraging of neural networks, the deep learning–based endeavors make spots and collaboration of patterns from huge datasets. With deep learning, a manufacturer identifies the defects in the manufactured products. The deep learning algorithms fetch the archetypes offered by the user and automatically create the clear understanding of the inspected part. Visual defects, scratches, or foreign objects could be identified. The higher the data, the higher will be the observation of faults or defects. While testing the proposed system with the solar
power plant, the measured variables are the geographic location, power, photovoltaic system, and solar power station [11–13].

3.1. Description of Dataset. Here, for the two endeavors mentioned for the testing of the proposed system, the transient simulation of the climate system model was employed for getting dataset of the proposed work. The dataset is created in the environment for MATLAB simulation. The error-free portion is taken as the reference, and the dataset is then created. The proposed system is simulated with ten various conditions with different induced errors for generating the sensors’ dataset for our mission. The datasets of the soft sensors are identified as s1, s2, s3, s4…s8. The data of the primary sensors are combined for obtaining the total soft sensor for the climate system model of the solar power plant. The variables, which are mentioned in the dataset, are the geographic location, power, photovoltaic system, and solar power station.

3.2. DLSS Algorithm. The deep learning–based soft sensors (DLSS) are described in this part. Learning with the neural networks forms the imitation of the biological neuron in the system of science and is famous for inducing artificial intelligence in various machines. Figure 1 highlights the basic neuronal representation having no inputs, one output, and bias.

The initiation of the neural network, also called as perceptrons were changed to Widrow-Haff learning rule, which is a back propagation learning rule used for the purpose of shallow learning and it is executed in diverse and different fields. Additionally, for enhancing the capacity of learning, the deep learning technique is introduced to resemble the human brain and has a high learning capacity. The deep neural network encompasses an output layer and input layer similar to an artificial neural network having two or more than two hidden layers as indicated in the above figure. In the deep neural network, the mathematical representation of a single neuron is given as

\[ y^L = \sigma (W^T x + b_0), \]  

where \( \sigma \) represents the activation function, \( W^T \) indicates the weight vector, and \( x \) indicates the input vector.

The DLSS algorithm, which is employed in the proposed system, is given as follows:

1. Choose the DNN, which is used for estimating having 10 layers
2. Configure the weights as \( w_1, w_2, w_3...w_n \)
3. Choose the outputs and the inputs
4. Separate the input data and output data into training data, testing data, and evidence data in the ratio 75:10:15
5. Employ the training dataset into the DNN (deep neural network)
6. Make a repetition of Steps 1 to 5 and an update of the weights until the output values are equal to the known values
7. The evidence data should be applied
8. Check for good results with the evidential data
9. Choose the fault determining the deep neural network having ten layers
10. The weights should be initialized as \( w_1, w_2, w_3...w_n \)
11. Choose the outputs and the inputs
12. Separate the input and output data into training data, testing data, and evidence data in the ratio 75:10:15
13. Employ the training data into the DNN (deep neural network).
14. The weights must be updated, and Steps 1 until 5 should be repeated until the output becomes equal to the known values of fault classification
15. The evidence data should be applied
16. Check whether good results are given by the evidence data
17. Start the estimated values of the correct data
18. Assign the default value, which is constant with the faulty data
19. Choose the testing data as given in Step 4
20. Check for expected results of the test data
21. Checks if a fault is detected by the test data in the 2nd DNN (Deep Neural Network)
22. Examine the faulty data
23. Make an estimation and replacement of the right data utilizing Step 18
24. Or else make a repetition of the steps from Step 1 to Step 20
4. The Proposed System

The proposed deep learning contemplated soft sensor (DLSS) system comprises of two deep neural networks having a simultaneous operation. One deep neural network is allotted for the estimation of the soft sensor output, and the other deep neural network is employed for the identification and classification of the faulty data of the inputs of the soft sensor. In addition, an estimator of the correct data is presented for combining the deep neural network that identifies and detects the fault with the deep neural network estimator. This makes an assurance of the update of the soft sensor in accordance with the available correct data got from the other hardware sensors. Figure 2 shows the block diagram of the proposed deep learning–based soft sensor system, which could be employed in the industrial automation.

The method could be summarized as above. The proposed algorithm is indicated in Figure 2 for understanding it easier. From the figure, two deep neural networks are used for representing the two operations with the estimation of the desired value and detection of fault simultaneously. The third block in the figure indicates the estimation of the correct value. The third block functions only when any inequalities or errors or faults are detected by the deep neural network. The simulations of the proposed system were carried out utilizing four citations for obtaining comparative results:

(i) The correct information gathered from all the existing sensors were utilized as sensor inputs for the design of soft sensor

(ii) This correct information is assumed to be gotten from $s_1$, $s_2$, $s_3$, $s_5$, $s_6$, and $s_7$, and the information, which is missing is got from the sensor $s_4$, were utilized as sensor inputs for the design of soft sensor

(iii) The information from $s_4$ is gathered as the random information, and correct information is gotten from $s_1$, $s_2$, $s_3$, $s_5$, $s_6$, and $s_7$. These are utilized as inputs for the design of soft sensor

(iv) The information from $s_4$ is gathered as the estimated information, and correct information is gotten from $s_1$, $s_2$, $s_3$, $s_5$, $s_6$, and $s_7$. These are utilized as inputs for the design of soft sensor

The regression plot and the performance plot compare the outputs of the soft sensor with the above four situations. The regression values and mean square errors are found and are tabulated.

The mean square error (MSE) indicates the variation between the target value ($\rho^{ca}$) and output value ($\rho^{exp}$). The ideal value is calculated as zero, and thus the value, which is nearer to zero, represents a good estimated value. The mathematical representation of the mean square error is given as follows:

$$\text{MSE} = \frac{1}{N} \sum_{i=1}^{N} (\rho^{exp} - \rho^{ca})^2. \quad (2)$$

The values of the mean square error during the testing, evidence, and training phase are indicated in the performance plots, and zero is approached by the three curves for a perfect model of a soft sensor. The regression value represents a correlation between the targets and the outputs. A greater correlation is indicated by an $R$ value near to 1. The relationship between the targets and the outputs is more linear than expected. The mathematical representation of the regression values is given as follows:

$$R^2 = \frac{\sum_{i=1}^{N} \left( (\rho^{exp} - \rho')^2 - (\rho^{exp} - \rho^{ca})^2 \right)}{\sum_{i=1}^{N} (\rho^{exp} - \rho')}^2. \quad (3)$$

The network output is related to the regression plot to target values for testing evidence and training. The output of the soft sensor is equal to the target value, when a 45-degree inclination is made by the data plot within the regression plot.

4.1. The Training Based on Deep Learning. The training within a deep neural network–based soft sensor model happens by choosing the best aspects of neurons’ weights in between the output layer and the hidden layer and the variable spreads for functioning in the output layer having neurons’ bias, center hidden layer, and the hidden layer. Although the deep neural network could be effectively used as a soft sensor model, the entire set of neurons in the DNN hidden layer influence the network complexity, and the ability of generalization of the network, thus is making a decision on the number of neurons hidden layers. When many neurons are used in the hidden layer, under fitting situations might occur. These are resolved with the early stopping regularization and drop-out techniques. The learning algorithm of DNN-based soft sensor model is as shown below:

(i) Initiate with the parameter model values like $b$ for biases and weights, $w$

(ii) Fetch a set of data samples, and propagate this data to the output layer with the input layer for obtaining the predicted values

(iii) Contemplated on the predicted values, the errors are calculated, and these errors have to be reduced

(iv) For discovering the optimal weights of the neurons, in the soft sensor model, based on deep neural network, the error must be back propagated

(v) The soft sensor model’s parameter based on DNN has to be updated utilizing the above algorithm. The above steps are repeated until ideal weights are gained. Figure 3 shows the DNN-based soft sensor model’s learning process

The training procedure is carried out on a laptop. The training time is between 20 seconds and one minute. The deep neural network fetches more time when compared with
an ordinary neural network, and additional layers consume more time for computation.

5. Results and Discussion

5.1. Case Study 1

5.1.1. Application to Solar Power Plants. Deep learning–based soft sensors can be utilized in the automatic solar power plant control. In a real solar power plant, there must be a system for data collection and monitoring the performance that offers monitoring parameters, which are eminent to the system. There are various methods, which makes use of classic hardware for collecting and transmitting data. This is very expensive in a large solar power plant because of a huge amount of required sensors, and thus it is impractical for executing. In a solar power plant, the parameters, which could be controlled, are the panel output current, output voltage, output power, and also temperature when employed in a solar tracking system. Such systems have a tough relationship between every parameter, and thus the technique for gathering one or many variables from other measured variable is employed. This is the reason for why soft sensors or virtual sensors are employed for minimizing the need for equipment and also the need for cost. If there exist a suitable number of sensors and equipment within the solar power plant, the control accuracy is enhanced by the soft sensors or the virtual sensors. The real sensors’ sampling rate will not be high all times, and thus the controllers’ capabilities could not be matched. Thus, by the increase of the data, which is gathered in the controller, it could be enhanced. Every 1 second, a signal is received from the real sensors by the controllers. Every T/5 second, a signal is received from the soft sensors. Here in the controller, the speed of data processing is “N” times higher than the multi-rate, which is the sampling period of the actual sensor. Sometimes, real sensors could not gather the relevant information, which could be gathered by the soft sensors. The information on the soft sensors enables the controller for continuing the task of control within the normal level and the impacts of missing information are reduced. Figure 4 shows the deep learning contemplated soft sensor model of a solar power plant, which is a multi-rate technique.

In this model, the real sensor and the DNN-based soft sensor is operated in parallel. Data is received in real-time of the soft sensor, and a signal of control is received additionally from the controller until the actuator. The benefit is the delay, which impacts in the control signal transmission, and the real sensor sampling rate in the real process is considered within the virtual environment offering various reliable information from the DNN- (deep learning network-) based soft sensor. From the figure, the multi-rate controller makes use of the virtual information gathered from the soft sensor contemplated on the process technique for calculating extra control actions transmitted with the actuator. The process of triggering is rigid when compared with the real sensors’ actual sampling rate, thus resolving the issue of minimizing the sensors’ sampling rate. Here, we propose the execution of the deep learning–based soft sensor model for a solar power plant. One among the eminent aspects of the proposed system is the generated electricity’s maximum power. The maximum power point tracking (MPPT) is needed for maximizing the system efficiency utilizing the solar panels. The solar irradiance is linear to the output power. The higher the solar energy, the higher is the system’s output power. Thus, it is eminent for receiving timely information on the solar irradiance level for adjusting the solar panel’s position. The maximum solar power plant power depends linearly on the performance ratio, which is given by

\[ PR = \frac{P_i}{P_{nom}} \times \frac{G_{STC}}{G_i} \]  

Figure 2: Deep learning contemplated soft sensor system (DLSS).
of a solar power plant.

2: Changes in the

Table

1: Forecast errors associated with the prediction of the output power in a solar power plant.

| Input data | Data types      | MSE ($10^{-1}$) | R ($10^{-1}$) |
|------------|----------------|-----------------|---------------|
| Correct data | Training data  | 7.49            | 9.865         |
|            | Evidence data  | 7.40            | 9.867         |
|            | Testing data   | 7.36            | 9.867         |
| Nil        | Training data  | 7.20            | 9.865         |
|            | Evidence data  | 7.51            | 9.869         |
|            | Testing data   | 7.30            | 9.869         |
| Random data | Training data  | 8.25            | 9.852         |
|            | Evidence data  | 7.95            | 9.856         |
|            | Testing data   | 8.15            | 9.853         |
| Estimated data | Training data | 7.48            | 9.865         |
|            | Evidence data  | 7.30            | 9.868         |
|            | Testing data   | 7.33            | 9.868         |

Figure 3: DNN-based soft sensor model’s learning process.

Figure 4: Deep neural network-(DNN-) based soft sensor model of a solar power plant.

Table 2: Changes in the R and MSE values of the corrected and faulty inputs in association with the correct input.

| Input data | Data types      | ΔMSE (MSEc – MSEu) | ΔR (Rc – Ru) |
|------------|----------------|--------------------|--------------|
| Nil        | Training data  | -0.07              | 0.002        |
|            | Evidence data  | 0.11               | -0.002       |
|            | Testing data   | -0.28              | 0.004        |
| Random data | Training data  | 0.78               | -0.013       |
|            | Evidence data  | 0.53               | -0.011       |
|            | Testing data   | 0.76               | -0.014       |
| Estimated data | Training data | -0.34              | 0.001        |
|            | Evidence data  | -0.10              | 0.002        |
|            | Testing data   | -0.00              | 0.000        |

Here, $P$ shows the instantaneous measured power and $P_{nom}$ measures the solar panel’s nominal power.

$G_l$ indicates the solar irradiance actual value, and $G_{STC}$ indicates solar irradiance during normal conditions. The value of performance ratio ranges from 0.6 to 0.8. Thus, the soft sensor would determine the solar radiation, which is needed for increasing the electricity and enhance the solar power plant’s efficiency.

In solar power plants, the deep neural network-(DNN-) contemplated soft sensors are utilized for predicting the output power. The performance plots are used here for representing the testing, evidence, and training MSE values with red, green, and blue color used in the plots, respectively, during running of the soft sensor system. When a soft sensor system is chosen, a well-trained soft sensor system should be determined with a test or independent dataset again. The required standard is offered by the test data, which is utilized for evaluating the soft sensor system. The performance evaluation is done with the prediction of the mean square error and regression value. Table 1 shows the forecast errors or MSE (mean square error) associated with the prediction of the output power in a solar power plant.

From the above table, it could be seen that the average regression value lies in the range of 9.86 for all data such as correct data, nil, random data, and estimated data. These data encapsulate all training, evidence, and testing data, which are used for a particular industrial process. Linearity could be observed between the soft sensors’ targets and the outputs. The $R$ value and the points of data, which approaches 45, makes sure the proposed soft sensors’ validity. The regression and the mean square observations are compared to the above table, and the changes are observed with the update of the soft sensor with the estimated data on the proposed system, which is indicated in Table 2.

Figure 5 indicates the mean square error (MSE) that got out of the above obtained information.

The following figure indicates the regression values got out of the above obtained information.

Figures 6 and 7 indicate the representation of $\Delta$MSE and $\Delta$R with the above values. The high efficiency is gathered from the training data. The correct values of $R$ and MSE are highlighted by $MSE_c$ and $R_c$, and the updated values of $R$ and MSE are highlighted by $R_u$ and $MSE_u$. When the MSE value increases, then it means that the entire system is deteriorating. The proposed system was found to offer only small error values and hence shows stability in the performance of the proposed system.

Regarding the $R$ value, the proposed system either retains a constant value or increases slightly.
5.2. **Case: Study 2.** Sustainable industrial development is related to increasing needs for the supplied electrical energy quality. Also, the eminent factor is the capability for accurately measuring the flow of power in any network level. This is eminent for both consumers and energy suppliers. With the production increase and quality enhancement of the industries’ finished products, there is also a growth in their energy consumption. Alternatively, the need for the power line’s capacity of the products is rising. There is a striking surge in the nonstationary and nonlinear loads in the power network, which results in reduced network throughputs because of the flow of reactive capacities observed between them. Here, the problem is related to the high usage of power electronic devices among the electric energy consumers. Variable speed drives, gas discharge lamps, heaters, and induction furnaces are suitable archetypes for these devices. The reactive power growth in these networks builds a high interference amount for the industry and impacts adversely the total distribution network. Along with the industrial power growth in these industries, there are also high losses observed during the transfer of electrical energy transported from one place to another and a
reduction in the consumers’ power factor. The measuring and reactive power measurement and control are related to a group of challenges encapsulating the high cost of the system in industries of processing and mining. It is due to the supply of various structural units of power lines and distributed structure. The volumes of reactive power could be calculated from measuring the parameters of the distribution network. In an electrical energy distribution system, which operates linearly in the sinusoidal signal mode, the reactive power is calculated by the following ratio:

$$Q = I \times U \times \sin \phi, \tag{5}$$

where \(I\) is the strength of the current in the network; \(U\) indicates the value of voltage in the network; and \(\phi\) refers to the variation in phase between the voltage and current. While taking into consideration, the system’s operating mode under the nonharmonic signal’s influence, the effective current, and voltage values in the electrical network is given as

$$U = \sum_{k=1}^{K} U_{k} \sin(2\pi f_{o}t - \theta_{k}),$$

$$I = \sum_{k=1}^{K} I_{k} \sin(2\pi f_{o}t - \psi_{k}), \tag{6}$$

Here, \(k\) indicates the harmonic number, \(f_{o}\) indicates the frequency, \(I_{k}\) is the current value of \(k^{th}\) harmonic, and \(\theta_{k}\) and \(\psi_{k}\) are initial signal phases. Here, a large number of quantities have to be measured, which is a complex problem, which is resolved with the use of deep learning–based soft sensors for measuring the reactive power. Let us assume that in a distribution substation, in a processing and mining plant, the reactive power consumption by every structural aspect of the object in the plant impacts the other aspects’ consumption. We consider here the statistical data on the reactive energy consumption in the mining and processing plant. Here, four structural elements are measured by the object. Here, the correlation coefficient is calculated with the existing statistical data for 7 consecutive days.

The results which gotten with the measured correlation coefficients of consumption of reactive power of elements
having the high reactive energy consumption of the objects 2 and 4 for 7 consecutive days are shown in Table 3. Here, a soft sensor is constructed for estimating the reactive power consumption value for every structural object, which is supplied along with the distribution substation electrical energy contemplated on the reactive power consumption quantity of one of the structural elements.

6. Conclusion

Thus, the research on the deep learning–based soft sensor model employed in the automation of industrial techniques indicates the benefits and versatility of theirs. The use of soft sensors usually acts as a replacement for the hardware due to the operation of the physical sensors in the extreme situations, which are expensive and require frequent change. Soft sensors are advisable to be utilized in conditions or mechanism that has similar conditions. The performance of a mechanism is measured for judging the situation. A different base is exhibited by the soft sensors and is environment friendly. Soft sensors contemplated on deep learning helps in making the automation of industrial processes very easier. The selection of the mathematical model of the soft sensor is contemplated on the specific task and situation. Thus, with the usage of soft sensors, the mechanical equipment amount could be reduced, and the parameters could be measured with the deep learning techniques for industrial automation.

Data Availability

The data that support the findings of this study are available on request from the corresponding author.

Conflicts of Interest

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

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