Hindawi
International Transactions on Electrical Energy Systems
Volume 2022, Article ID 8685235, 11 pages
https://doi.org/10.1155/2022/8685235

Research Article

Integrating Industrial Appliances for Security Enhancement in Data Point Using SCADA Networks with Learning Algorithm

Alaa O. Khadidos,[1] **Adil O. Khadidos**,[2] **Hariprasath Manoharan**,[3] **Khaled H. Alyoubi**,[1] **Abdulrhman M. Alshareef**,[1] **and Shitharth Selvarajan**[4]

[1]*Department of Information Systems, Faculty of Computing and Information Technology, King Abdulaziz University, Jeddah, Saudi Arabia*
[2]*Department of Information Technology, Faculty of Computing and Information Technology, King Abdulaziz University, Jeddah, Saudi Arabia*
[3]*Department of Electronics and Communication Engineering, Panimalar Engineering College, Poonamallee, Chennai, India*
[4]*Department of Computer Science, Kebri Dehar University, Kebri Dehar, Ethiopia*

Correspondence should be addressed to Shitharth Selvarajan; shitharths@kdu.edu.et

Received 5 August 2022; Accepted 20 August 2022; Published 15 September 2022

Academic Editor: Albert Alexander Stonier

Copyright © 2022 Alaa O. Khadidos et al. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

The process of ensuring automatic operation for industrial appliances using both supervision and control techniques is a challenging task. Therefore, this article focuses on implementing Supervisory Control and Data Acquisition (SCADA) for controlling all industrial appliances. The design process of implementation case is performed using an analytical framework by examining the primary energy sources at the initial state; thus, a smart network is supported. The designed mathematical model is integrated with a learning technique that allocates resources at proper quantities. Further, the complex manual tuning of individual appliances is avoided in the projected method as the input variables are driven in a direct way at reduced loss state. In addition, the data processing state of individual appliances is carried out using central data controller where all parametric values are stored. In case any errors are observed, then SCADA network fixes the error in an automated way, reducing end-to-end delays in all appliances. To validate the effectiveness of the proposed method, five scenarios are examined and simulated where outcomes prove that SCADA network using learning models provides optimal results on an average of 84 percent as compared to the existing models without learning algorithm.

1. Literature Survey

SCADA, which is used for different industrial operations, is implemented under both large and small scale processes. Thus, it is always necessary to analyze the effect of SCADA systems by examining existing models and procedures that are followed to update the current security mechanisms. Therefore, the existing models are analyzed with respect to implementation, data gathering, and security, thus providing a clear analytical model with derivative frameworks. In [1] multiple layers are represented using two different units such as primary and secondary terminal units where a key preservation is made for enhancing security of the network. Both terminal units use satellite as one mode of communication link with SCADA at intermediate junction. It is necessary that two terminal lines must be connected to the central station which is not processed; thus, as a result, individual monitoring is prepared. In addition to the terminal lines, the transmission stability of SCADA plays a vital role in all industrial operations in case of automated determinations [2]. Therefore, the stability of entire SCADA is initialized using state vectors where a specialized software tool is implemented for gathering information at output units. Even though hardware and software tools are combined, the process of time domain is carried out, which cannot determine complete stability of SCADA networks.

An evaluation model is framed and determined in comparison with multiple methods in case of risk factor determinations [3], where all protocols for managing separate keys are provided. The above-mentioned determinations can be used for enhancing the security of SCADA network, but the complete risk in a particular process cannot be avoided at any point of time.

Some of the techniques are developed for micro grid operations in order to manage energy much effectively in building platform [4]. These kinds of application developments are made using SCADA network where high infrastructure is needed and it is processed even with critical loads. While processing critical loads, some control strategies are designed and it is modified during the implementation stage. The above-mentioned modifications are not processed in real time cases if SCADA is implemented at a particular time period. If any changes are processed after the implementation phase, an effective connection is needed for the transmission network [5]. Thus the connection arrangements are formulated using mathematical representations by converting all connections at the same amount. However, if the same amount for different lines is used, then the critical distance of measurement must also be observed in coupling stage periods which is a difficult management process. To manage complexity conditions, both real and reactive measurements are taken for distribution systems using scheduling operation where a greater number of energy resources are introduced [6]. During this scheduling process, the energy in SCADA network and the cost of implementation are reduced, but in case of distribution level measurements, active voltage measurements can only be made which is observed as a major drawback. If SCADA networks are implemented in distribution systems, then it is essential to check reliability of parametric values using Q-terms [7]. If the raised Q factor is lesser, then the security of the entire SCADA network falls below a certain limit and this measurement is processed for every appliance on an hourly basis. Due to hour-basis measurements, the system fails to explore disturbance time in individual appliances; thus, as a result, more than 50 percent of SCADA units are not handled in a perfect way[8–10].

In order to ensure a proper handling mechanism of all appliances, a multiple variation system is established [11] which monitors all curves if power is varied in SCADA network. Moreover, in real time, it is possible to control additional dissimilarities with voltage and current parameters; thus, multiple variations do not occur if SCADA networks are incorporated. The aforementioned changes in each curve can be established only if different appliances are installed without any external limitations. Hereafter, a medium scale distribution system is introduced with SCADA measurement process and this is termed as the hybrid implementation effect on distinct systems [12]. Since two different combinations are made, SCADA measurements provide appropriate outcomes with perfect estimation in state lines. But then again the hybrid measurement increases the switching complexity of the measurement process; thus, only small scale systems are assimilated and tested. To increase the testing phase with large scale system, four unique methods are followed by using reactive variable phases [13] in all appliances. Due to reactive variables, estimation of voltage scales is processed using pi-type architecture for SCADA networks. On the other hand, implementation cost of pi-type networks is much higher as it requires curved shape data to be represented in the system. As much failure occurs in implementation of the automated process, more steps are taken in the initialization phase using learning algorithms [14]. The type of learning algorithm that is present in automated process must begin with normal characteristics, and high security state must be provided for proper decision making. As a result of using an appropriate decision-making mechanism, values are created and tested in real time by enabling smart metering systems [15]. All executive measures are carried out in implementation of smart metering systems, but assimilation of hardware and software tools is not processed; thus, decision-making systems are much slower than expected.

A comparative study is made with SCADA networks using support vector machine [16–18] for removing all types of uncertainties in the entire data handling process. In this method, also power curves are represented to solve complexities, but as indicated earlier large scale uncertainties cannot be deciphered using individual SCADA measurements. An integration process of cloud security using SCADA is carried out for industrial application where a greater number of remote units are installed in communication path. Since more units are installed, if any SCADA network fails, then other networks will carry out the entire operation with high security features [19]. However, a bigger number of remote units increase the cost of a communication unit inside the infrastructure medium. To reduce the number of remote units, operations are carried out using allocation of renewable energy sources in the path between two SCADA networks [20], and as a result, the IoT-based operation is flexible by reducing the cost of installations. On the other hand, the IoT operation is carried out using low security open source tool, and this type of SCADA operation requires modernization of the entire network. Thus, after careful comparison, SCADA networks are incorporated in the proposed method by incapacitating the disadvantages of the existing techniques, and a distinctive mathematical model is formulate in Section 2.

1.1. Objectives. In the proposed method, multiple SCADA networks are implemented and used for industrial appliances for ensuring proper operation by identifying parametric changes. Therefore, the primary objectives of the projected method are framed as a minimization problem as follows.

(i) To integrate a learning technique that extends sustenance to SCADA networks in terms of data segments area of installation.

(ii) To minimize the energy resource constraint of all appliances, therefore overload capacity cases being avoided.

(iii) To reduce the amount of loss and delay in terms of data transmission using different state vector, thus increasing the security of operation.

2. SCADA for Industrial Applications: An Analytical Model

The process of implementing SCADA is processed by designing a mathematical model that supports the generation process when a system is located in open or closed loop conditions. In addition, the process of SCADA operation is carried out using a solar panel where the battery is stored for a secondary purpose. As the battery is stored in a regular medium, it is necessary to measure all the industrial appliances that are operated without the presence of primary energy source. The above-mentioned operation is designed using

$$PE_i = \sum_{i=1}^{n} \frac{I_i * d_i}{a_t}, \quad (1)$$

where I_i indicates the disturbance time period, d_i represents downcast time, and a_t describes the total number of operating appliances.

Equation (1) indicates the time period of operation that is separated using all appliances that are present inside industry and in this case total impaired measurements are observed. However, the SCADA system is highly effective only if individual measurements are taken for separate appliances. Thus an individual determination is made using

$$d_a(i) = \sum_{i=1}^{n} \frac{I_s(i) * f_i}{a_s(i)}, \quad (2)$$

where I_s represents distinct appliance disturbance time, f_i indicates frequency supplied to appliances, and a_s denotes discrete operating appliances.

In (2) it is necessary to minimize disturbance time period by supplying the necessary amount of frequency to all appliances. In case the disturbance period is much higher, then the loss rate is determined using full scale capacity as follows:

$$\text{loss}_i = \min \sum_{i=1}^{n} \left(l_a(i) + l_c(i)\right) * e_i, \quad (3)$$

where l_a, l_c denotes loss of electricity due to absence of squall and presence of full load appliance capacity and e_i represents expected appliance energy loss.

The major objective function in SCADA is to minimize the energy loss that is present in the entire appliance, but this type of minimization is possible only if the critical distance of appliance is within the boundary limits. Thus the limitations are formulated using

$$\text{dist}_i = \min \sum_{i=1}^{n} CD\left(t_1 - t_i\right) + \delta_i, \quad (4)$$

where CD indicates critical distance of appliances, t_1, t_i represents distance between first and end transmission appliance, and δ_i denotes total life period of appliances.

The second minimization objective is framed using critical distance measurement by considering a reference potential point at the beginning of SCADA connections [21–23]. In addition to variations in critical distance measurements, the schedule period of storage for all appliances provides great advantage in the entire process as storage points can be shifted from one end to the other. This scheduling process is formulated using

$$S_i = \sum_{i=1}^{n} E_o(i) * E_c(i), \quad (5)$$

where E_o, E_c represent original and unoccupied energy rates.

In case of delayed SCADA measurements at the output unit, unoccupied energy rate increases and it cannot be controlled. Thus the delay in measurements is minimized using

$$\text{dealy}_i = \min \sum_{i=1}^{n} \left(w_i * c\right) + z_i, \quad (6)$$

where w_i indicates the weight of appliance, c denotes the random measurement function, andz_i represents the period of energy supplied to appliances.

If the delay period is reduced, then data measurements phase is monitored where all changes in data pathways are controlled using SCADA data transmission and reception blocks. The data control phase is formulated using

$$DC_i = \min \sum_{i=1}^{n} \begin{bmatrix} P_1 & \cdots & P_i \\ \vdots & \ddots & \vdots \\ P_i & \cdots & P_n \end{bmatrix} + \begin{bmatrix} V_1 & \cdots & V_i \\ \vdots & \ddots & \vdots \\ V_i & \cdots & V_n \end{bmatrix} + \Delta t_i, \quad (7)$$

where P_1, P_i, P_n describes control data, V_1, V_i, V_n denotes rapidity data, and Δt_i indicates the change in time period intervals.

All the analytical equations that are framed represent the operation of SCADA in closed condition cases where the objective can be represented in terms of analytical equations using

$$\text{obj}_i = \min \sum_{i=1}^{n} \text{loss}_i, \text{dist}_i, \text{dealy}_i, DC_i. \quad (8)$$

The multiple objective functions in (8) are termed as the minimization function that represents SCADA parametric values to be much lower than values in operational cases. All the formulated equations are derived using a basic set of formulations from SCADA parametric real and reactive power phase [24–27]. Thus in order to increase the accuracy of SCADA measurements in industrial systems, an optimization algorithm is integrated and it is described in the subsequent section.

3. Optimization Algorithm

One of the major problems in the implementation of SCADA system is that security of data must be enhanced as separate commands are implemented for each appliance. Thus it is necessary to drive SCADA system which is termed as a large factor setup using an optimization algorithm. Hence a learning algorithm is chosen for preprocessing all the necessary data where the appliances in industries are protected without any external intrusion attacks [28, 29]. In addition, SCADA system requires the input data to start

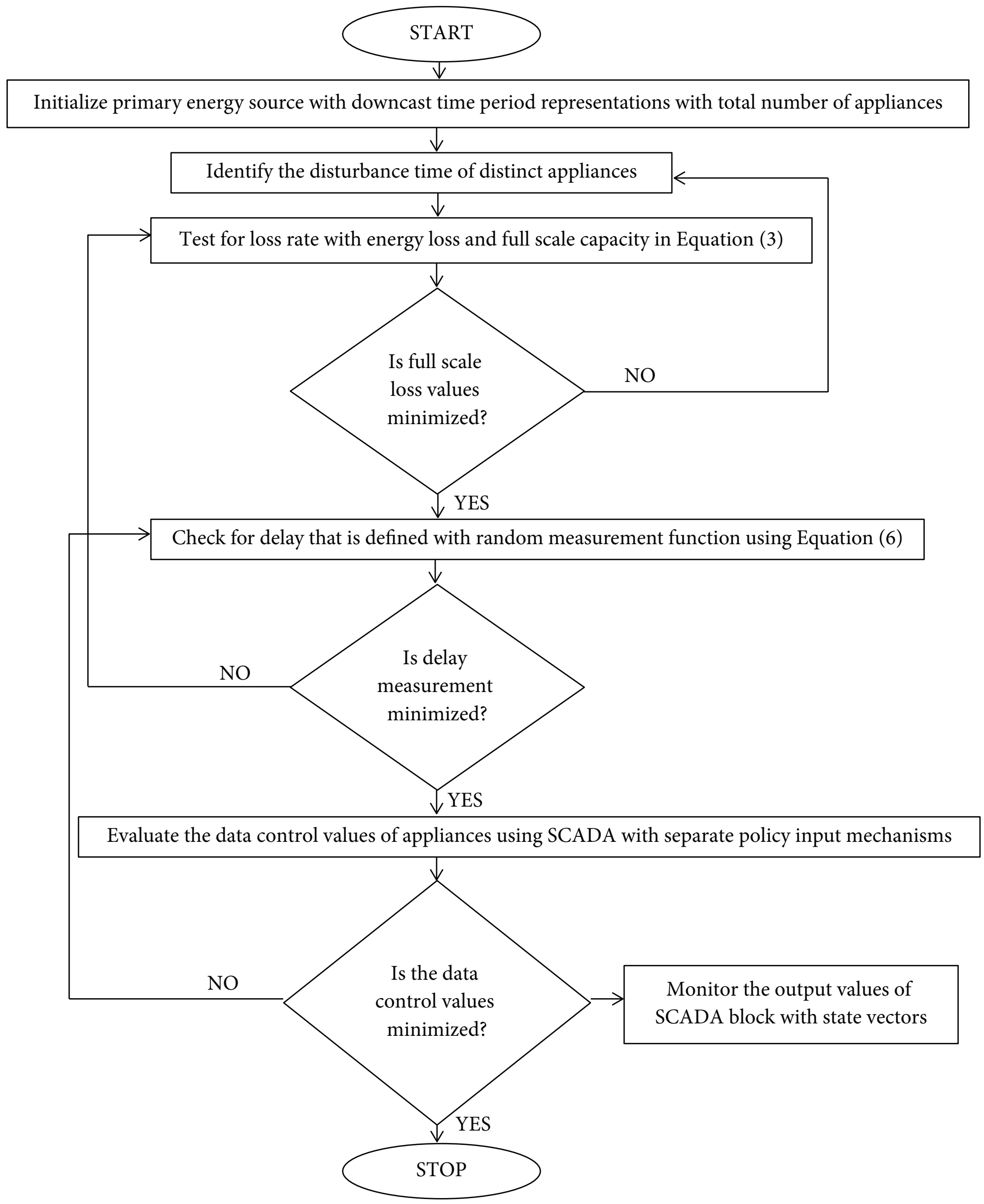

Figure 1: Integration flow of the proposed method with learning technique.

from the initial state, thus providing multiple solutions for controlling a particular problem [27, 30, 31]. Since multiple solutions are provided, optimal paths are chosen at the output end for handling distinct alert situations, and one of the major advantages of reinforcement learning algorithm is that all decisions are made in a sequential manner and thus the next state output is determined using previous case problems. Therefore, if reinforcement learning algorithms are applied in real time for SCADA systems, then it is not possible to overcome current problems without solving the existing problem conditions. Even if high complexities are present around SCADA environs, the objective of solving all uncertainties is always assured if behavior learning is processed in the best mode of operation (Figure 1). The optimization process under a particular area is framed using

$$\text{area}_i = \sum_{i=1}^{n} \alpha_i + (\rho_i * \omega_i), \tag{9}$$

where α_i indicates reduced policy input, ρ_i denotes frequency of SCADA examination, and ω_i describes improvement input policy.

The two procedures that are described in (9) provide great improvement in SCADA feedback process; thus, the entire area is examined using frequency source.

Therefore, the stability of SCADA system in industrial application increases to a certain extent which is measured using

$$\sigma_i = \max \sum_{i=1}^{n} \left(q_i(r) - q_i\right) + w_i, \tag{10}$$

Input: Initialize the primary energy source with disturbance factor and downcast time periods $PE_i\,(PE \le i \le n)$, $I_i\,(I \le i \le n)$ and state representation values using matrix representation of individual appliances a_i;
Output: Optimized values for automation of appliances in industrial process using learning model at reduced policy rate and good control rate;
Step 1: At first, the objective function is constructed with the loss factor using loss_i;
Step 2: Initialize the frequency of operating appliances with appliance disturbance time that must be followed by certain improvements in policy factor $a_s(i)$ with $0 \le i \le 1$, and its individual determination $d_a(i)$ with the indication of full scale capacity values;
Step 3: While $(d_a(i) < N)$ do.
Provide the loss values loss_i in both presence and absence of full scale appliances in a systematic way for computing the total loss in automation process by using equation (3);
Verify the energy loss values in both previous and current state using distance vector separation dist_i for identifying the critical changes;
If the critical distance changes are higher, CD_i is not at $(CD_i < N)$;
Modify the transmission appliance values using life period of a particular appliance that is having different energy rates using equations (4) and (5), S_i with $1 \le i \le N$ into N number of unoccupied energy states;
//Delay phase
Update the delay values $delay_i$ with random measurement function r_i by generating the weight function w_i using supplied energy as shown in equation (6);
//Data control phase
Select the control and rapidity scale matrix with changes in time periods Δt_i as defined in equation (7);
Update the control function state variables using equation (11) with probability values of corresponding state vectors followed by the data segment values and compute the new secured data position σ_i as defined in equation (10);
The improvements in policy segments in separate areas are updated by using equation (9);
$\text{area}_{\text{new}} = \text{area}_{\text{old}} + 1$;
End;
Step 4: If $(\sigma_i < 0)$ then
$\sigma_i \leftarrow 0$;//Interchange the existing solution in the current loop with the new solution;
End if;
Step 5: If $(\sigma_{\text{MAX}}\,[0, 1] < 1)$ then
Reinitialize the appliance values with new segments;
Obtain the overall best solution;
End if;
Step 6: If $(I_{\max} < N)$ //Existing solution is replaced with the new solution
$\gamma_i = \gamma_{\text{modified}}$;
$I_{\min} = N$;//Attain the most feasible solutions for determining the overall best solution;
Increment the count area_{new} by 1;
Return the best overall solution;
End;

Algorithm 1: Reinforcement Learning Algorithm.

where $q_i(r)$, q_i denotes quality of repeated and nonrepeated data segments in SCADA.

The stability margin defined in (10) must be maximized under the expectation region of separation where the state equation for SCADA using reinforcement learning algorithm for different appliances in industry is described using

$$\gamma_i = \sum_{i=1}^{n} \begin{bmatrix} \tau_1 & \cdots & \tau_i \\ \vdots & \ddots & \vdots \\ \tau_{i+1} & \cdots & \tau_n \end{bmatrix} * \left[\partial_1 \ldots \partial_i\right], \tag{11}$$

where $\tau_1 \ldots \tau_i \ldots \tau_{i+1}$ denotes corresponding state vectors for separate appliances and $\partial_1 \ldots \partial_i$ indicates probability of different appliances in industry.

Even though many related networks are installed in supporting industrial applications, SCADA remains a unique network in industrial operation of all appliances. Even for monitoring the usage of high end applications, SCADA network can be modernized in the existing infrastructure networks [32–34]. Therefore, the major advantage of SCADA industrial appliance is the storage system that is used for detecting all types of problems in connected network. Further, the appliance downtime is much reduced due to proper supply of energy resources which is turn provides a better maintenance period for all operating appliances. In addition, even secondary advantages of SCADA provide appropriate graphical status for all real time environmental verifications.

4. Experimental Verification

The combined model of analytical representations with optimization algorithm is verified using real time experimental cases in order to prove effective automatic operation of several appliances. In this process, the SCADA networks are installed in the industrial appliances with low critical distance which is modified to produce low power drop in the considered area. Further the full scale capacity of SCADA networks for proposed system is taken as 500 Megawatts supporting the entire appliances in the automated mode of operation. The above-mentioned full scale capacity can also be increased to further extent in case if appliances are added at critical points. But in the proposed method, addition of appliances is avoided as it leads to a raise in instabilities and even a delay in data processing increases. At the initial stage, the process started with random SCADA data error measurement where less than 1 percent of distribution values is provided. However, as appliances are increased, the error rate is varied to nominal phase for about 1.5; thus, the disturbance period is much lesser in case of the proposed method. In addition, the control process in SCADA network provides a valuable pseudo rate using true and measurement values. Moreover, these values are directly integrated in software tool where outcomes are generated using MATLAB at low uncertainty cases. To observe the adeptness of proposed SCADA network in industries, five scenarios are distributed based on analytical design as follows:

Scenario 1: measurement of primary energy

Scenario 2: minimization of loss

Scenario 3: observation of critical distance

Scenario 4: SCADA data delay

Scenario 5: data control phase

All the above-mentioned scenarios are simulated and compared with existing models that incorporated different data set. However, the data set used in the proposed method is much similar to the existing cases with a variation of 2 percent with respect to the distribution base. In addition to data base, complete state periods are measured in the system in order to prevent initial delay in control phase of the network. The detailed description of all the aforementioned scenarios is as follows.

4.1. Scenario 1. The amount of primary energy source is a much important measurement to be considered as the appliances operate in a perfect way if the disturbance period is much lesser than the actual operating amount. Also the downcast time period of appliance is considered in this design in order to check the amount of fluctuation during the automated mode of operation. In case fluctuations are much higher than expected, then the frequency of selected appliances will change, thus resulting in low disturbance period. Therefore, a separation is made in the design process by reproducing disturbance, downcast, and frequency values. All these changes are observed in the system for making individual determinations of each appliance, and as a result primary energy sources are established at transmission end. Moreover, the total number of operating appliances is converted to discrete form, thus ensuring less changes in terms of battery operating system. Figure 2 portrays the amount of energy sources for various appliances with disturbance time periods.

From Figure 2, it is observed that the total number of appliances is varied from 10 to 50 and individual disturbance times are measured as 2.33, 2.98, 3.11, 3.36, and 3.42, respectively. All the disturbance time periods are measured in the average form with respect to changing appliances only. Since more variations are not found with respect to disturbance time, the frequency of appliances is changed in a direct form. Thus the frequency of variations is considered as 60, 89 , 103, 116, and 127 kHz, respectively, for a set of appliances that are mentioned earlier. By considering the above-mentioned specifications, energy source determinations are made and it is observed that appliances are operated in automated mode with low primary energy source in the proposed method. This can be proved with 30 different appliances inside the industry where 5.1 watts is allocated for individual operation [11] whereas with same number of appliances the proposed method operates at 50 percent of primary energy source which is equal to 2.05 watts at high effective time periods.

4.2. Scenario 2. In case of the automated operation of appliances, it is necessary that low disturbance period must be assured and if any failure rate occurs in this period, then losses in SCADA network will be determined. Thus this scenario is provided to measure the amount of total loss in the system with full scale operating capacity of appliances. For this type of determinations, two individual values are considered such as summation of original value and full scale capacity which is reproduced using energy loss in the system. Further this reproduction rate must be minimized in such a way that it should be less than 40 percent on an average as compared to appliances that are operated without full scale capacity. If appliances are not operated at full scale capacity, it will directly affect the energy rate of subcomponents, thus leading to manual adjustment in the entire process which in turn should be avoided. Figure 3 illustrates the total loss that is calculated due to high disturbance time periods.

From Figure 3, it is perceived that full load capacity of appliances is varied as 100, 200, 300, 400, and 500, respectively, and even the capacity can be increased to further extent if appliances are added. As the proposed method measures the loss rate for medium scale appliances, the allocated full load capacity is much sufficient for operational cases. During this simulation study, the energy loss of particular appliance is observed to be 2.1, 2.4, 2.8, 3.2, and 3.4 and with this loss the amount of full scale capacity is reproduced. In addition, a comparison plot is provided where the total loss for the proposed method is much lesser and it is lesser than 1, but the existing method provides high variation of loss if appliances are increased. This can be demonstrated with full load capacity of 300 and with energy loss of 2.8 where implementation of SCADA network provides 0.89 as a loss factor. But with the same amount of capacity, the existing method operates at 1.39 loss rate which is much higher in case of individual appliances.

4.3. Scenario 3. The starting and end time periods of SCADA network in all appliances are selected for determining the critical distance points. Additionally, the total life period of individual appliances is used for determining distance measurements with summation cases. Thus when a distance

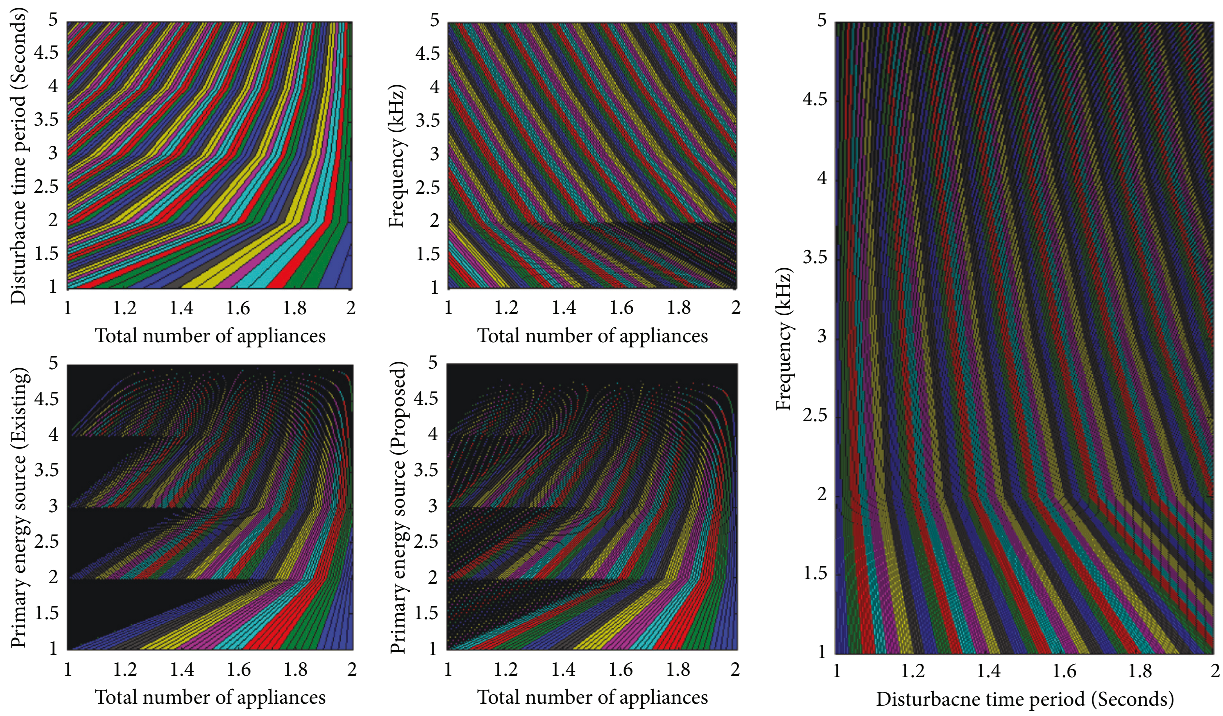

Figure 2: Comparison of primary energy source.

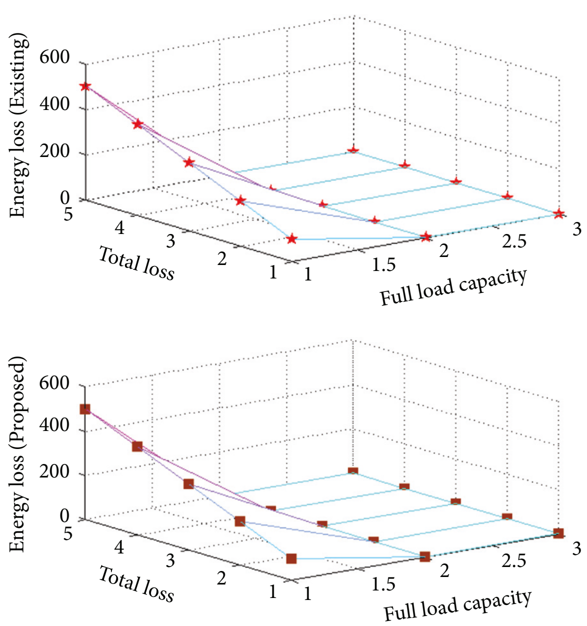

Figure 3: Observed energy losses at full load capacity.

point is marked, then the difference between the first point and the end point is termed as critical distance value. This type of determinations is made in such a way that end-to-end appliances are considered without any gap between available industrial space. Since the process is automated using a set of SCADA networks, the critical distance must be minimized as low as possible. In case distance is much larger, then the total life period of appliances will be reduced at great extent. Therefore, to avoid such circumstances, the

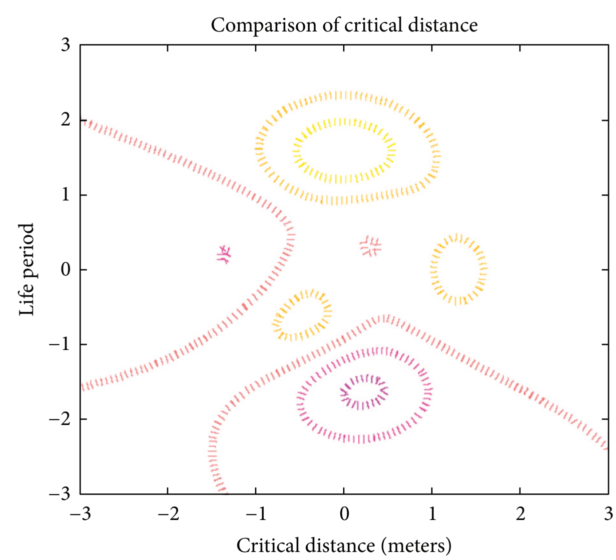

Figure 4: Measurement of critical distance.

corresponding distance of appliance and end distance of other appliances which are connected using same communication unit must be minimized. Figure 4 deliberates the simulation plot of critical distance measurements.

From Figure 4, it is pragmatic that difference in terms of critical distance is set as 120, 180, 240, 280, and 360, and this distance is not varied until new appliances are added inside the boundary of SCADA network. The average life time of all appliances inside the industry is gathered from existing data set and it cannot be varied; thus, a total appliance life period is represented in this simulation study. Thus the life period

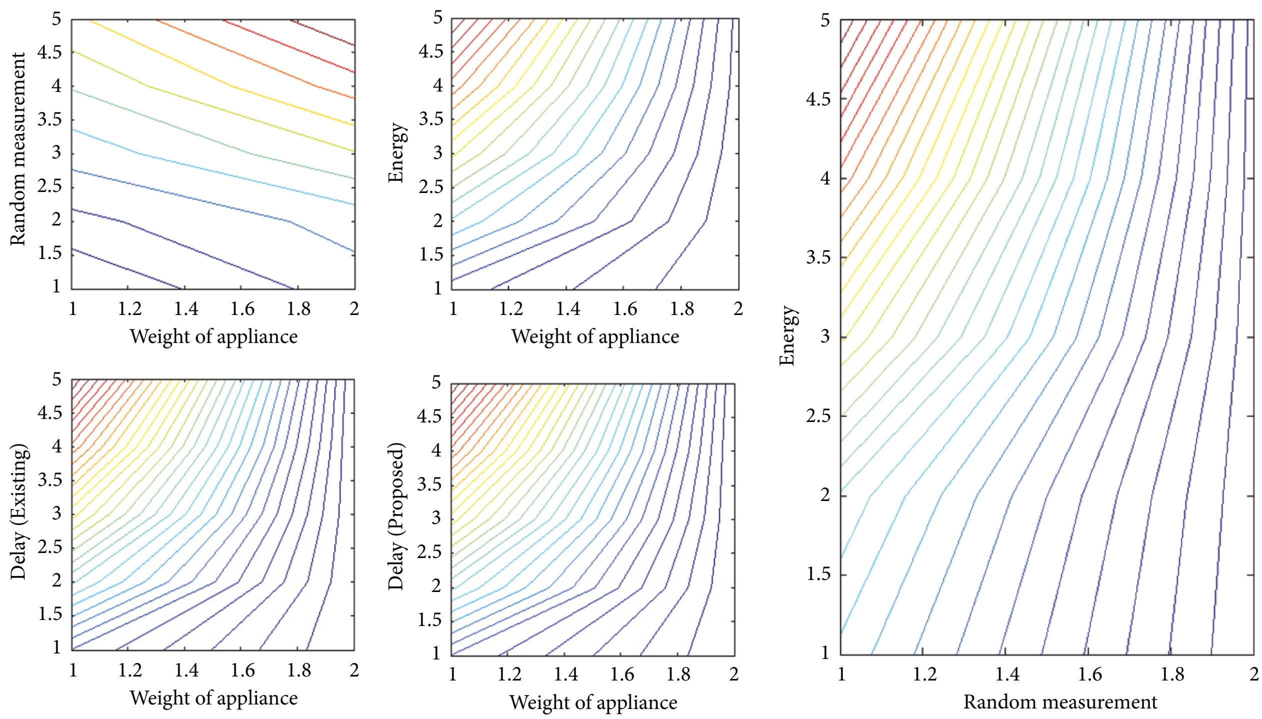

Figure 5: Delays in data measurement.

of appliances is set as 1000, 1300, 1600, 1900, and 2100 which exactly matches with critical distance values. By using the above-mentioned specifications, total distance is measured and compared with the existing method that operates under manual distance changing operations. Since the proposed method using SCADA network is operated in automated mode, total distance is minimized for average life time separation. This can be observed with critical distance of 280 meters and life period of 1900 days where the distance of separation in allocation of data is equal to 172 meters, whereas in case of existing method, it is maximized to 502 meters.

4.4. Scenario 4. The SCADA network is incorporated in the industrial system by combining multiple appliances; thus, there is a need to integrate all the data that is present in the entire network. Hence, the delay in processing data must be minimized by considering random measurement function. Moreover, the delay is calculated using weight functions of all appliances that are directly reproduced with measurement values. Further, the data delay phase that is reproduced in the system is summed with total energy supply where it is completely occupied in the SCADA network. However, the unoccupied energy rate is not increased in proposed method as it leads to more delay in entire process. For the input data set, the implemented SCADA network must maintain 0.54 second of delay and this limitation factor cannot be changed even during processing stage. Therefore, all individual appliances that are connected within the industry must reach the control center at correct time periods. Figure 5 provides simulation plot of delay functions with variation in energy rates.

From Figure 5, it is detected that the weight of appliance is varied from 10 to 50 kilograms where random measurements are provided as 25, 30, 45, 60, and 75, respectively. For each variation, the total energy of appliance is taken and a new ingenuity energy loss is considered in a direct way. This type of consideration is usually processed in special case if appliances are operated in an automatic way. Moreover, the weight of total appliances is much higher; thus energy loss can be used in direct cases as 2.1, 2.4, 2.8, 3.2, and 3.4 respectively. By using random measurements, comparisons are made for the delay period calculation where it is much reduced in case of the proposed method as compared to the existing cases. This can be verified in real time by considering 40 kilograms of appliances in an industry where the delay periods are kept within defined limits of 0.4. But in the existing method, the delay period is maximized above limitations and at last phase exact boundary limit is achieved.

4.5. Scenario 5. One of the important processing units is SCADA network data processing that is made using parametric matrix type. Hence in the proposed method, control data are determined from transmission to end user appliances, thus making necessary modifications in the entire data. In addition to control data, another type of measurement matrix is provided which is termed as rapidity data matrix that is used for selecting appropriate rate. Further, these two matrixes are separated from pathways and finally it is summed up and used for initial cases. Once the pathways are separated, then change in time intervals is measured using delta matrix values. Thus total data phase variation in individual appliances is provided and marked as separate cases for large scale automation using SCADA networks. If

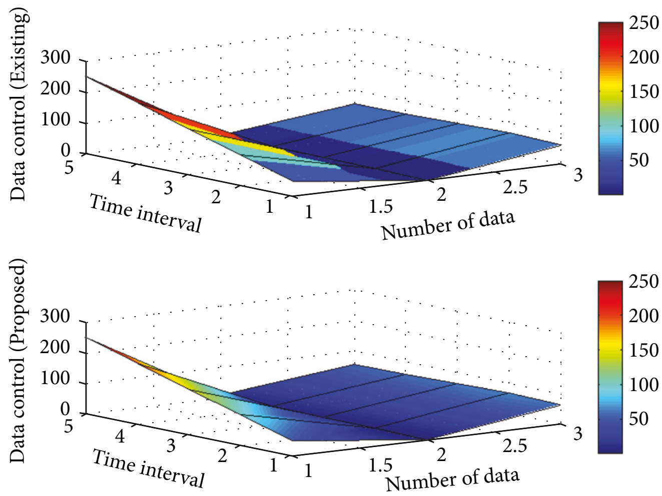

Figure 6: Observation of data control phase.

any changes are observed in certain interval for data measurements, then it must be minimized at appropriate phases. Figure 6 illustrates the minimization plot of SCADA data control phase.

From Figure 6 it is observed that the total number of SCADA data is varied in step size of 50 with two second time interval periods. During this data dissimilarity, the entire data that are transferred to control unit must be minimized and it is guaranteed in case of the proposed method as compared to the existing method. For verification, if the number of data is equal to 150 with six second break periods, then the percentage of data control that is achieved in case of SCADA network with the proposed method is 87 percent whereas the existing method controls and secures the central data around 63 percent. Furthermore, complete data control is attained only in case of the proposed method up to 92 percent, but the controlling factor of SCADA network with the existing system without any learning model decreases to 57 percent. Since the data phase is reduced, the proposed method can be applied in real time to all automated industries with high security features.

4.6. Robustness of SCADA. The robustness of SCADA determines the tractability solutions when it is incorporated in any type of medium. Usually SCADA networks operate at different time periods, thus creating multiple delays in a communication channel. However, in case of multiple delays, both data and security of industrial appliances are highly sensitive; thus, network operation must be highly robust against distinct type of scalable parameters. In other terms, robustness is measured using primary energy source where operation of all appliances is started. During this energy source operation, the distance between two different SCADA networks causes low robustness as much better hardware setup is installed. Figure 7 portrays robustness characteristics of SCADA network with changing iteration values.

From Figure 7, it is observed that the best epoch is chosen between 10 and 100 as 20, 40, 60, 80, 100,

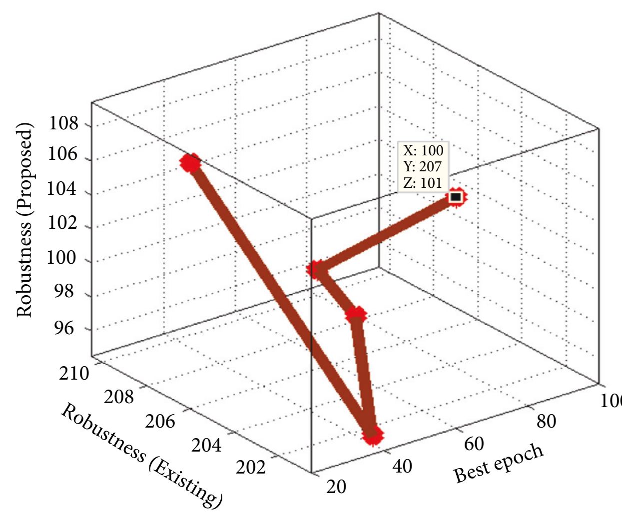

Figure 7: Comparison of robustness with the best epoch.

respectively, where for all best iteration values robustness is calculated. In the proposed method, robustness characteristics are simulated by accumulation of primary energy sources and critical distance in SCADA networks; thus high values are achieved. Moreover, in the comparison case study, the proposed method using learning technique performs much better as compared to the existing method [11]. This can be substantiated with the best epoch as 80, and during this period, the robustness of existing model in absence of the learning-based technique is 210 whereas the projected method provides low robustness of 96 due to much reduced primary sources.

5. Conclusions

The process of implementing SCADA networks for processing automated operations in large scale appliances using learning technique is illustrated. Whenever appliances are introduced in a particular system, then it is necessary to perform automatic operations as some of the parametric values change with immediate effect. In addition, the weight of a particular appliance must be managed in entire industry as all appliances are combined and operated using a common control network (SCADA). Also the resources that are shared by supervisory blocks must be fulfilled to all appliances in small, medium, and large scaling factors. Thus a primary energy source is determined in the proposed method where all the appliances are trained and learned to operate in innocuous mode. Since primary energy sources are measured at initial state, all the appliances are protected by changing the down time of the appliance using frequency shift factors. Therefore, as a result, the difference in loss periods is much reduced where all appliances in industries are operated at low energy rate. This type of minimization process is framed using an analytical representation that turns out as an action point for automatic operational conditions. Moreover, several constraints provided for appliance operation are much reduced and thus high flexibility is provided in projected SCADA network implementation process. In case of data handling process, high security is provided by SCADA network where data of all appliances are transferred only to control center. The analytical model is framed in such a way for integrating multiple objectives such as minimization of delay, critical distance, and energy loss where all the objectives are tested by combining SCADA hardware setup with realization software tool. Furthermore, experimental verifications are carried out by examining five scenarios, and in the comparison study it is comprehended that SCADA network with learning models provides high effectiveness for about 84 percent. In future, the proposed model on SCADA network can be extended for industrial applications using artificial intelligence and machine learning techniques as the cost of installation will be reduced in a suitable way.

Data Availability

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

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

This project was funded by the Deanship of Scientific Research (DR) at King Abdulaziz University (KAU), Jeddah, Saudi Arabia, under grant no. RG-4-611-43. The authors, therefore, acknowledge with thanks DSR for technical and financial support.

References

[1] D. Upadhyay, M. Zaman, R. Joshi, and S. Sampalli, "An efficient key management and multi-layered security framework for SCADA systems," *IEEE Transactions on Network and Service Management*, vol. 19, no. 1, pp. 642–660, 2022.

[2] A. A. Suvorov, A. A. Zaki Diab, A. S. Gusev et al., "Comprehensive validation of transient stability calculations in electric power systems and hardware-software tool for its implementation," *IEEE Access*, vol. 8, pp. 136071–136091, 2020.

[3] Y. Cherdantseva, P. Burnap, A. Blyth et al., "A review of cyber security risk assessment methods for SCADA systems," *Computers & Security*, vol. 56, pp. 1–27, 2016.

[4] A. O. Khadidos, H. Manoharan, S. Selvarajan et al., "A classy multifacet clustering and fused optimization based classification methodologies for SCADA security," *Energies*, vol. 15, 2022.

[5] S. Shitharth, K. M. Prasad, K. Sangeetha, P. R. Kshirsagar, T. S. Babu, and H. H. Alhelou, "An enriched RPCO-BCNN mechanisms for attack detection and classification in SCADA systems," *IEEE Access*, vol. 9, pp. 156297–156312, 2021.

[6] S. Shitharth, N. Satheesh, B. Praveen Kumar, and K. Sangeetha, "IDS detection based on optimization based on WI-CS and GNN algorithm in SCADA network, architectural wireless networks solutions and security issues," *Lecture Notes in Network and Systems*, vol. 196, no. 1, pp. 247–266, 2021.

[7] S. Shitharth, K. Sangeetha, and G. B. Mohammed, "Enhanced SCADA IDS security by using MSOM hybrid unsupervised algorithm," *International Journal of Web-Based Learning and Teaching Technologies*, vol. 17, no. 2, 2022.

[8] Z. Lv, S. Lv, H. Feng, and H. Lv, "Clinical characteristics and analysis of risk factors for disease progression of COVID-19: a retrospective cohort study," *International Journal of Biological Sciences*, vol. 17, pp. 1–7, 2021.

[9] X. Liu, J. Zhao, J. Li, B. Cao, and Z. Lv, "Federated neural architecture search for medical data security," *IEEE Transactions on Industrial Informatics*, vol. 18, no. 8, pp. 5628–5636, 2022.

[10] B. Cao, J. Zhang, X. Liu et al., "Edge-cloud resource scheduling in space-air-ground integrated networks for internet of vehicles," *IEEE Internet of Things Journal*, vol. 9, no. 8, pp. 5765–5772, 2022.

[11] D. Astolfi, "Perspectives on scada data analysis methods for multivariate wind turbine power curve modeling," *Machines*, vol. 9, no. 5, p. 100, 2021.

[12] X. Kong, Y. Chen, T. Xu et al., "A hybrid state estimator based on SCADA and PMU measurements for medium voltage distribution system," *Applied Sciences*, vol. 8, no. 9, p. 1527, 2018.

[13] H. Kong, M. Lu, L. Que, F. Xu, J. Zhao, and A. Xue, "A new four-step method to identify the parameters of transmission line based on SCADA data," *IET Generation, Transmission & Distribution*, vol. 16, no. 9, pp. 1822–1835, 2022.

[14] S. Shitharth, M. Shaik, and S. Sirajudeen, "Mining of intrusion attack in SCADA network using clustering and genetically seeded flora based optimal classification algorithm," *Information Security IET*, vol. 14, no. Issue 1, pp. 1–11, 2019.

[15] J. Temido, J. Sousa, and R. Malheiro, "SCADA and smart metering systems in water companies. A perspective based on the value creation analysis," *Procedia Engineering*, vol. 70, pp. 1629–1638, 2014.

[16] R. Pandit and A. Kolios, "SCADA data-based support vector machine wind turbine power curve uncertainty estimation and its comparative studies," *Applied Sciences*, vol. 10, no. 23, pp. 8685–8718, 2020.

[17] M. B. Mollah and S. S. Islam, "Towards IEEE 802.22 based SCADA system for future distributed system," in *Proceedings of the 2012 International Conference on Informatics, Electronics and Vision, ICIEV*, Dhaka, Bangladesh, May, 2012.

[18] S. Shitharth, Sangeetha, and P. Kumar, "Integrated probability relevancy classification (IPRC) for IDS in SCADA', design framework for wireless network," *Lecture Notes in Network and Systems*, vol. 82, no. 1, pp. 41–64, 2019.
[19] F. A. Osman, M. Y. M. Hashem, and M. A. R. Eltokhy, "Secured cloud SCADA system implementation for industrial applications," *Multimedia Tools and Applications*, vol. 81, no. 7, pp. 9989–10005, 2022.
[20] M. O. Qays, M. M. Ahmed, M. A. Parvez Mahmud et al., "Monitoring of renewable energy systems by IoT-aided SCADA system," *Energy Science & Engineering*, vol. 10, no. 6, pp. 1874–1885, 2022.
[21] H. Cheng, M. Shojafar, M. Alazab, R. Tafazolli, and Y. Liu, "PPVF: privacy-preserving protocol for vehicle feedback in cloud-assisted VANET," *IEEE Transactions on Intelligent Transportation Systems*, vol. 23, no. 7, pp. 9391–9403, 2022.
[22] J. Chen, Y. Liu, Y. Xiang, and K. Sood, "RPPTD: robust privacy-preserving truth discovery scheme," *IEEE Systems Journal*, vol. 16, no. 3, pp. 4525–4531, 2022.
[23] F. Liu, G. Zhang, and J. Lu, "Multi-source heterogeneous unsupervised domain adaptation via fuzzy-relation neural networks," *IEEE Transactions on Fuzzy Systems*, vol. 29, no. 11, pp. 3308–3322, 2021.
[24] D. Li, S. S. Ge, and T. H. Lee, "Fixed-time-synchronized consensus control of multiagent systems," *IEEE Transactions on Control of Network Systems*, vol. 8, no. 1, pp. 89–98, 2021.
[25] X. Wu, W. Zheng, X. Chen, Y. Zhao, T. Yu, and D. Mu, "Improving high-impact bug report prediction with combination of interactive machine learning and active learning," *Information and Software Technology*, vol. 133, Article ID 106530, 2021.
[26] M. Zhang, Y. Chen, and W. Susilo, "PPO-CPQ: a privacy-preserving optimization of clinical pathway query for E-healthcare systems," *IEEE Internet of Things Journal*, vol. 7, no. 10, pp. 10660–10672, 2020.
[27] J. Yan, H. Jiao, W. Pu, C. Shi, J. Dai, and H. Liu, "Radar sensor network resource allocation for fused target tracking: a brief review," *Information Fusion*, vol. 86, pp. 104–115, 2022.
[28] D. Shitharth and D. Prince Winston, "An enhanced optimization algorithm for intrusion detection in SCADA network," *Journal of Computer Security*, vol. 70, pp. 16–26, 2017.
[29] D. Shitharth and D. Prince Winston, "A new probabilistic relevancy classification (PRC) based intrusion detection system (IDS) for SCADA network," *Journal of Electrical Engineering*, vol. 16, no. 3, pp. 278–288, 2016.
[30] W. Zheng and L. Yin, "Characterization inference based on joint-optimization of multi-layer semantics and deep fusion matching network," *PeerJ Computer Science*, vol. 8, p. e908, 2022.
[31] J. Yu, L. Lu, Y. Chen, Y. Zhu, and L. Kong, "An indirect eavesdropping attack of keystrokes on touch screen through acoustic sensing," *IEEE Transactions on Mobile Computing*, vol. 20, no. 2, pp. 337–351, 2021.
[32] K. Cao, B. Wang, H. Ding et al., "Improving physical layer security of uplink NOMA via energy harvesting jammers," *IEEE Transactions on Information Forensics and Security*, vol. 16, pp. 786–799, 2021.
[33] Z. Lv, J. Guo, and H. Lv, "Safety poka yoke in zero-defect manufacturing based on digital twins," *IEEE Transactions on Industrial Informatics*, vol. 1, 2022.
[34] Z. Lv, L. Qiao, and I. You, "6G-Enabled network in box for internet of connected vehicles," *IEEE Transactions on Intelligent Transportation Systems*, vol. 22, pp. 5275–5282, 2021.