Parallel Mode Estimation Improvement in Power Networks based on Optimal ANFIS Approach

Meisam Arabpour, Alimorad Khajehzadeh, Mehdi Jafari Shahbazzadeh, Mahdiyeh Eslami

Department of Electrical Engineering, Kerman Branch, Islamic Azad University, Kerman, Iran

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ABSTRACT

In this research, the issue of non-technical losses in the distribution network was addressed, which should have been detected. Distribution networks and transmission lines have different parameters, so their state estimation and modeling are completely different. This problem causes the detection of non-technical losses in the distribution network by mode conversion to suffer a series of computational complications. Therefore, an attempt has been made to improve the parameters of voltage, primary current, passing current and bus energy along with error estimation after estimating the state of the distributed network so that non-technical losses can be detected. Therefore, a hybrid approach based on observer-based fuzzy neural network filter and genetic algorithm is used. Due to the existence of errors, the fuzzy neural network filter has been used, the reason for its three-dimensionality is that the system is non-linear and the errors and states may be different at different times. This research, in one case, has estimated the state of the distribution network with the aim of detecting non-technical losses. The observer can check these different situations at different times. Also, because the problem of detecting non-technical losses in the distribution network based on state estimation is assumed as a hard problem, therefore, the distribution network environment can be assumed as a main platform as a search environment for optimization algorithms. . Therefore, the use of intelligent algorithms from the family of fuzzy neural network and evolutionary algorithms and crowd intelligence can be interesting for estimating the optimal state with the aim of detecting non-technical losses in the distribution network. Hence, genetic algorithm is also used for optimization. After considering the main parameters to estimate the system state with the proposed approach, the results obtained from the simulation indicate the improvement of the state estimation and the detection of non-technical losses in the distribution network along with the minimization of the error estimation compared to the initial state.

Keywords: Parallel Mode Estimation, Power Networks, Neuro-Fuzzy (ANFIS), Genetic Algorithm (GA)

INTRODUCTION

Microgrid is becoming an effective way to solve the problem of power supply in off-grid islands. Investment economics is one of the main factors affecting its development and application, which is very challenging due to the various uncertain information involved in the investment decision process. The presence of distributed sources and microgrids in the power system, despite the many economic and environmental benefits, have added new problems to the power system. Among these problems, voltage and frequency fluctuations can be mentioned during possible events such as extreme load changes or errors in the power system. In the island mode, due to the lack of backup power, the intensity and range of these fluctuations and the possibility of microgrid instability and collapse are much higher. In addition, due to the low inertia of the scattered sources in the microgrid and the high switching speed of the power electronics, the dynamics of an island microgrid is much faster than conventional power systems. Therefore, it is necessary to have an effective control structure with fast performance when disturbances occur in the system [1-4].

In traditional distribution networks, frequency and voltage deviations are considered as an indicator to detect system security. Hence the opposite the frequency and voltage deviations in the microgrid due to power and load disturbances are well controlled by the real power frequency controller and the reactive voltage-power controller while in an independent microgrid with sources with power electronic interface. Whether it happens in traditional distribution networks, frequency and voltage deviations are not considered an important issue for determining the security of independent microgrids with sources with power electronic interface. But in an independent microgrid, the balance between power generation and consumption is considered as an index to evaluate its security, especially when power and load disturbances occur. Therefore, if this balance is not established in the microgrid, the microgrid is considered unsafe. In this case, there is a need for preventive measures such as load shedding and production adjustment in the shortest time in the microgrid. In this research, a new strategy to investigate the dynamic security of the microgrid is proposed in the form of a short-term planning decision-making model, and the occurrence of power and load disturbances as well as the use of adaptive fuzzy neural network are evaluated in an evolutionary way. Also, if it is detected that the microgrid is insecure, it is suggested to predict preventive control actions by other neural networks [6, 5].

Microgrids connected to distribution networks have many advantages, including improving power quality and reliability, reducing losses, economic benefits, and reducing environmental pollution. Optimal distribution of load in distribution networks is an important issue. This necessity stems from the fact that the lack of optimal load distribution can lead to economic and environmental problems on a large scale. The presence of voltage fluctuations is one of the most important problems that can lead to the destruction of equipment. The existence of internal and external disturbances in the micro-grids connected to the distribution networks can lead to an increase in the frequency in the form of momentary events, which aggravates the severe load changes and the creation of errors. In microgrids connected to distribution networks, it is necessary to use UPFC for optimal load distribution, but there are still weaknesses in these systems. Therefore, it is necessary to create a short-term decision-making model. It is essential to provide an optimal structure that has the ability to train and detect errors for the establishment and placement of the phase measurement unit based on parallel mode estimation and to prevent any internal and external disturbances. Providing control solutions for this is an issue that has been discussed by scientific societies for many years. Due to the uncertainty in microgrids connected to distribution networks, fuzzy structures can be used, but since there is no improvement capability in fuzzy systems, therefore, a combined method with it can be an interesting issue. Therefore, this research deals with the use of neural network along with fuzzy logic, which is called neuro-fuzzy or ANFIS. The neural network can automatically create a learning structure during the periodicity in the structure of the fuzzy membership functions and create the defuzzification operator, which provides an interesting result. After the learning structure of the neural network, the input signals in the neural network continuously learn the membership functions and fuzzy scientists. For this research, the study is of a library type, and the study about electricity and power networks in [7-9], microgrids in [10-32], neural networks in [34, 33], fuzzy logic in [37-- [35], neural-fuzzy network has been done in [38].

LITERATURE REVIEW

A microgrid is a set of distributed generation resources and loads. Various classifications have been proposed for energy sources in microgrids. One of these cases is the classification based on the way energy sources are connected to the microgrid. Based on this, one group of units are connected to the microgrid through a synchronous machine, and the other group are those whose power electronic interface provides the connection to the microgrid. In microgrids with distributed generation sources with power electronic interface, an energy storage system is usually needed when the microgrid is operated in independent island mode to operate in transient mode of the network or changes especially in load demand (DS) [44-39]. The microgrid can be used in two modes connected to the grid and Independent Island in the mode of connecting to the main grid, the distribution system, it can be used as a Slack 4 electric bus, and to maintain the power balance in the microgrid, it supplies/absorbs any difference in production power. But when the microgrid is slowly transferred to the independent island operating mode due to voltage drops, errors, shutdowns, etc., the power balance in the separate microgrid, especially when there are power and load disturbances is raised as a vital issue for the continued safe operation of the microgrid. In the case of an independent island, due to power disturbances or increased load consumption, the distributed production sources in the microgrid are not able to supply power, the energy storage system can be used, which of course, due to its limitations, should be used to drop if needed 5 times. But the minimum amount of load shedding and faster reaching the power balance in the microgrid is an issue that must be achieved [45-47]. In the microgrid, frequency and voltage droop control is used to adjust the real and reactive power in order to realize the feature of installing and removing resources.

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In this method, the contribution of each source is obtained with an inverter interface based on the characteristics of the droop curve, which will cause a quick response and by assigning the reference amount to each unit, it will prevent damage to scattered products. The frequency deviation can be limited by defining the frequency droop characteristic and can even be returned to the nominal value by using the frequency recovery loop. Also, by using the voltage drop feature, the terminal voltage changes are limited, as a result, the distributed generation units react to the voltage deviation caused by the microgrid or local load changes with the power electronics interface within the allowed range. So, with this method, the frequency and voltage of the microgrid can be adjusted in such a way that they are prevented from going out of the allowed value. This makes frequency and voltage deviations not considered as an indicator for evaluating microgrid security, unlike traditional systems in microgrids. Therefore, it is important to find methods to quickly diagnose the security of independent microgrids, especially when power and load disturbances occur. Also, if the microgrid is unsafe, taking immediate measures for the safe operation of the microgrid is a necessary thing that must be investigated. To evaluate microgrid security in the traditional way, the most accurate method is to solve a set of nonlinear equations, which is a very difficult and time-consuming calculation method. But using tools based on artificial intelligence is a suitable alternative for quick and accurate description of microgrid security [47].

The frequency deviation and performance of the storage equipment in the microgrid have been investigated [48-51] and an index has been presented to evaluate the security of the microgrid in case of unexpected transfer to the isolated state during disturbances in the high-voltage medium voltage network. In [52], the use of artificial neural network emphasized due to its computational speed in online operation and its flexibility to predict corrective actions in unsafe operating modes in order to achieve a smooth transition between connected and isolated operation. In order to evaluate the security of the traditional distribution network, the voltage deviation has been investigated. In [53], an artificial neural network used to evaluate the security of the 9-bus standard network. When a system is designed with only artificial neural networks, the network is a black box that needs to be defined. This problem is a very computational and heavy process. After extensive experiences and exercises regarding the complexity of the desired network and the learning algorithm that should be used and the degree of accuracy that is acceptable in this application, the designer can achieve a relative satisfaction. If we include the functions of fuzzy logic in neural networks and learning, and classify neural networks in fuzzy systems, then the shortcomings of neural networks and fuzzy systems can be covered. The result of this work will be an adaptive neural-fuzzy network.

In adaptive neural network-fuzzy, first the neural network part is used for learning it and classifying the abilities and for linking the pattern and modifying the pattern. The neural network part automatically generates fuzzy logic rules and membership functions during the learning cycle. In general, even after learning, the neural network continues to modify membership functions and fuzzy logic rules, in such a way that it learns more and more from its input signals. On the other hand, fuzzy logic is used to infer and provide a deterministic or non-fuzzy output (when fuzzy variables are created). In general, it can be said that microgrids are systems that come from the integration of distributed generation units, energy storage systems and controllable loads in low voltage and medium pressure networks and can be operated in both modes connected to the network or independently. Microgrids have many advantages, including improving power quality and reliability, reducing losses, economic benefits, and reducing environmental pollution. In recent years, electric cars as an energy storage system as well as a public vehicle have faced significant development and progress, which has been noted due to the lack of fossil fuels as well as the reduction of environmental pollution. According to the predictions, it seems that the presence of electric cars as an emerging phenomenon in the power grid should be investigated. Each microgrid can exchange power with other microgrids and the main network or buy and sell power in some way. This will increase reliability and help balance supply and demand. Energy sources in microgrids consist of units such as wind power plant, photovoltaic power plant, which have uncertainty in power production, and units such as microturbine, fuel cell, power and heat generation plant, which have emissions [54].

Dr. Seyed Abbas Taher and his colleagues conducted a research entitled "Optimum load distribution in the optimal microgrid considering the uncertainty in the presence of electric vehicles" for optimal load distribution from a multi-objective algorithm in order to reduce the operating costs and pollution of the units in two modes in presence of electric cars and without considering electric cars, and the results showed that the presence of electric cars leads to a reduction in costs and pollution [55]. In [56], presented a stochastic multi-period investment planning model for island microgrid. The applicability of the model in dealing with various uncertainties is enhanced through a hybrid optimization framework in which the long-term uncertainty of energy price fluctuations is captured by a stochastic programming approach, and the short-term changes in renewable energy generation and load are considered. Dynamic information from load growth, unit cost changes and device degradation are considered to make the decision more practical and economically attractive. The multi-period investment planning model is formulated as a mixed integer linear programming problem, and the conservatism of the decision can be flexibly adjusted by adjusting the power of the model. Simulation results based on real data show that the proposed model shows better economic performance and synergy than the traditional multi-year optimization model, with the total planning cost reduced by approximately 3.6% and the initial investment cost by approximately decreased by 36.6% and the use of renewable energy increased by almost 5.4%. In addition, sensitivity analysis for load growth rate, loan ratio, unit cost and uncertain budgets further confirm the applicability of the proposed model under different conditions.

In [57], the estimation of the state of the quantum microgrid has been done. This article examines the feasibility and efficiency of algorithms based on quantum circuits for estimating the state of microgrids. The novel innovations of this paper are: 1) a general quantum state estimation (GQSE) formulation for microgrids containing an oscillating bus via quantized Gaussian-Newton iteration, 2) a preconditioned quantum linear solver (PQLS) to deal with inappropriate GQSE with limited quantum resources, and 3) an enhanced quantum state estimation (EQSE) algorithm is developed for hierarchical control-based microgrids with exogenous disturbances. Extensive case studies demonstrate the accuracy of GQSE, PQLS and EQSE in two typical microgrids. The robustness and convergence performance of EQSE are also confirmed.

In [58], estimation of the dynamic input state has been done for power networks connected to microgrids and active distribution systems with unknown inputs. Conventional dynamic state estimation in power networks in the transmission system relies on predictive methods to obtain the transition state model of the state variables. However, under highly dynamic conditions in the operation of microgrids and active distribution networks, this approach may become ineffective, as the prediction accuracy is not guaranteed. To overcome such problems, this paper uses the model of power networks derived from the physical equations of branch currents. Specifically, the power network model is a linear state space model where the state vector consists of branch currents and the input vector consists of bus voltages. To estimate state and input variables, dynamic filter algorithms based on linear Kalman are proposed in the form of batch state regression, considering the mutual correlation between states and inputs. For the scalability of the proposed scheme, a distributed implementation is also presented. Complementarily, the predicted mode and input vectors are used to detect irregular data. The results performed on a 13-bus microgrid system on the real-time Opal-RT platform show the effectiveness of the proposed method in comparison with the traditional weighted least squares state estimation and tracking methods.

In [59], distributed state estimation for renewable energy microgrids with sensor saturation is considered. An explicit model of microgrid with sensor saturation is proposed. The distributed regression estimator in this paper guarantees an upper bound of the estimation error covariances, and the increment matrices of the estimator are designed by minimizing such an upper bound at each time. In addition, calculations have been made to ensure that the estimation error is bounded exponentially in the mean square, and the results show an improvement in state estimation. In [60], dynamic state estimation for island microgrids has been done with multiple fading measurements. An explicit model of islanded microgrid with fading measurement is proposed. The fading phenomenon makes the measurements happen randomly and the attenuation coefficients are characterized by a set of random variables with a known probability distribution. Attention is focused on the design of a regression mode estimator in the presence of faded measurements. In terms of the solutions of two sets of matrix difference equations, first an upper bound is obtained on the covariance of the estimation error, and then such an upper bound is minimized with the appropriate design of the gain of the estimator. Finally, the simulation is performed on an islanded microgrid to demonstrate the effectiveness of the proposed dynamic state estimation scheme.

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PROPOSED METHOD

In this research, a new strategy is proposed to estimate the state of power consumption of buses with the help of state estimation system and detect non-technical losses in microgrids connected to distribution networks and the occurrence of power and load disturbances as well as state estimation using network algorithm. Neuro-fuzzy is investigated. The communication bridge between Tavanir organization for electricity supply and subscribers is done in distribution networks. The importance of consumers and subscribers in distribution networks, as well as the economic ability of the organization and affiliated companies, and having expertise in the type of network operation, and finally, according to the science and expertise of engineers, can be used in operation. A series of demands must be met from these networks, no matter what they are.

Although the types of distribution networks do not achieve all the above points, but in the construction of the networks, the demands mentioned in the distribution networks should be met by observing the standards. Electric energy transmission methods are divided into two general parts: aerial wires with accessories and ground cables with accessories. Reliability of electricity transmission to customers is one of the main concerns of organizations and electricity distribution companies. The method of energy transmission that is discussed in this research is based on ground cables with accessories. Underground networks that use underground cables are a defined and pre-existing method with its own standards. The reason for its widespread use, as well as its trust is the response to environmental concerns and today most companies provide single-phase electricity to residential houses (5 houses or more) underground, and also many companies are also converting their three-phase aerial systems to underground systems, and most engineers are of the opinion that the reliability of underground systems is higher than aerial systems, and it has been heard many times that the probability of error occurring in underground systems is less. But, the time required to fix it is more and in addition, in underground systems and almost all short-term errors that sometimes make up 80% of the total errors in a system, this is lost in the current era when blackouts in networks are considered a big fault, it reduces blackouts to a great extent.

Transmission line criteria is an important issue based on which state estimation can be done. One of the most important factors directly involved in choosing the type of ground or air network is the transmission route. The reason is to obtain information about the surrounding environment as well as how the components are placed. Basically, the path of the transmission line in different environmental has diversity. Assuming the path of the transmission and distribution line in a mountainous environment is completely different from a desert area. Also, the length of the route is very important. If the distance from the distribution point and post to the point of consumption where the subscribers are in houses or companies is short, ground cables are completely preferable to aerial wiring. For example, in the mountains, where there are successive twists and turns, if the distance between the distribution point and post to the point of consumption is long and also the electrical pressure of the network is strong, aerial wiring is used. But in a flat environment like deserts, ground wiring is used.

Another important parameter in transmission and distribution line criteria is the route type. In some areas, such as airports or highways in plain areas, as well as railway lines in plain areas, terrestrial networks are compulsorily used, which are more economical. Aerial networks may be used in a railway that is in mountainous and winding areas. The transverse limit parameter of the path is also known as a basic parameter in different areas and its investigation is necessary in the type of cabling for electricity transmission and distribution in the areas. Due to the lack of roads in different areas, as well as the non-possibility of aerial cabling, ground cabling is forced to be used. Especially in the case of 400 volt and 20 kilowatt lines inside industrial complexes, this situation is far more visible. As the voltage of the transmission lines becomes stronger, aerial wiring is preferable to ground cabling. Generally, weak pressure networks are made from ground cables. In 20 kV networks, due to other factors, ground cabling is seen. But for lines of 63 kV and above, ground cabling is not essential due to the huge costs. In spite of all the problems and disadvantages of distribution networks that are caused by the past insignificance towards them, it can be done by employing expert people in this field and investing more effort and paying attention to the following suggestions in these distribution networks (which soon these funds will be returned) reduce or even eliminate problems and disadvantages.

In this research, a new strategy for checking the dynamic security of microgrid is proposed to investigate this issue and the occurrence of power and load disturbances as well as the use of adaptive neural-fuzzy network are investigated. Also, if the microgrid is detected to be insecure, it is suggested to predict preventive control actions by other neural networks. First, in table (1), the names that are used as abbreviations in the pictures of this chapter and relationships are stated.

Table (1) Abbreviated name

APF	active power filter
ANFIS	adaptive neuro fuzzy inference
MG	microgrid system
MGU	microgrid system utility
PQ	power quality
PCC	point of common coupling
UPFC	unified power quality conditioner
VSI	voltage source inverter

In Figure (1), you can see the initial configuration of the microgrid.

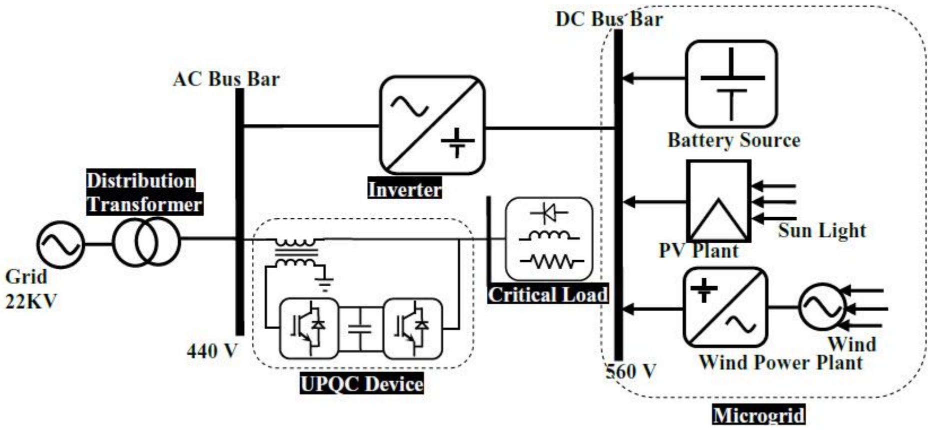

Figure (1) Initial microgrid configuration

Microgrid is a combination of several alternating energy sources connected to a common bus. The microgrid structure must be clear. The distribution network integration presented in this research is designed to detect non-technical losses and determine the state estimation of two voltage source inverters or VSIs with a common DC link capacitor or C_{dc}. A VSI is connected in series with the transformer connection source, which functions as a series APF. APF series are responsible for compensating the PQ distortion at common points. Other VSIs are connected in parallel, placed between the series APF and the load acting as a shunt APF. The shunt APF is responsible for compensating for power quality issues associated with customers and regulating the DC link voltage. In the arrangement presented in this research, the shunt passive series capacitor or C_{sh} plays an important role to support the shunt APF. In the load section, the passive series capacitor or C_L supports the reactive power flow in the connection. Series control technique is designed to adjust the rate of loads. The block diagram of series control technique in distribution networks is shown in Figure (2). Microgrid is a combination of several alternating energy sources connected to a common bus. The microgrid structure must be clear. The distribution network integration presented in this research is designed to detect non-technical losses and determine the state estimation of two voltage source inverters or VSIs with a common DC link capacitor or C_{dc}. A VSI is connected in series with the transformer connection source, which functions as a

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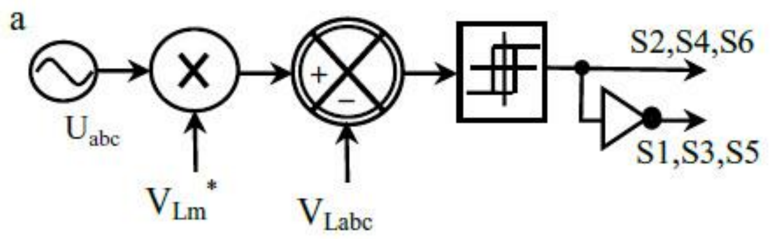

Figure (2) series control technique in distribution networks

The series control technique in distribution networks deals with load voltage regulation using a process such as reference signal generation and works by recording PQ distortion instruments and generating pulses for VSI series. The reference load voltage is formed from the generation of the voltage or V_{Lm} as well as the sinusoidal signal of the phase unit or U_{abc}, whose relationship is in the form of equation (1).

$$\begin{bmatrix} {V_{La}}^* \\ {V_{Lb}}^* \\ {V_{Lc}}^* \end{bmatrix} = \begin{bmatrix} {V_{Lm}}^* sin(\omega t) \\ {V_{Lm}}^* sin(\omega t + 120) \\ {V_{Lm}}^* = sin(\omega t - 120) \end{bmatrix} \quad (1)$$

According to the equation (1), the number 120 means 120 degrees Celsius. The PQ distortion tool is recorded from different references and the actual load voltage using equation (2). The pulses for the VSI series of disturbance instruments are generated using a hysteresis controller.

$$\begin{bmatrix} V_{Ca} \\ V_{Cb} \\ V_{cb} \end{bmatrix} = \begin{bmatrix} {V_{La}}^* \\ {V_{Lb}}^* \\ {V_{Lc}}^* \end{bmatrix} - \begin{bmatrix} V_{La} \\ V_{Lb} \\ V_{Lc} \end{bmatrix} \quad (2)$$

The proposed shunt control technique is designed to regulate the current source and link voltage or V_{dc}. The block diagram of the shunt control technique in the distribution network is shown in Figure (2).

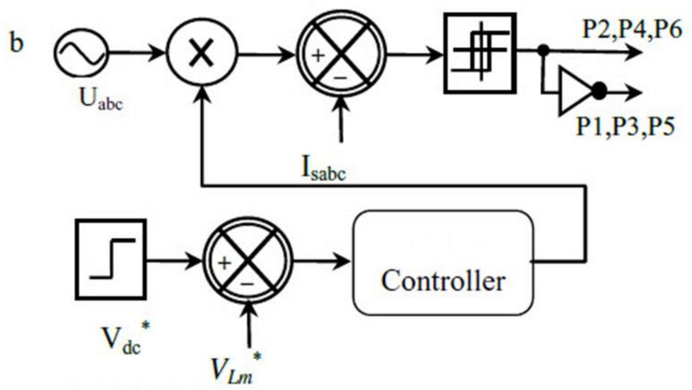

Figure (2) shunt control technique in the distribution network

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The objective function of shunt APF is obtained, such as the process of estimating reference DC link voltage or ${V_{dc}}^*$, controlling V_{dc}, generating reference source current, recording PQ distortions from distribution network customers and generating pulses for shunt VSI. In the proposed technique, fuzzy neural network model based on observer is trained to estimate ${V_{dc}}^*$, and V_{dc} controller. The fuzzy neural network model is trained based on the observer to generate the basis of the real components of resource consumption. The reference source current creates the basic production of the real components of the source current and the three-phase sinusoidal vector with the help of equation (3).

$$\begin{bmatrix} I_{sa}^* \\ I_{sb}^* \\ I_{sc}^* \end{bmatrix} = \begin{bmatrix} I_1^* sin(\omega t) \\ I_1^* sin(\omega t + 120) \\ I_1^* sin(\omega t - 120) \end{bmatrix} \tag{3}$$

The PQ distortion from the customer side of the distribution network is recorded and obtained from different sources and the actual source current using the equation (4) and the pulses for the shunt VSI are generated from the PQ distortion related to the customers using the hysteresis current controller.

$$\begin{bmatrix} I_{Ca} \\ I_{Cb} \\ I_{Cb} \end{bmatrix} = \begin{bmatrix} I_{sa}^* \\ I_{sa}^* \\ I_{sa}^* \end{bmatrix} - \begin{bmatrix} I_{sa} \\ I_{sb} \\ I_{sc} \end{bmatrix} \tag{4}$$

After the distribution network connections, the source voltage and current can be found together in one phase and they can be freed from harmonic distortion with the help of equation (5). The parameters of the series and APF of the shunt can also be obtained from the equation (6) and (7), which is done with the fuzzy neural network based on the observer.

$$V_s \prec 0 = Z_s I_s \prec Since\ \emptyset_s = 0, \begin{bmatrix} P_s \\ Q_s \end{bmatrix} = \begin{bmatrix} V_s I_s \\ 0 \end{bmatrix} \tag{5}$$

$$V_{sr} \prec (\emptyset_{sr}) = (Z_{sr} + Z_s) I_s \prec 0 = V_R \prec 0 - V_s \prec 0;\ \begin{bmatrix} P_{sr} \\ Q_{sr} \end{bmatrix} = \begin{bmatrix} V_s I_s cos(\emptyset_{sr}) \\ V_s I_s sin(\emptyset_{sr}) \end{bmatrix} \tag{6}$$

$$I_{sh} \prec \emptyset_{sh} = I_L \prec \emptyset_L - I_s \prec 0, \begin{bmatrix} P_{sh} \\ Q_{sh} \end{bmatrix} = \begin{bmatrix} V_L I_s cos(\emptyset_{sr}) \\ V_s I_s sin(\emptyset_{sr}) \end{bmatrix} \tag{7}$$

Therefore, after compensation, the real load and the load of the reaction force are calculated in the form of equations (8) and (9).

$$P_L = V_s I_s \left(1 - cos(\emptyset_{sr})\right) + V_L I_s (cos(\emptyset_{sr}) - cos\emptyset_{sh}) - V_s I_s cos\emptyset_{sh} \tag{8}$$

$$Q_L = V_L I_s (sin(\emptyset_{sr}) - sin\emptyset_{sh}) + V_L I_L sin\emptyset_{sh} - V_s I_s sin(\emptyset_{sr}) \tag{9}$$

In the following, it is necessary to apply the genetic algorithm in order to be able to optimally distribute the power and state estimation, as well as predict the existing risks for state estimation. Genetic algorithms are one of the members of the family of computational models inspired by the evolution process. These algorithms encode the solutions of a problem in the form of simple chromosomes and then apply combinatorial operators on these structures. Genetic algorithm, which is an optimization method inspired by living nature (living things), can be mentioned as a numerical method, direct and random search in classifications. This algorithm is an algorithm based on repetition, and its basic principles are adapted from genetic science and invented by imitating a number of processes observed in natural evolution, and it effectively uses the identification and exploration of a population, to create new and improved solutions. This algorithm is used in various problems that were mentioned earlier, such as optimization, system identification and control, image processing and composite problems, topology determination and training of artificial neural networks and decision and rule-based systems.

In the following, it is necessary to consider distribution network equipment to detect non-technical losses after applying fuzzy neural network with genetic algorithm to optimize state estimation. For this purpose, the failure rate of the entire equipment is the sum of the failure rate of the independent components, which is defined as equation (10).

$$\lambda_i(t) = \sum_{d=1}^{D} \lambda_i^d(t) \tag{10}$$

According to the equation (10), $\lambda_i(t)$ is the error rate of equipment i in cycle t, and $\lambda_i^d(t)$ is the error rate of equipment i in cycle t. D is the number of decaying mechanisms in the distribution network. The characteristics of each component error rate can be described in the form of its own error curve. Each component error rate failure is modeled by the Weibull function with different coefficients in the form of equation (11).

$$\lambda_i^d(t) = h_i^d \left[\left(\frac{\beta_{1,i}^d}{\alpha_{1,i}^d}\right)\left(\frac{t}{\alpha_{1,i}^d}\right)^{\beta_{1,i}^d - 1} + \left(\frac{\beta_{2,i}^d}{\alpha_{2,i}^d}\right)\left(\frac{t}{\alpha_{2,i}^d}\right)^{\beta_{2,i}^d} \right] \tag{11}$$

According to the equation (11), h_i^d, $\alpha_{1,i}^d$, $\beta_{1,i}^d$, $\alpha_{2,i}^d$ and $\beta_{2,i}^d$ are coefficients of the function They are Weibull. The values of these parameters based on experimental data can be estimated using the least square fitting method. Very high temperature due to heavy load leads to loss of insulation of distribution network transformers. As a result, the insulation failure rate increases, and the need for repair and identification of the lost power is necessary and necessary. According to the Arrhenius law, the loss of transformer insulation life is obtained by equation (12).

$$\Delta T_{loss} = \int_{t_1}^{t_2} V' dt = \int_{t_1}^{t_2} 2^{(\theta_{t,h} - 98)/6} dt \tag{12}$$

According to the equation (12), V' refers to the relative aging rate of the insulation. $\theta_{t,h}$ shows the hot spots of the winding transformer. t_1 and t_2 show heavy load interruption in power distribution time cycles. The influence of other operating conditions in the equipment, such as the effects of unfavorable weather in the transformer pole and insulation damage, are modeled as equations (11) and (12). After the response of the deterioration type error rate in the power distribution network equipment, an initial value is returned against the new state. Therefore, the feeder error rate after maintenance is obtained as equation (13).

$$\lambda_i^d(t) = max_{t'=1}^{t}\{k_i^d\left(t' + t_{i,initial}^d - 1\right) \times [1 - \sum_{n=0}^{t'-1} X_i^d(t-n)]\} \tag{13}$$

According to equation (13), $k_i^d(t')$ refers to the error rate of type d deterioration in feeder i in cycle t'. $t_{i,initial}^d$ is the initial period of time taken after detection of non-technical losses of the distribution network and state estimation for type of deterioration d of feeder i. With the help of operation information in power distribution networks, the failure rate model accurately quantifies the effects of operating conditions and feeder maintenance activities, as well as their stability, which is shown by providing services as the basis of the distribution maintenance planning model.

Both issues of maintenance and creating errors in the operation of electricity distribution networks may lead to disconnection with the equipment and reduce the stability of the distribution system. On the one hand, disconnection of equipment to prevent their maintenance may lead to load shedding. Therefore, the level of stability of the electricity distribution network decreases during maintenance cycles. On the other hand, maintenance leads to reducing the equipment error rate and improving the level of system stability in the current cycle. The economy in the distribution network at the time of state estimation is another important issue that is listed as a secondary goal in this research and its modeling is also done in this section. Therefore, in the simulation section, the issue of cost and economy is considered after the main goals, which is a secondary goal in such projects, and many reference articles have also considered this issue. Therefore, considering the strengths of the previous articles is an obvious thing in this research, while solving the challenges and research gaps that cover the weaknesses of the previous articles.

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In order to obtain the best preventive maintenance program economically, the impact of maintenance interruptions and errors should be evaluated in a comprehensive and intensive manner. Therefore, the objective function is formulated as the minimization of the total cost rate of the distribution system in the overall planning horizon, which includes three main parts, i.e. the preventive cost of maintenance and repairs, the cost of corrective maintenance, and the cost of penalty for lost loads that are The general form is to estimate the power consumption of the basses. This objective function is formulated as equation (14).

$$Minimize\ f = \sum_{t=1}^{T_{max}} \{(C^M(t) + C^R(t) + C^{EENS}(t)) \times (1+r)^{-\frac{t}{12}}\} \qquad (14)$$

According to the equation (14), $C^M(t)$ is the preventive cost of maintenance, which includes labor resources and the cost of materials for maintenance and repair activities, which is equivalent to the initial population of the genetic algorithm. The preventive cost of maintenance in cycle t is calculated as equation (15).

$$C^M(t) = \sum_{d=1}^{D}\sum_{i=1}^{N}(C_{p-h}^{d,M} \times L_i^{d,M} + S_{M,i}^{d,M})X_i^d(t)$$

$$t = 1,2,\dots,T_{max} \qquad (15)$$

According to equation (15), $C^R(t)$ is the corrective maintenance cost of electricity distribution networks, which depends on the random error rate of equipment $\lambda_i^d(t)$. Therefore, it is a probabilistic value and it will be diverse with time conditions. λ_i^din equation (13) based on the time variation error rate of the equipment, the expected amount of electricity distribution network repair cost in cycle t is calculated from equation (16).

$$C^R(t) = \sum_{d=1}^{D}\sum_{i=1}^{N}(C_{p-h}^{d,R} \times L_i^{d,R} + S_{M,i}^{d,R})X_i^d(t)$$

$$t = 1,2,\dots,T_{max} \qquad (16)$$

$C^{EENS}(t)$ is the penalty cost of lost loads in electricity distribution networks. The penalty cost of lost loads for the purpose of preventive maintenance, corrective maintenance and making errors is calculated according to the stability index of expected and not used energy in the form of equation (17).

$$C^{EENs}(t) = I_{EAR} I_{EENS}\left(\lambda_i^d(t), X_i^d(t)\right)$$

$$t = 1,2,\dots,T_{max} \qquad (17)$$

According to the equation (17), I_{EAR} is the coefficient of the stability value obtained from the analysis of the load composition or the customer satisfaction survey of the electricity distribution network. $I_{EENS}\left(\lambda_i^d(t), X_i^d(t)\right)$ refers to the expected energy and not to the supplied energy in the time cycle t, which is evaluated through the reliability assessment of distribution systems using the equivalence methods of the electricity distribution network. According to the observation of the corrective maintenance cost according to the equation (16) and also the cost of lost loads according to the equation (17), we can refer to the failure rate $\lambda_i^d(t)$ which is an important data to evaluate the total cost is considered a distribution system.

Considering the limitation of the maintenance strategy in distribution networks based on the identification of the lost power to estimate the state of power consumption of buses is also very important. Constraints of maintenance strategy and identification of lost power include maintenance time limits, budget constraints and manpower constraints. Maintenance interval limits are the beginning of a preventive maintenance cycle that should be performed at certain intervals. Its relation is as equation (18).

$$T^{EAR}(i, d_i) \le T(i, d_i) \le T^{LAT}(i, d_i)$$

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$$t = 1,2, \dots, N \qquad (18)$$

There is no time window restriction for corrective maintenance due to its high priority level after faults occur. Budget limitation is another limitation. The cost in each cycle should be calculated according to equation (19).

$$C^{EENS}(t) + C^{M}(t) + C^{R} \leq C_{budget}(t)$$

$$t = 1,2, \dots, T_{max} \qquad (19)$$

Limitation of workers in distribution networks is another important issue that needs to be formulated. The maximum number of employees for preventive and corrective maintenance in electricity distribution networks is limited and is formulated in the form of equation (20).

$$\sum_{i=1}^{N} \sum_{d=1}^{D} (L_i^{d,M} X_i^d(t) + L_i^{d,R} \lambda_i^d(t)) \leq L_{AVA}(t)$$

$$t = 1,2, \dots, T_{max} \qquad (20)$$

It is also necessary to consider the operational limitations of the system. During maintenance operations, it is critical to ensure a solid level of power supply stability. The stability indices, which include the average system interruption frequency index and the average system interruption duration index, show the frequency and duration of interruption supply and reflect the average level of stability of power supply in distribution networks. System operational limitations in maintenance planning are as follows:

Limitations of the average system interruption frequency index: In order to guarantee the stable level of decisive power supply, the average interruption frequency index of the system in each cycle should not exceed its limit, i.e. I_{SAIFI}^{Max}, and is calculated in the form of equation (21).

$$I_{SAIFI}\left(\lambda_i^d(t), X_i^d(t)\right) \leq I_{SAIFI}^{Max}$$

$$t = 1,2, \dots, T_{max} \qquad (21)$$

According to the equation (21), $I_{SAIFI}\left(\lambda_i^d(t), X_i^d(t)\right)$, is the average interruption frequency index of the system in cycle t.

Limitations of the system average interruption duration index: The average system interruption duration index in each cycle should not exceed its permissible limit, i.e. I_{SAIDI}^{Max}, and it is calculated in the form of equation (22).

$$I_{SAIDI}\left(\lambda_i^d(t), X_i^d(t)\right) \leq I_{SAIDI}^{Max}$$

$$t = 1,2, \dots, T_{max} \qquad (22)$$

According to the equation (22), $I_{SAIDI}\left(\lambda_i^d(t), X_i^d(t)\right)$ is the index of the system's average interruption frequency in cycle t.

In power distribution networks, the value of I_{SAIDI}^{Max} and I_{SAIFI}^{Max} can be set as the required level of stability, which leads to the guidance of different sizes of the optimization space for equipment maintenance and repair planning. Calculating the limits of the average system interruption frequency index and the limits of the average system interruption duration index includes a complete process of evaluating the stability of the distribution system. The required data includes equipment stability model and distribution system configuration information. In general, the power flow in some components of the distribution system is

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severely limited. For these components, the overload limits according to equation (23) must be satisfied during the maintenance cycle.

$$|f_i(t)| \leq f_i^{max}$$

$$t = 1,2, \dots, T_{max} \qquad (23)$$

which in equation (23), f_i^{max} is the power flow limit of component i. $f_i(t)$ is the power flow value of component i in the peak load state during the cycle t of maintenance and repair of equipment to estimate the state in the power distribution network. At the start of the maintenance operation, $T(i, d_i)$ is a discrete value for simplicity in calculations. The problem $T(i, d_i)$ is a correct programming problem. For this reason, $\lambda_i^d(t)$ is a nonlinear function for the time cycle t, which is calculated in equation (10), and the constraints in equation (23), is a nonlinear constraint relation. In addition, since the stability indices in the proposed model are $\left(E_{EENS}\left(\lambda_i^d(t), X_i^d(t)\right)\right.$ and $I_{SAIFI}(\lambda_i^d(t), X_i^d(t))$ and $I_{SAIDI}(\lambda_i^d(t), X_i^d(t))$ involves evaluating the stability in the distribution system, which is a nonlinear function of t. Therefore, the formulated problem is an exact optimization problem with both nonlinear constraints and the objective function. It is nonlinear, which is a difficult method for mathematical programming. Metaheuristic methods, such as the genetic algorithm whose theory was explained, are suitable for solving non-linear correct optimization problems. The genetic algorithm has the advantage of simplicity and high efficiency in the problem space. But it also has a series of weaknesses, which include premature convergence and immersion in the local optimum. Adapting this algorithm will help to overcome these limitations and produce a candidate solution and expand the search space. Therefore, it has strong and robust search ability locally and globally. In order to detect non-technical losses in distribution networks using state estimation, from the proposed approach of observer-based fuzzy neural network by optimizing parameters with genetic algorithm in this research has been used. The work steps are as follows:

Step 1) the problem data is given as input and the algorithm parameters are set. The required data includes distribution network equipment data, loaded data, operational condition data, and distribution network system configuration information. The equipment data includes the deterioration and aging data of the equipment in the distribution network and the continuous maintenance data along with the corrective maintenance data. Load data includes node load data and required power supply stability limits. In the following, the fuzzy neural network and the observer are considered for the initial estimation of the state.

Second step) accurate identification of non-technical losses and optimization of state estimation with genetic algorithm need to be applied. Chromosome positions and a list of search factors. The position vector of the chromosomes refers to the starting cycle of various equipment for maintenance in order to reduce the power lost in the bus.

Step 3) the position and movement speed of the chromosomes are updated, taking into account the constraints, the chromosomes remain mobile, and if they do not satisfy the constraints after the update, these events will occur. The equation (24) will use here.

$$\Delta T_j^{s+1}(i, d_i) = \omega . \Delta T_j^s(i, d_i) + c_1 . rand_1(value) . \left(T_j^{s,Best}(i, d_i) - T_j^s(i, d_i)\right)$$
$$+ c_2 . rand_2(value) . \left(T_j^{s,Best}(i, d_i) - T_j^s(i, d_i)\right) \quad ,$$

$$T_j^{s+1}(i, d_i) = T_j^s(i, d_i) + \Delta T_j^{s+1}(i, d_i) \qquad (24)$$

The difference between the genetic algorithm combined with the observer-based fuzzy neural network and the classical genetic algorithm is the adaptive inertia weight. In this research, in order to improve the capabilities of the genetic algorithm, the inertial weight ω is reduced in a non-linear way, which is reduced as a repeated increase and the degree of dispersion Δ. Both of these tasks create an impact on the inertia of the weight in the iterative process of the genetic algorithm, which is calculated using the random selection section in the form of equation (25).

$$\omega = \frac{1}{\{1 + exp\left[\left((a+b).(1-\Delta).\frac{s}{I_{iteration}^{max}}\right) - b\right]\}}$$

$$\omega \epsilon [\omega_{min}, \omega_{max}] \qquad (25)$$

According to the equation (25), s is the number of repetitions and $I_{iteration}^{max}$ is the maximum number of repetitions. Coefficients a and b are calculated according to the hypothesis $\omega = \omega_{max}$ at the beginning of the iteration $s = 0$ and $\omega = \omega_{min}$ at the end of the iteration i.e. s $s = I_{iteration}^{max}$. Δ describes the degree of dispersion of chromosomes in the genetic algorithm, which are calculated through the equation (26).

$$\Delta = \frac{(M_{MaxDist} - M_{MeanDist})}{M_{MaxDist}} \qquad (26)$$

According to the equation (26), $M_{MeanDist}$ refers to the average and the maximum distance of the current chromosomes from the best position obtained, which is calculated in the form of equations (27) and (28).

$$M_{MeanDist} = \frac{\{\sum_{j=1}^{Np} \sqrt{\sum_{i=1}^{N} \left(T^{s,Best}(i,d_i) - T_j^s(i,d_i)\right)^2}\}}{N_P} \qquad (27)$$

$$M_{MaxDist} = max_{j=1,2,\ldots N_P}\{\sqrt{\sum_{i=1}^{N} T^s, Best(i,d_i) - T_j^s(i,d_i))^2} \qquad (28)$$

In the formation of adjacent solutions, each element of the chromosomes is assigned to a new and random value including the start cycle of maintenance and repair of the equipment, which maintenance interruption is allowed. When all the elements have been moved successfully, all the elements obtained from the solution have solutions of adjacent current chromosomes. The movement of adjacent chromosomes in an adaptive manner puts a logical pressure on the local optimum and leads to the improvement of global search capabilities that can provide an estimate of the optimal state in the distribution network.

SIMULATION AND RESULTS

In order to detect non-technical losses in the distribution network, we have used the fuzzy neural network based on the observer by optimizing the state estimation parameters with the genetic algorithm. In this section, first, the state estimation is made, which assumes a system in the distribution network as equation (29).

$$\dot{x} = M(x, u; \theta)$$

$$y = N(x, u) \qquad (29)$$

In this regard, x is a vector to define the state of the system, u is the input of the system and y is the output of the system. θ is a vector that contains parameters to define the system and M and N are functions that are used to relate x, u, y and θ and determine the operators of the system. Considering that the proposed approach includes the use of observer-based fuzzy neural network by optimizing the state estimation parameters with the genetic algorithm, it is considered as a method in discrete computer simulation, so the more appropriate definition of the system is based on equation (30) and the application of these models for state estimation is in the form of equation (30).

$$x(k+1) = F(x(k), u(k); \theta)$$

$$y(k) = G(x(k), u(k)) \qquad (30)$$

If θ is a time variable vector, this case will be considered as the application of this research. It should be noted that the functions F and G in equation (30) are not equal to M and N in equation (29). The proposed approach of this research, which was considered for state estimation, has factors that parameter estimators based on this approach assume that the structure of functions F and G in equation (30) is known and in the equations, they act in the form of equation (31).

$$\hat{x}(k+1) = F(\hat{x}(k), u(k); \hat{\theta}(k))$$

$$\hat{y}(k) = G(\hat{x}(k), u(k)) \tag{31}$$

Where $\hat{\theta}(k)$ is an estimate of the correct system parameter vector θ at time k and $\hat{x}(k)$ is the state of this system estimate. $\hat{y}(k)$ is the estimated output of the system. A general block diagram for the proposed approach to estimate the state presented in this research is considered as Figure (3) and in which each parameter is estimated by the vector $\hat{\theta}(k)$ as a trait in the genetic algorithm. Chromosomes are coded, it is considered. Therefore, each chromosome of the genetic algorithm for state estimation will completely represent an estimator of the parameter $\hat{\theta}(k)$ and hence, it will completely represent an estimated system. Of course, this work is done when two function values F and G are assumed to be known, which will also be a hypothesis in the upcoming simulation. When the genetic algorithm works with a population of chromosomes, the block presented in Figure (3) representing the estimated system is considered as a population of candidate systems. By applying factors such as combination, mutation, selection and elitism in the iteration round to achieve the best fit in this initial population in the candidate system, the genetic algorithm displays the best state for a state of the most optimal state possible in the system. At each time k, the current set of parameter estimates $\hat{\theta}(k)$ is provided by the best fits named chromosomes with the highest fit value at time k.

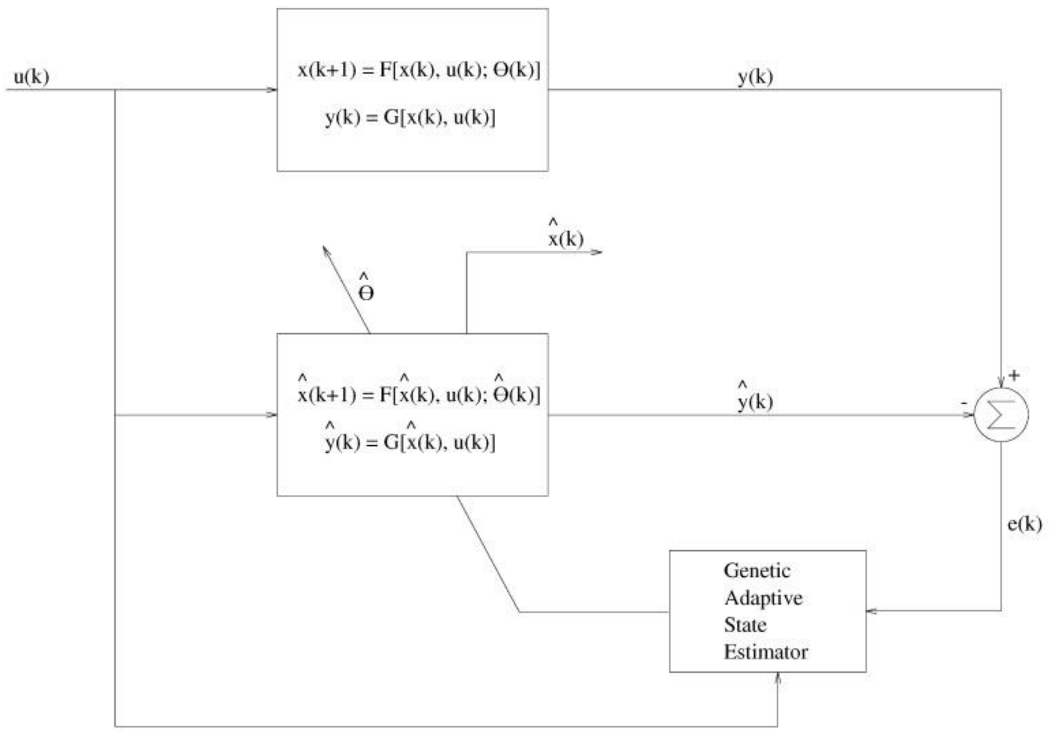

Figure (3) Block diagram for a state estimation system with genetic method

In this case, the fitting function for the genetic algorithm is selected to estimate the mode to minimize the mean square between the output $y(k)$ of the real system and the estimated system $\hat{y}(k)$ over a time window $W+1$ of the most recent data points. However, since the maximum fitted member is sought, the fitting function becomes equation (32).

$$j = \alpha - \frac{1}{2}E^T E \tag{32}$$

Based on equation (32), E is calculated as equation (33).

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$$E = \begin{bmatrix} e_{k-w} \\ e_{k-w+1} \\ \vdots \\ e_k \end{bmatrix} \tag{33}$$

And similarly $e_k = y(k) - \hat{y}(k)$ for $k > 0$ and $e_k = 0$ for $k \leq 0$. To guarantee that each member has a positive fitness value, α is chosen to be the largest $\frac{1}{2}E^T E$ of each member of the initial population at time k. It should be noted that $\frac{1}{2}E^T E$ itself is the worst member of the genetic algorithm's initial population set. The genetic algorithm uses the current population of parameter estimators along with the past and present values of input $x(k)$ and output $y(k)$ to produce an estimate of the state of the system $\hat{x}(k)$. The time window of the $\hat{y}$ value is considered for each candidate set of parameter estimates, and hence, each candidate is assigned a fitting value according to (32) and (33). Now we enter the simulation phase. First, it is necessary to estimate the state of the distribution network system to detect non-technical losses. It should be noted that the simulation of the proposed approach has been done in the combined environment of coding (script) and Simulink. The first part is related to the coding part. Therefore, according to table (2), the main parameters of the system are defined.

Table (2) main system parameters for state estimation

Time vector	0.005
Time interval vector	0 to 10 seconds
initial value of x(k)	0.05
initial value u(k)	0.001
Initial known values for G and F	$2E-5$
initial state $x(k)$	[0 0]
initial state $u(k)$	[0 0]
initial state $\theta(k)$	[0 0]

When the state estimation is done, the output is as shown in Figure (4).

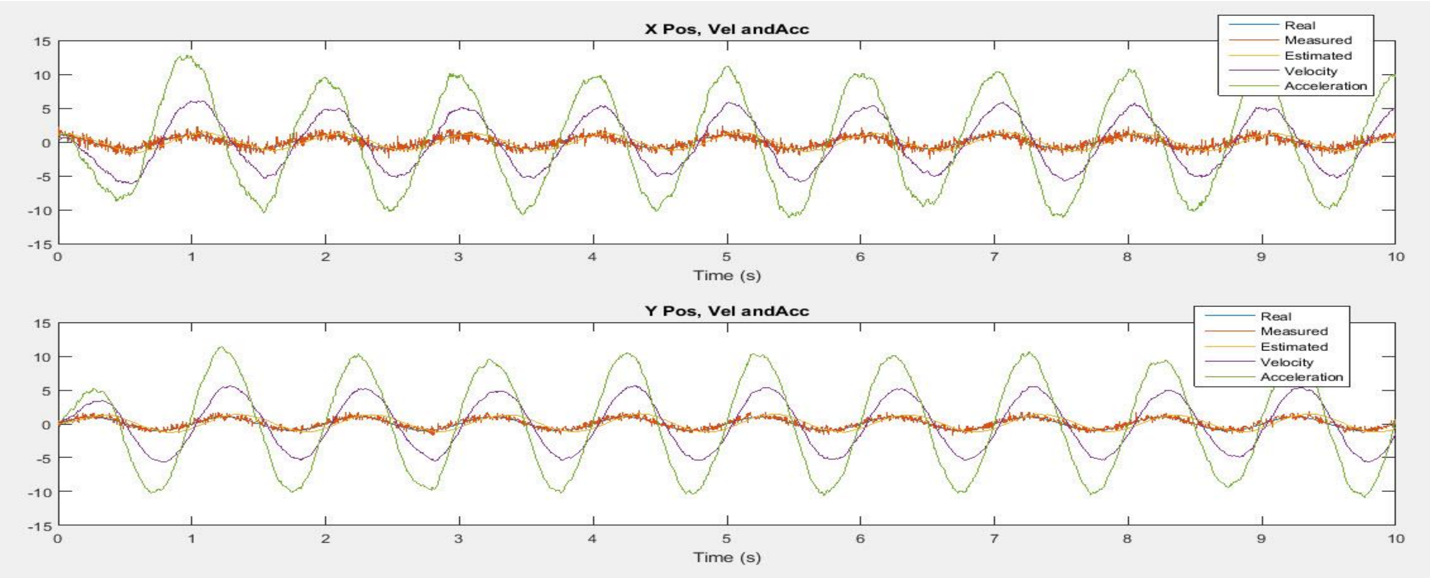

Figure (4) system state estimation

The output of figure (4) is the result of the coding part. According to Figure (4), the upper diagram shows the initial state of the system and the lower diagram shows the estimate after applying the proposed approach. In the upper figure, which is the initial state of the system, and the lower figure, which is the estimated state of the system, the actual value is in blue, the measured value is in red, the estimated value is in orange, the velocity value is in purple, and the acceleration value is the same. The functions M and N are for the initial state part and the known functions F and G are for the state estimation part. It is shown that states are better at state estimation time in the lower figure. In order to detect non-technical losses by estimating states, other parameters are considered, including voltage, primary current, passing current and bus energy. The voltage rate is 0.6534, the initial current rate is 0.6521, the passing current rate is 0.6594, and the bus energy rate is 0.6587. In the same way, the gravity rate for estimating the state is also 9.81 in the detection of non-technical losses in the distribution network. There are a total of 4 modes for the overall estimation after the estimation of the initial mode and at the end, the estimation error and its improvement are measured. When the bottom output was shown in Figure (4), in fact the proposed approach, namely the fuzzy neural network method based on the observer and the genetic algorithm, was applied, and in the following, 4 other modes will be considered to detect non-technical losses. The setting of the parameters of the genetic algorithm has been considered from an experimental point of view and classically, and it is in the form of settings presented in table (3).

Table (3) genetic algorithm parameters

The initial population of chromosomes	100
Crossover value	2
Mutation value	0.02
Selection mode	random
Iteration number	4000

After the final application of the proposed approach, the detection of non-technical losses of the distribution network at the level of voltage and primary current will be real and estimated as shown in Figure (5).

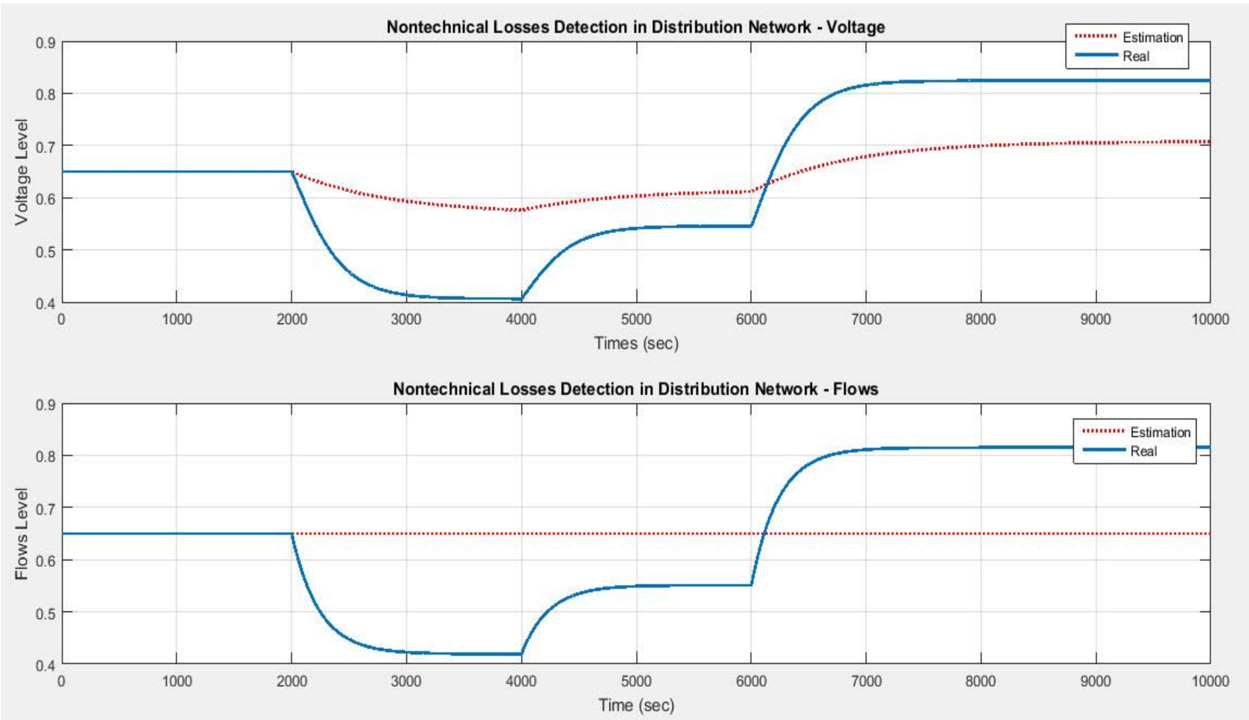

Figure (5) detection of non-technical losses of the distribution network at the actual and estimated primary voltage and current levels

The output of Figure (5) is the result of the coding part. According to Figure (5), it can be seen that in the upper figure, the voltage level to 10,000 seconds to detect non-technical losses, shows that the estimated section in red has a lower state than the actual state is blue in color. Likewise, this issue for detecting non-technical losses in terms of initial flow to 10,000 seconds, in the context of initial flow, it shows that the estimated graph in red color has a lower state than the real state in blue color. In the following, the detection of non-technical losses of the distribution network at the level of passing current and bus energy is shown in Figure (6).

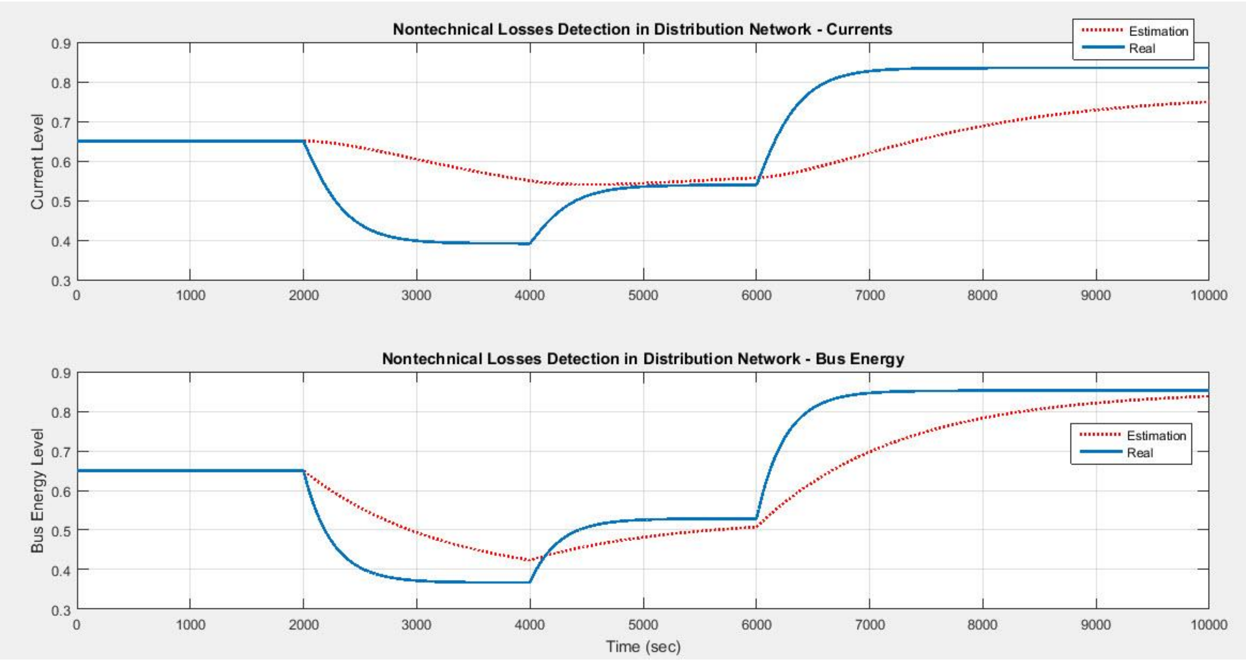

Figure (6) detection of non-technical losses of the distribution network at the level of passing current and bus energy

The output of Figure (6) is the result of the coding section. According to Figure (6), it can be seen that in the upper figure, the level of flow passing to 10,000 seconds to detect non-technical losses, shows that the estimated section in red color has a lower state than the actual state. It is blue in color. Likewise, this problem for detecting non-technical losses in terms of bass energy to 10,000 seconds, in the context of the initial current, shows that the estimated graph in red color has a lower state than the real state in blue color. But the problem of error estimation remains in the system. According to the Figure (6), we can see the error estimation in the electricity distribution network.

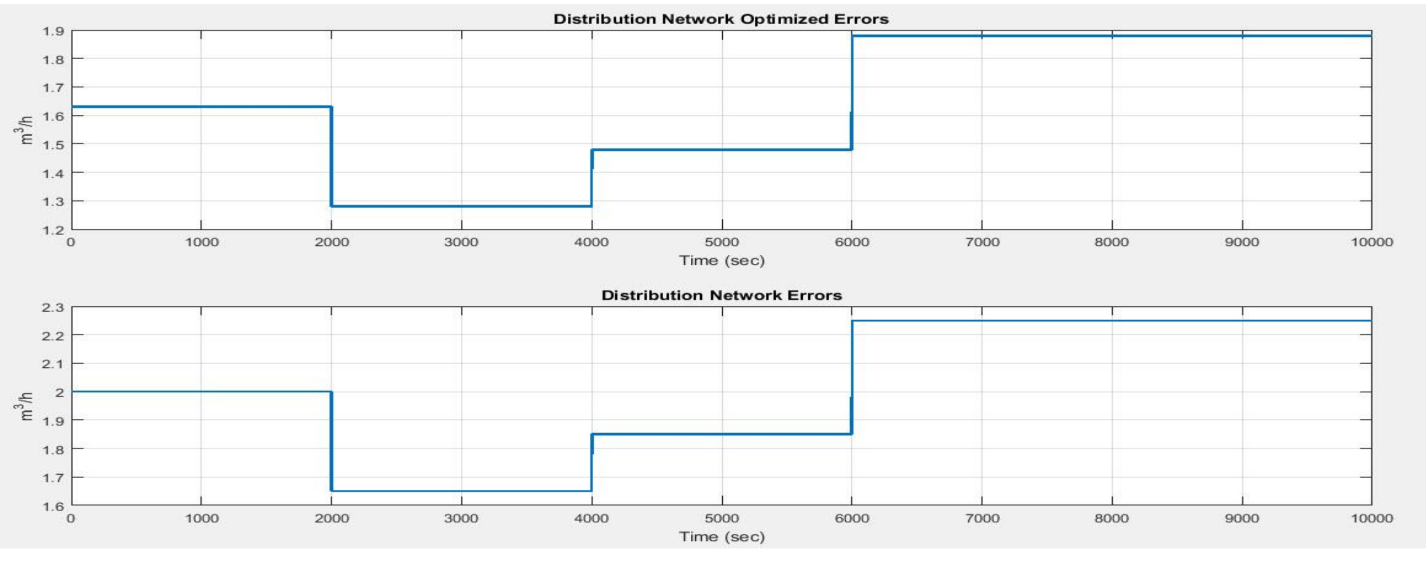

Figure (6) error estimation in the detection of non-technical losses in the distribution network

The output of Figure (6) is the result of the coding section. According to Figure (6), it can be seen that in the upper part, the optimized error estimation at the time of detection of non-technical losses in the distribution network by applying the proposed approach and state estimation and then checking 4 levels including voltage, initial current, current Passage and bass energy, in 10000 seconds, has a minimum of 1.3 and a maximum of 1.9 square meters per hour of error. In the initial state of the system, the range of this error is at least 0.5 to 2.25 square meters per hour. It has been shown that the error estimation is also minimized after applying the proposed approach for state estimation in the detection of non-technical losses in the distribution network, which means that there will be minimal error in the system.

Now it is necessary to use Simulink to investigate non-technical losses in the distribution network along with the reduction of errors, which are the most important goals of this research. For this purpose, the main environment of the distribution network is displayed, which is shown in Figure (7). It should be noted that the type of distribution network is circular distribution network. In this distribution network, the beginning and the end are connected to a power source. This distribution network is used to feed points with high consumption density, so many technical and non-technical errors may occur in it. Therefore, in such a distribution network, more sensitive and accurate protective devices such as directional relays should be used. The circular DC distribution network is an LVDC microgrid type. The specifications of this microgrid are as described in Table (4).

Table (4) characteristics of LVDC microgrid

Parameter and specification of LVDC microgrid	Quantity and unit
Source voltage	KV 20 of photovoltaic type (for LVDC microgrid, it is basically of photovoltaic type)
Voltage of photovoltaic sources	20 KV
X/R	4
Short circuit power	100 MVA
load model	Single phase, two phase and three phase impedance
The total length of the line	29596
Bus voltage	240 V
resistance	0 to 100 Ohm

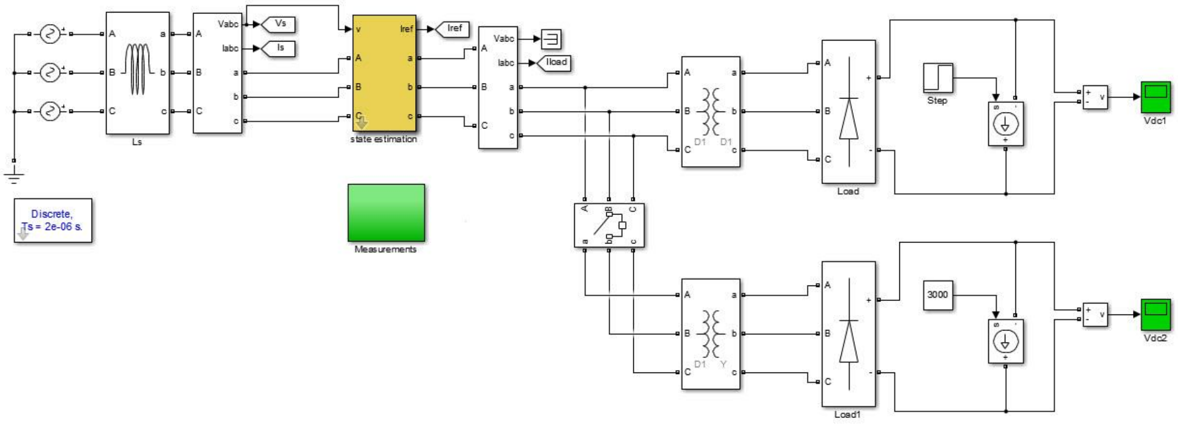

Figure (7) DC circular distribution network environment in Simulink MATLAB

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There is also a subsystem for the state estimation part, which is shown in Figure (8).

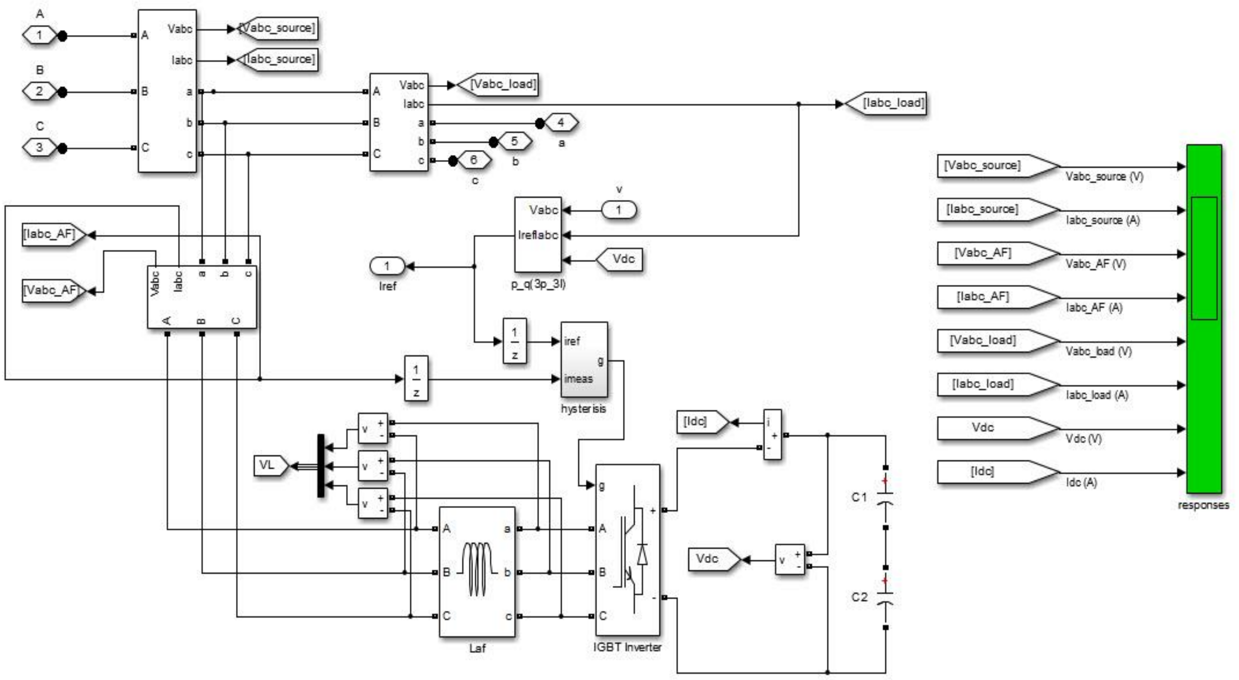

Figure (8) DC ring distribution network subsystem for state estimation section

In this subsystem, there are buck blocks, converter and amplifier inverter. Reduction of errors and detection of non-technical losses after implementation can be seen in Figure (9).

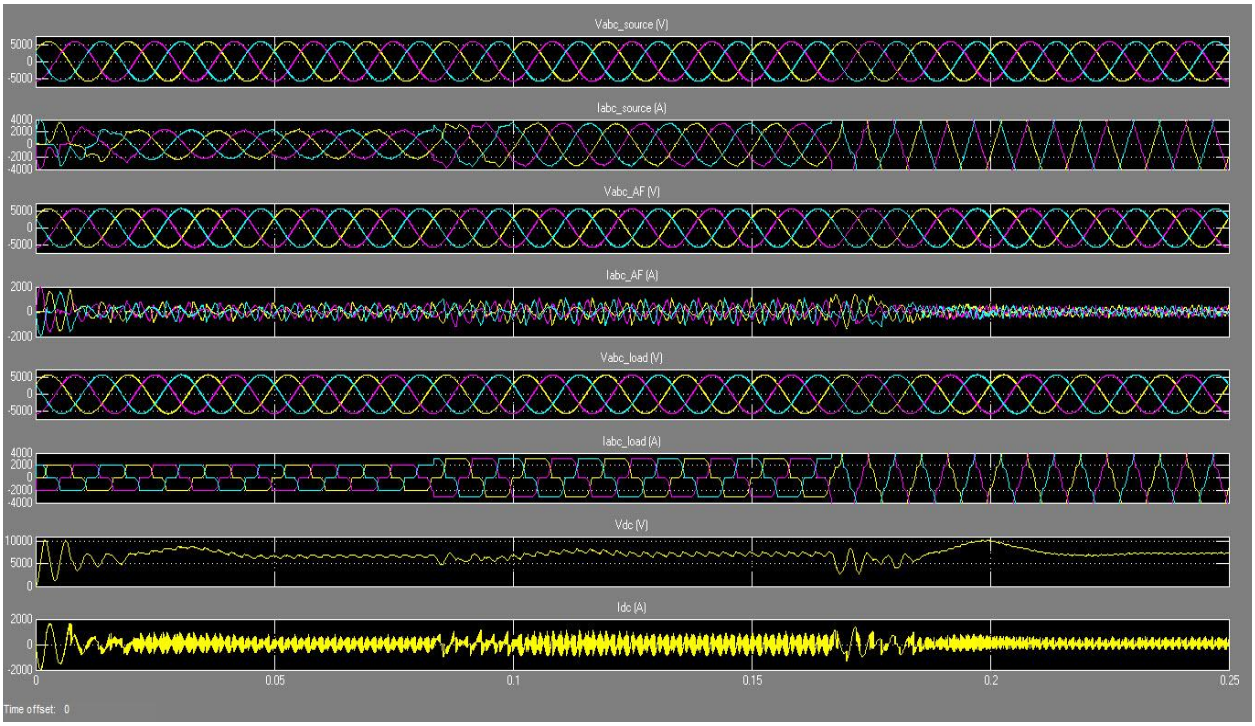

Figure (9) reducing errors and detecting non-technical losses

It can be seen that there are 8 different sections in this figure. The first section is for source V. Then source L, then voltage based on state estimation, then energy consumption, then load in distribution network with source V, then load in distribution network with source L, then V_v and finally L_A have been checked. In Figure (10), the reference source L in the distribution network is shown in the upper part, and the known errors in the distribution network when using state estimation are shown in the lower part.

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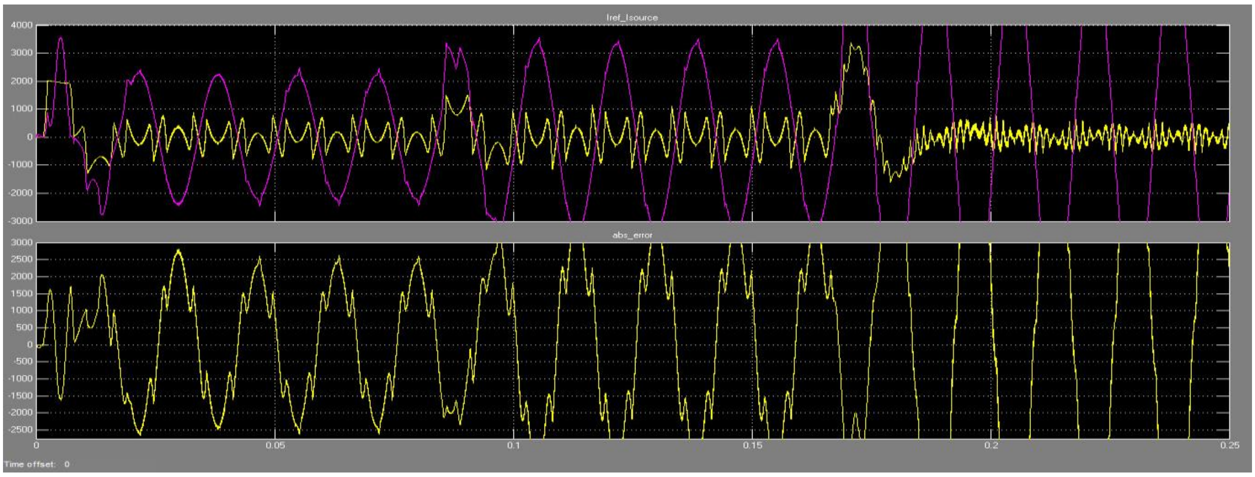

Figure (10) reference source *L* in the upper part and the lower part of those known faults in the distribution network

Fault parameters affect the accuracy of fault location in the distribution system. Among these parameters, the effect of the type of fault, the effect of fault resistance, the effect of the angle of the fault and the effect of different locations can be considered. Of course, there are more parameters, but they are not considered in this research. Aerial and underground system errors at different voltage levels were previously shown in the third chapter and in Table (4). After the proposed approach was applied on the circular DC distribution network, after using the voltage and current data and calculating their phasors, the impact effect of feeders or power sources was considered as an error-prone part, which is in the positive pole. Are. In general, Table (5) can be considered for the standard voltage level in the circular DC distribution network, where errors have been found with the proposed approach. The fault resistance at two high levels (10 Ohms) and low level (1 Ohms) has been taken into consideration that in general, Table (5) shows the impact of the types of errors in the proposed algorithm of this research.

Table (4) comparing the errors of aerial and underground systems at different voltage levels after finding the error rate in the circular DC distribution network

Error rate (number of errors per year per mile of length)		Voltage Level (KV)
Underground cable	air Line	
15%	0.13	5 to 11
40%	0.04	11 to 220
23%	0.01	33
17%	0.02	66

Table (5) the impact of error types in the proposed algorithm

Fault resistance	error location	Error type		
		Single phase to ground	Two phases to ground	Three phases to ground
		percentage error		
0	1-2	0.0052	0.0089	0.1011
	2-3	0.0111	0.0749	0.1841

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	3-9	0.0725	0.0138	0.092
	5-11	0.1242	0.1869	0.4879
50	1-2	0.0149	0.1105	0.3891
	2-3	0.0332	0.0701	0.3511
	3-9	0.0498	0.0039	0.1251
	5-11	0.2041	0.1689	0.2439
100	1-2	0.0070	0.1169	0.0628
	2-3	0.0186	0.0679	0.2217
	3-9	0.0112	0.0029	0.1714
	5-11	0.2048	0.1754	0.2597

The results from Table (5) show that the maximum error of the proposed method is 0.5% and its minimum is 0.005%. These results show that the proposed approach of this research has high accuracy in estimating and finding faults in the circular DC distribution system. The type of fault and the impact of the fault angle in this table include single-phase, two-phase and three-phase to ground sections, where the location of the fault is considered in four sections with different resistances.

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