# Voltage and Reactive Power Control Simulations Using Neural Networks

Jalal M. Abdallah[1] and Abdullah R. Al-Zyoud[2]

[1]Tafilah Technical University /Electrical Engineering Department
P.O. Box: 851229 code 11185/ Amman - Jordan
e-mail: jalal_abdallah@hotmail.com
[2]Al Balqa Applied University/ Engineering Technology College
Electrical Department
e-mail: alzyoud_a@yahoo.com

*Abstract:* **This paper presents a simultaneous formulation for the optimal reactive power control problem using the Artificial Neural Network (ANN). The objectives are to minimize active power losses and improve the voltage profile of the given system. The voltage and reactive power controlled by utilization of the power transformers transformation ratio and the injected reactive power to optimize system performance based on Feed-forward ANN with Back Propagation training algorithm is used and the training data is obtained by determination optimal transformations ratios and injected reactive power are performed for different real operating modes of Jordanian Electrical Power System by the ANN and compared with an other regression model. The active powers losses are expressed in terms of voltage increments by relating the control variables, i.e., tap positions of transformers and reactive power injections of VAR sources. The back propagation artificial neural network model has been performed and tested to predict the minimization of the active power losses and to voltage control.**

*Keywords:* ANN, optimization, transformations ratios, active power losses, reactive power.

## I. INTRODUCTION

In the electrical power systems, the active power losses and voltage profiles are the two widely used indices on which the performance of power systems can be evaluated. Nowadays, the necessity to automate the tasks of complexes power systems operation and control has o be achieved with utmost accuracy and speed [Swarup. 2005].
The needs for faster and automotives, which can be used online and in real time application is raised. The artificial neural networks (ANN) are an ideal choice, given the ability to cover the nonlinearity and its fast response time.
Neural network considered to be the most promising area in artificial intelligence as it is based on human experiences and on link of the input and output sets, learning or training concepts and a pattern recognition function. The neural network adopts various learning mechanisms and self-organization. They have been successfully applied to problems in the fields of pattern recognition, image processing, data compression, forecasting, and optimization [Swarup. 2005, Al-Thaimer and Abdallah 2003].
The ANN can be trained to generate the control parameters for minimizing the active power losses and determining reactive power to be injected in the system. The neural network allows not only solving multi complex mass problems in the electrical system, but also to adapt with continuous variation of conditions in real time. There are many different neural network types that can be widely used in applied different cases [Freeman and Skapura. 1991, Tarafdar and Kashtiban. 2005].
On the other hand real power systems have thousands of variables at the system level. If all the measured variables are used as inputs to neural network, it results in large size of the network and hence larger training time. To make the neural network approach applicable for large scale power system problems, some dimensionality reduction is mandatory [Al- Zyoud and Abdallah. 2008].
The problem of minimizing electric power losses in electrical networks is a major aspect of power systems research. There are many control methods used to improve the performance of the electrical system, in order to obtain the optimal mode of operation which satisfies the voltage quality and the reliability of the electrical system. The power losses are affected by means of the automatic voltage control for power transformers and control of the injected reactive power. On load tap changers and shunt capacitors where used to minimize the power losses and maintain voltage profile in the permissible values at the consumers' terminals.
As the loads of consumers of electrical power system are variable with time, obtaining the optimal operation mode could be realized by controlling the means of regulating devices.

Minimization the power losses are the main criteria of this study to determinate the economic operation of the power system.
Calculations for determining optimal transformations ratios and optimal injected reactive power are performed for different real operating modes [maximum, normal, and minimum loading] of Jordanian electrical power system [NEPCO. 2009, Gonen .1988].
The operating modes loading values and parameters of the Jordanian electrical power system are entered to **Digsilent Power Factory** program. The DIGSILENT (GmbH, Germany) is consulting software providing highly specialized services in the field of electrical power systems for generation, transmission as well as distribution and industrial plants.
The results of each case study are introduced in tables. The mathematical models are studied to estimate the power losses using transformation ratio (and/or) injected reactive power using MATLAB [Penny and Lindfield.1995, MATLAB.2009]

## II. POWER LOSSES OPTIMIZATION (MINIMIZATION)

The power losses in electrical network as well as real and reactive power flows for all equipment connecting the buses can be computed by means of load flow simulation. The quantification and minimization of losses is important because it will determine the economic operation of the power system [Lukman. 2003]. If we know how the overall losses occur, we can take steps to minimize them. Active power losses can be determined by various methods.

In General the power losses can be calculated by the equation [Narain et. al. 2000]:

$$\Delta P = \sum_{i=1}^{n} R_i (I_{ia}^2 + I_{ir}^2) \qquad (1)$$

With the following constraints:

$$MI_a = J_a$$
$$MI_r = J_r$$
$$(I_{ia}^2 + I_{ir}^2)^{1/2} \le I_{i.per}$$
$$J_{ia\min} \le J_{ia} \le J_{ia\max}$$
$$J_{ir\min} \le J_{ir} \le J_{ir\max}$$

where M: the first incidence matrix, R: branch resistances, I: branch currents, J: nodal currents
The system power loss represents the objective function which is linearized around the current operating point with respect to bus voltages. The relationships between voltage increments, transformer tap positions and VAR sources (generator reactive power outputs and switchable capacitors) are derived, and correlations between them are given by a modified Jacobian matrix [Al-Thaimer 2001, Abdallah and Al-Thaimer 2003].
The objective function in this case is represented by:

$$P_L = \sum_{k=1}^{nl} g_k [V_i^2 + V_j^2 - 2V_i V_j \cos(\delta_i - \delta_j)] \qquad (2)$$

The real power loss is mostly a non-linear function of bus voltages and phase angles which are implicitly a function of the control variables. The variation of the variables is limited to a small range by introducing restricted step sizes for voltage magnitude and tap setting changes. Thus, the linearized objective function will be the minimization of:

$$\min \quad \Delta P_L = [\frac{\partial P_L}{\partial V_1} \quad \frac{\partial P_L}{\partial V_2} \cdots \frac{\partial P_L}{\partial V_n}] \begin{bmatrix} \Delta V_1 \\ \Delta V_2 \\ \vdots \\ \Delta V_n \end{bmatrix} \qquad (3)$$

The minimization problem (the power system) is subjected to operating constraints which are the inequality constraints (i.e., limits on the variables), and the equality constraints (i.e., reactive power demands):

$$Q_i^{\min} \le Q_i \le Q_i^{\max} \quad i = 1, \cdots, m$$
$$V_j^{\min} \le V_i \le V_i^{\max} \quad j = 1, \cdots, n \qquad (4)$$
$$Q_k = Q_{dk} \quad k = 1, \cdots, l$$

There are m + n + $l$ constraints. The first m's constraints are for reactive power sources and tap changing transformer terminals. We will refer to the matrix of reactive power injections at these buses as $Q_1$.
The next n's constraints are the bus voltage constraints. The last equality constraints are for loads and junction buses that are not connected to transformer terminals.
The relationship can be to estimate between the losses and the transformation ratio $\Delta P_* = f(K_*)$ different numerical analysis methods are used to define the final formula [Abdallah and Al-Thaimer 2003, Abdallah and Al-Thaimer. 2001]:

$$\Delta P_* = aK_*^{\alpha} + bK_*^{\beta} \qquad (5)$$

Where:

$$\Delta P_* = \frac{\Delta P}{\Delta P_0}; \quad K_* = \frac{K}{K_0}$$

The $a, b, \alpha, \beta$ - are constants that reflect the influences of the transformation ratio on the operating mode.
The eq. 5 is considered as a regression model which has a determined amount of errors in each case. And this model has no adaptive specialization for any kind of normal (small) divergences or disturbances. The estimated relations are satisfied, but not for all the online control process which characterized with continuously variation and small disturbances and

ripples. The adaptive models are the solutions in such control problems.
The power loss in a line can also be calculated by taking the algebraic sum of the total power flows in either direction and the total loss would be the sum of all the line losses [Weedy, 1998]. Two methods in order to reduce the losses on the system network will be discussed in this paper. They include: the change of transformer tap settings and addition of different values of capacitor banks to control reactive power distribution.
The main objective of this paper is to create and investigate the real time optimization voltage and reactive power control to achieve the minimizing of the electric power losses in electrical networks by means of artificial neural networks. As the artificial neural networks successfully minimizing the noise and errors that arise by using other methods linearization.

## III. REACTIVE POWER CONTROL BY TAP CHANGERS AND CAPACITORS

Tap changers and capacitors banks can control the reactive power flow so optimum bus voltages can be determined and reduce the losses. A method of controlling the voltages in a network makes the use of transformers, the turns ratio of which may be changed.
The tap selector selects the tapping; its electrical contacts are designed to carry the rated current of the transformer but not to make or break this current. However, the diverter switch needs to be designed to carry, make and break the load current in circuits previously selected by the tap selector. During the operation of the diverter switch the transition resistors 13 and 14 bridge the tap in use and the tap next to be used, thereby limiting the circulating current due to the inter-tap voltage. For example, changing from tap 5 to tap 6, as the moving contact 19 traverses from left to right, arcing occurs at all the fixed contacts 15, 16, 17 and 18 during the current making and breaking process [Cooke and Williams. 1992].
A schematic diagram of the tap changer is shown in Figure 1. The off-load tap changer requires disconnection of the transformer when the tap setting is to be changed. Many transformers now have on-load tap changers.
Capacitors are used in the transmission and distribution line to increase line loadability (maximum power transfer) and to adjust the system voltage [Gonen .1988]. Shunt capacitors are used to deliver reactive power and increase the voltage magnitudes during heavy load conditions. Figure 3 shows the effect of adding a shunt capacitor bank to a power system bus. The system is represented by its Thevenin equivalent at the node, where the capacitor will be applied by closing the switch. With the switch open, the node voltage $V_t$ is equal to the Thevenin voltage $-E_{th}$.

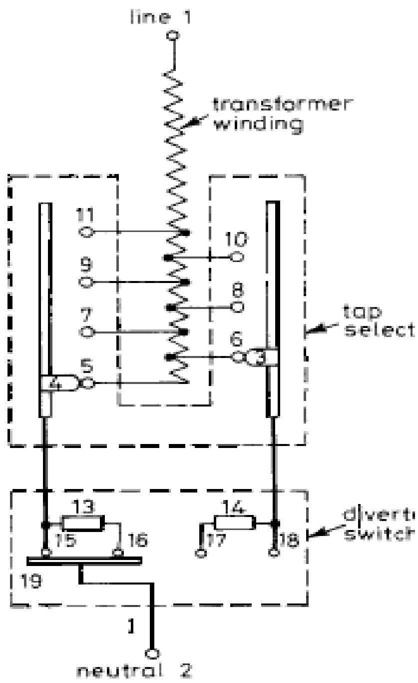

Fig. 1: Tap changer schematic diagram

From the power flow standpoint, the addition of a shunt capacitor bank to a load bus corresponds to the addition of a negative reactive load. The power flow program computes the increase in bus voltage magnitude along with the small change in phase angle.
The addition of capacitor bank changes the bus admittance matrix similar to the change of tap setting of transformer. However, it only affects the element of the diagonal admittance matrix of the bus where the capacitor is added [Abdallah and Jalal. 2008].
Note that in this paper the investigated transformers were 400/132kV with auto-tap-changers.

## IV. THE BACK PROPAGATION ARTIFICIAL NEURAL NETWORK

The application of the back propagation (BP) ANN in different electrical power system operation and control strategies has lead to acceptable results [Tarafdar and Kashtiban. 2005]. The important advantage of neural network lies in its flexibility with any high noisy data and its main drawback is the need for long time for, training feed forward network with BP training algorithm, especially when dimension of the power network is high.
BP is the generalization of the Least Mean Square (LMS) learning rule to multiple-layer networks and

nonlinear differentiable transfer functions. Input vectors and the corresponding target vectors are used to train a network until it can approximate a function, associate input vectors with specific output vectors, or classify input vectors in an appropriate way as defined [Cirstea, et. al.2002 , Al-Taee, et. al. 2001].

The network weights of BP which is a gradient descent algorithm, as is the LMS learning rule, are moved along the negative of the gradient of the performance function. The term BP refers to the situation in which the gradient is computed for nonlinear multilayer networks. There are a number of variations on the basic algorithm that are based on other standard optimization techniques, such as conjugate gradient and Newton methods.

The BP algorithm is aiming to minimize the total operation error of the neural network. The total error is a function defined by equation (7) where $O_i$ ref is the column vector of the reference outputs and $O_i$ is the column vector of the actual network outputs corresponding to the input pattern number '*i*'. The total error Err is the sum of the errors corresponding to all *np* input patterns.

$$Err=\sum_{i=1}^{n_p}(O_i^{ref}-O_i)^T.(O_i^{ref}-O_i)=\sum_{i=1}^{n_p}\|O_i^{ref}-O_i\|^2 \quad (7)$$

For each training step, the vector of all neuron weights and threshold weights (*W*) is updated in such a way that the total error Err is decreased. The vector *W* can be associated to a point in a $N_W$-dimensional space (the parameter space), where $N_W$ is the total number of weights and thresholds in the neural network. For each training step, the vector of all neuron weights and threshold.

High and well trained networks lean to give reasonable answers when presented with inputs that they have never seen. Typically, a new input leads to an output similar to the correct output for input vectors used in training that are similar to the new input being presented. This generalization property makes it possible to train a network on a representative set of input target pairs and get good results without training the network on all possible input/output pairs. There are two features of Neural Network often called Least Mean Square.

One of the most important features of neural networks is their ability to learn (to be trained) and improve their operation using a set of examples named training data set [ Varadarajan. 2008].

The training process is controlled by mathematical algorithms that fall in two main classes: constructive and non-constructive. The non-constructive training algorithms adapt only the connection weights and the threshold levels. The constructive algorithms modify all the network features including its architecture (neurons and even layers are added or eliminated as necessary).

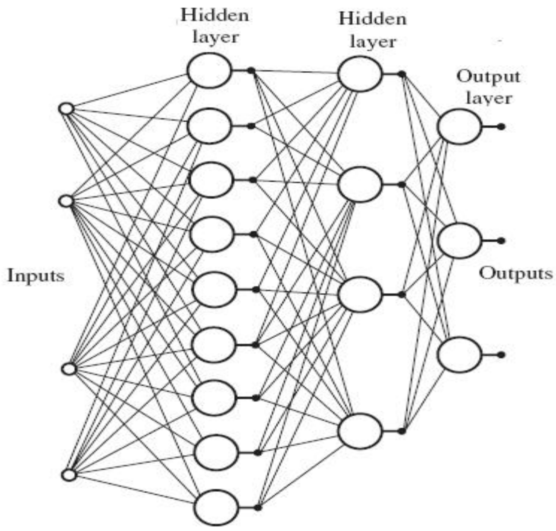


Fig. 2: Feed-forward neural network architecture

Back-propagation is not a constructive algorithm; the network architecture has to be chosen in advance. Unfortunately, there is no clearly defined set of rules to be followed in order to decide which is the most appropriate architecture for the problem. Choosing the architecture is a result of a trial and error process supported by previous experience. All the algorithms modify the neuron weights and thresholds based on calculations that analyses the network response to particular inputs [Cirstea, et. al. 2002].

## V. MEASUREMENTS, CALCULATIONS AND TECHNIQUES

Calculations are performed using a real data obtained from the Jordanian electrical power system, Jordan Electric Power Company (JEPCO). The substations Al Qatrana and Amman north are studied, to measure the expected effect of adding these substations to Jordanian electrical power system. To explore the result in this paper we introduce only the data and the calculations for Amman South substation (maximum loading).Power losses calculations for Jordanian Electrical Power System 400–132–33 KV. Power losses reduction using voltage and reactive power control.

To obtain the relationship between the active power losses and automatic tap changing (transformation ratio), $\Delta P = f(K_T)$ to pre-optimize and predict the effect of the control operations of the electrical system. The initial training data of the neural network are gathered from the power system and initialized by the measuring devices. The values of the weights and biases the output values are compared with the desired values the total error in all cases was less than the approximated model. The final formula of active power losses as a function of transformation ratio and injected reactive power are introduced for each substation.

The effects of the injected reactive power in table 1, the results of measuring the actual data, regression model, and the ANN model are introduced. Power losses due to reactive power injected are given by the regression model:

$P_{losses} = 0.0001 * Q_{injected}^2 – 0.0245 * Q_{injected} + 30.9400.$

$Q_{losses} = 0.0801 * Q_{injected}^2 – 0.66 * Q_{injected} - 112.7$

And obviously, he difference between the ANN model and the regression one can be realized and the ANN model matches the actual data of the system.

Table 1: The effect of the injected reactive power

| REACTIVE POWER INJECTED (MVAR) | HIGH VOLTAGE TERMINAL (KV) | LOW VOLTAGE TERMINAL (KV) | ACTUAL ACTIVE POWER LOSSES (MW) **REAL DATA** | ACTUAL REACTIVE POWER LOSSES (MVAR) **REAL DATA** | ACTIVE POWER LOSSES (MW) BY **REGRESSION MODEL** | REACTIVE POWER LOSSES (MVAR) BY **REGRESSION MODEL** | ACTIVE POWER LOSSES (MW) BY **ANN** | REACTIVE POWER LOSSES (MVAR) BY **ANN** |
|---|---|---|---|---|---|---|---|---|
| **5** | **396.30** | **133.41** | **30.83** | **- 118.05** | **30.82** | **-115.25** | **30.83** | **- 118.05** |
| **10** | **397.24** | **133.78** | **30.72** | **- 121.25** | **30.71** | **-118.41** | **30.72** | **- 121.25** |
| **20** | **399.14** | **134.52** | **30.52** | **- 127.44** | **30.51** | **-124.46** | **30.52** | **- 127.44** |
| **25** | **400.10** | **134.89** | **30.43** | **- 129.99** | **30.42** | **-127.35** | **30.43** | **- 129.99** |
| **40** | **403.00** | **136.02** | **30.21** | **- 138.65** | **30.19** | **-135.46** | **30.21** | **- 138.65** |
| **60** | **406.97** | **137.57** | **30.01** | **- 148.38** | **30.00** | **-145.00** | **30.01** | **- 148.38** |
| **70** | **406.99** | **138.35** | **29.96** | **- 152.64** | **29.95** | **-149.21** | **29.96** | **- 152.64** |
| **80** | **411.04** | **139.15** | **29.94** | **- 156.47** | **29.92** | **-153.06** | **29.94** | **- 156.47** |

The optimum injected reactive power for maximum load operation is: $Q_{injected} = 80$ (MVAR).
The minimum power losses due to optimum injected reactive power are: $P_{losses} = 29.94$ (MW).

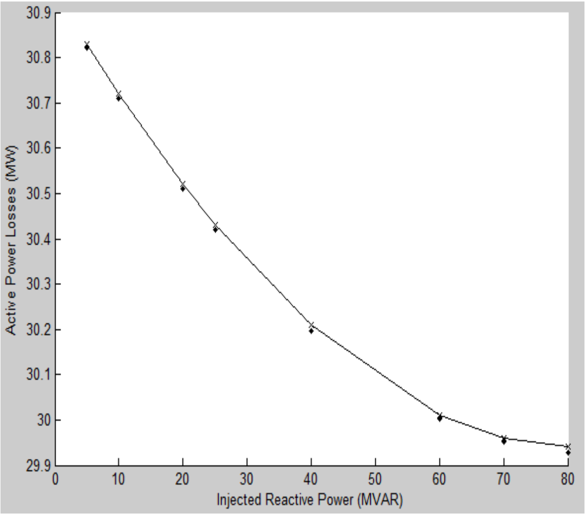

Fig.3: The effect of the injected reactive power on the active power losses.

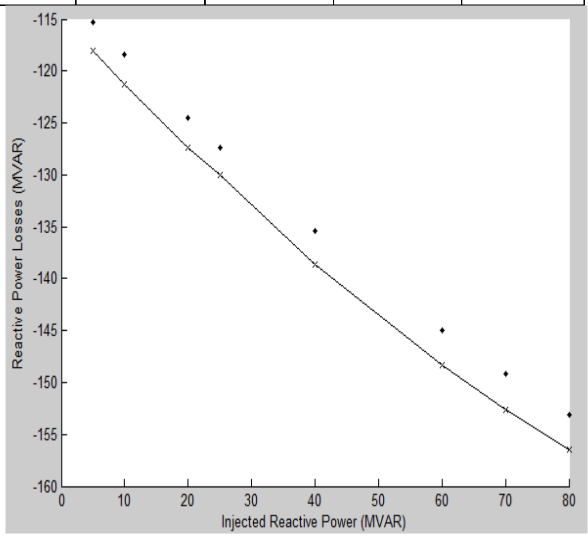

Fig.4: The effect of the injected reactive power on the reactive power losses.

The effect of the injected reactive power on the power Active power losses is illustrated in figure 3 and in figure 4 the effect of the injected reactive power on the reactive power losses.

Table 2: The effect of the tap changer

| TAP CHANGER | TRANSFOR-MATION RATIO | HIGH VOLTAGE TERMINL (KV) | LOW VOLTAGE TERMINL (KV) | ACTUAL ACTIVE POWER LOSSES (MW) **REAL DATA** | ACTUAL REACTIVE POWER LOSSES (MVAR) **REAL DATA** | ACTIVE POWER LOSSES (MW) **BY REGRE-SSION MODEL** | REACTIVE POWER LOSSES (MVAR) **BY REGRE-SSION MODEL** | ACTIVE POWER LOSSES (MW) **BY ANN** | REACTIVE POWER LOSSES (MVAR) **BY ANN** |
|---|---|---|---|---|---|---|---|---|---|
| **-9** | **0.280** | **407.65** | **118.65** | **42.62** | **- 26.38** | **41.89** | **- 20.25** | **42.619** | **- 26.38** |
| **-8** | **0.286** | **407.57** | **120.58** | **40.28** | **- 51.07** | **39.46** | **- 46.75** | **40.2** | **- 51.07** |
| **-7** | **0.291** | **407.30** | **122.34** | **38.19** | **- 73.10** | **37.59** | **- 66.50** | **38.19** | **- 73.10** |
| **-6** | **0.297** | **406.83** | **124.05** | **36.35** | **- 92.56** | **35.6** | **- 87.49** | **36.35** | **- 92.56** |
| **-5** | **0.302** | **406.18** | **125.68** | **34.74** | **- 109.53** | **34.16** | **- 102.78** | **34.74** | **- 109.53** |
| **-4** | **0.308** | **405.35** | **127.24** | **33.36** | **- 124.12** | **32.65** | **- 118.60** | **33.36** | **- 124.12** |
| **-3** | **0.313** | **404.36** | **128.73** | **32.19** | **- 136.42** | **31.59** | **- 129.72** | **32.19** | **- 136.42** |
| **-2** | **0.319** | **403.21** | **130.14** | **31.22** | **- 146.50** | **30.53** | **- 140.71** | **31.22** | **- 146.50** |
| **-1** | **0.324** | **401.92** | **131.48** | **30.44** | **- 154.45** | **29.83** | **- 147.94** | **30.44** | **- 154.45** |
| **0** | **0.330** | **400.49** | **132.74** | **29.85** | **- 160.37** | **29.18** | **- 154.41** | **29.85** | **- 160.37** |
| **1** | **0.336** | **398.93** | **133.94** | **29.44** | **- 164.34** | **28.74** | **-158.56** | **29.44** | **- 164.34** |
| **2** | **0.341** | **397.25** | **135.07** | **29.18** | **- 166.45** | **28.53** | **-160.33** | **29.18** | **- 166.45** |
| **3** | **0.347** | **395.45** | **136.13** | **29.08** | **- 166.77** | **28.44** | **- 160.51** | **29.08** | **- 166.77** |
| **4** | **0.352** | **393.55** | **137.12** | **29.13** | **- 165.39** | **28.49** | **- 159.10** | **29.13** | **- 165.39** |
| **5** | **0.358** | **391.55** | **138.05** | **29.31** | **- 162.39** | **28.71** | **- 155.62** | **29.31** | **- 162.39** |
| **6** | **0.363** | **389.47** | **138.91** | **29.63** | **- 157.86** | **29.01** | **- 151.30** | **29.63** | **- 157.86** |
| **7** | **0.369** | **387.29** | **139.72** | **30.06** | **- 151.86** | **29.5** | **- 144.51** | **30.06** | **- 151.86** |
| **8** | **0.374** | **385.04** | **140.46** | **30.61** | **- 144.46** | **30.01** | **- 1137.58** | **30.61** | **- 144.46** |
| **9** | **0.379** | **382.73** | **141.15** | **31.26** | **- 135.76** | **30.61** | **- 129.54** | **31.26** | **- 135.76** |

The effects of power losses due to transformation ratio in table 2, the results of measuring the actual data, regression model, and the ANN model are introduced.

The power losses due to transformation ratio (tap changer) regulation by the regression model are given as:

$$P_{losses} = (-0.8864 * K_T^{\,3} + 1.1645 * K_T^{\,2} - 0.4880 * K_T + 0.0690)*10^4.$$

$$Q_{losses} = (-7.6989 * K_T^{\,3} + 10.837 * K_T^{\,2} - 4.7255 * K_T + 0.6405)*10^4.$$

From the results, the optimum transformation ratio for maximum load operation is: $K_T = 0.3470$.

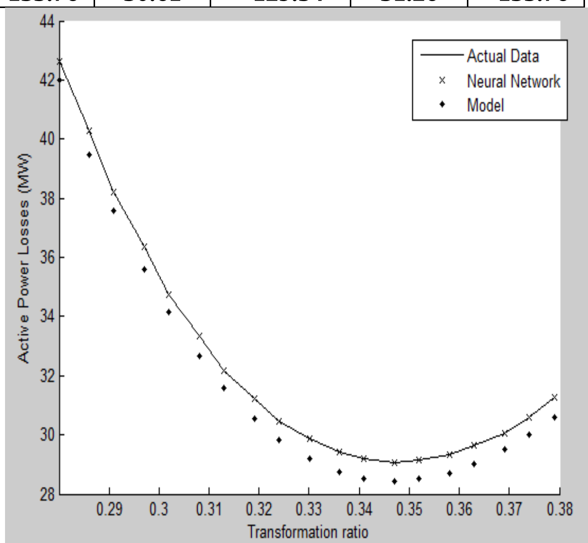


Fig.5: The effect of the tap changer a on the active power losses.

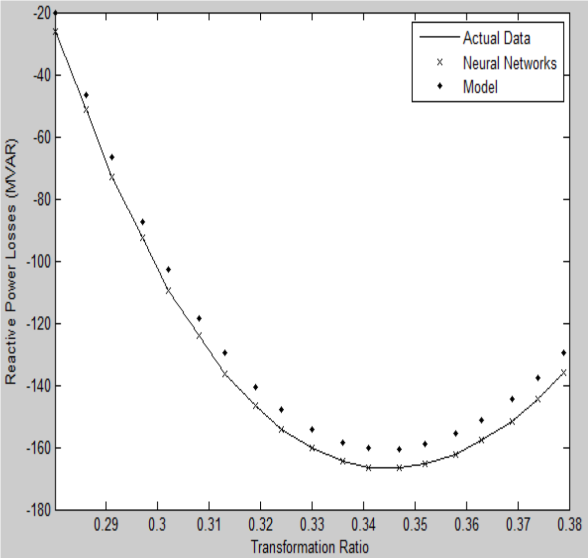


Fig.6: The effect of the tap changer a on the reactive power losses.

And the minimum power losses due to this transformation ratio are: $\Delta P$ = 29.13 (MW).

Also, the difference between the ANN model and the regression one can be realized and the ANN model matches the actual data of the system.

The Power losses reduction using automatic tap changing transformer (transformation ratio) and shunt capacitors (reactive power control) are shown table 3.

To obtain the relationship between the active power losses using automatic tap changing transformer (transformation ratio) and reactive power injected $P = f(K_T, Q_{ini})$, MATLAB curve fitting was used according to the real results

Table 3: The duel effects of the transformation ratio and the injected reactive power

| Injected reactive power (MVAR) / Transformation Ratio | Q=10 MVAR | Q=20 MVAR | Q =30 MVAR | Q=40 MVAR | Q=50 MVAR | Q=60 MVAR | Q=70 MVAR | Q=80 MVAR |
|---|---|---|---|---|---|---|---|---|
| **0.280** | 42.87 | 42.01 | 41.29 | 40.71 | 40.26 | 39.95 | 39.77 | 39.74 |
| **0.286** | 40.12 | 39.84 | 39.40 | 38.38 | 38.08 | 37.81 | 37.50 | 37.56 |
| **0.291** | 38.27 | 38.02 | 37.59 | 36.83 | 36.47 | 36.18 | 35.83 | 35.78 |
| **0.297** | 36.28 | 36.06 | 35.62 | 35.11 | 34.70 | 34.38 | 33.99 | 33.84 |
| **0.302** | 34.82 | 34.60 | 34.16 | 33.80 | 33.35 | 33.01 | 32.60 | 32.39 |
| **0.308** | 33.29 | 33.07 | 32.62 | 32.37 | 31.91 | 31.53 | 31.11 | 30.87 |
| **0.313** | 32.21 | 31.96 | 31.51 | 31.31 | 30.85 | 30.44 | 30.03 | 29.77 |
| **0.319** | 31.13 | 30.85 | 30.39 | 30.21 | 29.76 | 29.33 | 28.94 | 28.69 |
| **0.324** | 30.41 | 30.10 | 29.64 | 29.43 | 29.01 | 28.57 | 28.20 | 27.97 |
| **0.330** | 29.76 | 29.41 | 28.94 | 28.67 | 28.30 | 27.86 | 27.53 | 27.34 |
| **0.336** | 29.34 | 28.94 | 28.46 | 28.13 | 27.81 | 27.38 | 27.10 | 26.98 |
| **0.341** | 29.16 | 28.73 | 28.24 | 27.83 | 27.58 | 27.17 | 26.94 | 26.88 |
| **0.347** | 29.14 | 28.67 | 28.18 | 27.68 | 27.51 | 27.15 | 27.00 | 27.02 |
| **0.352** | 29.29 | 28.79 | 28.31 | 27.73 | 27.64 | 27.34 | 27.25 | 27.35 |
| **0.358** | 29.66 | 29.15 | 28.66 | 28.01 | 28.03 | 27.81 | 27.82 | 28.02 |
| **0.363** | 30.13 | 29.61 | 29.13 | 28.43 | 28.54 | 28.43 | 28.52 | 28.79 |
| **0.369** | 30.87 | 30.36 | 29.89 | 29.17 | 29.40 | 29.43 | 29.63 | 30.01 |
| **0.374** | 31.64 | 31.16 | 30.69 | 29.99 | 30.32 | 30.50 | 30.80 | 31.25 |
| **0.379** | 32.54 | 32.10 | 31.65 | 30.99 | 31.44 | 31.79 | 32.19 | 32.72 |

The result of the duel effect of the transformation ratio and the injected reactive power by the ANN model.

Power losses due to transformation ratio and reactive power injected are expressed as the following:

The optimum transformation ratio and optimum injected reactive power for maximum load operation is:

$K_T$ = 0.341. ; $Q_{injected}$ = 80 (MVAR). The minimum power losses due to optimum transformation ratio and optimum injected reactive power are: $P_{losses}$ = 26.88 (MW).

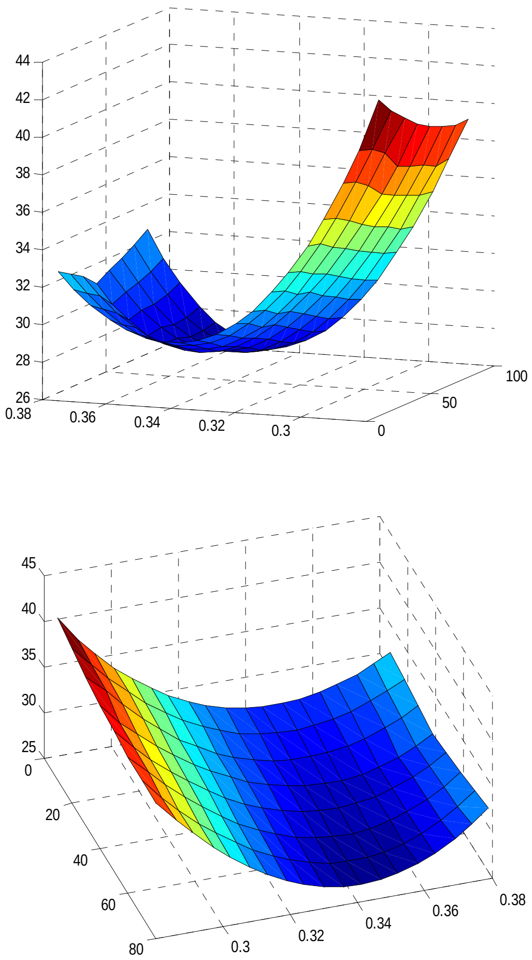


Fig 7: The duel effects of the transformation ratio and the injected reactive power on the active power losses

## VI. CONCLUSIONS

The investigations show that by means of the real time optimization voltage and reactive power control to achieve the minimizing of the electric power losses in electrical networks using the artificial neural networks. As the artificial neural networks successfully minimizing the noise and errors that arise by using regression methods linearization.

The effect of the injected reactive power on the active power losses has been investigated also the power losses due to transformation ratio by the ANN Back Propagation training algorithm and compared with regression model. Furthermore the duel effects of the transformation ratio and the injected reactive power on the active power losses has been proved.

According to the optimal results obtained, recommendations for improving the performance of the power system are introduced. The regulation limits of the optimization process are taken into consideration and are not to be exceeded.

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## ABOUT THE AUTHORS

**Jalal Abdallah** Was born in Amman, Jordan. He received his M.Sc.1994 and the Ph.D.1998 in Electrical Engineering from Vinnitsa Stat Technical University, Ukraine. Since 1998 He joint Al Balqa Applied University. And by 2005 he joint Tafila Technical University where he is currently an Associate Professor at the electrical Engineering Department. His main research interests are: Electrical power system modeling and analysis, Power plants monitoring and diagnostics.

**Abdallah R. Al- Zyoud** - was born in Zarqa, Jordan, in 1956. He received the M.Sc. degree in electrical engineering from the Donetsk Polytechnic Institute in 1980 and the Ph.D. from the Kiev Polytechnic Institute, Ukraine, in 1992. Since 1985 He worked in Amman Polytechnic Institute in electrical department tell 1997. After that he joined Al-Balqa Applied University, Jordan, were he is currently an Associate professor at the electrical department. His interests are in optimization and protection of electrical networks.