Reactive Power Allocation Using Support Vector Machine

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ABSTRACT
This paper proposes a new modified nodal equations (MNE) method to identify the reactive power transfer between generators and load. It further focuses on creating an appropriate support vector machine (SVM) in which support vector regression is used as an estimator to solve the same problem in a simpler and faster manner. Almost all system variables obtained from load flow solutions are utilized as input to the SVM. The actual 25-bus equivalent power system of south Malaysia is utilized as a test system to illustrate the effectiveness of the SVM technique compared to that of the modified nodal equations method.

Keywords: Load flow, modified nodal equations method, radial basis function network, reactive power and support vector machine.

1. INTRODUCTION
The reactive power provision becomes an important issue under competitive environment. Implementing transparent rules that allocate transmission use fulfill this concept of fairness in the industry. Fairness can only be achieved by adopting a fair and transparent usage allocation methodology acceptable to all parties. In view of market operation, it is vital to know the role of individual generators and loads to transmission wires and power transfer between individual generators to loads. This is necessary for the restructured power system to operate economically, efficiently and ensure guaranteed open access to all system users [1]. Several schemes have been developed to solve the allocation problem in the last few years. Methods based on the Y-bus or Z-bus system matrices have recently received great attention since these methods can integrate the network characteristics and circuit theories into line usage and loss allocation. The method reported in reference [2] is based on Kirchhoff’s current law (KCL), equivalent linear circuit transformation and superposition principle. In general it assumes that the current at each network injection point may reach all lines and loads. Another circuit concept method was proposed by Chang and Lu [3]. It was based on the system Y-bus matrix and Z-bus modification. This algorithm utilizes the network decomposition concept as proposed in reference [4] by Zobian and Ilic which determines the use of transmission network by individual bilateral contracts. Teng [5] proposed a systematic method, very similar to as presented in reference [3], to allocate the power flow and loss for deregulated transmission systems.

The tracing methods [1, 6-9] based on the actual power flows in the network and the proportional sharing principles are effectively used in transmission usage allocation. Bialek [6] proposed a novel power tracing method to allocate the real and reactive power flow, however the main drawback of this method is that it requires inverting a large matrix. F.F Wu et al. [7] proposed a graph theory to calculate the contribution factor of individual generators to line flows and loads and the extraction factor of individual loads from line flows and generators, which is theoretically efficient. This method cannot handle loop flows and losses must be neglected initially. Reference [10] is based on the concept of generator ‘domains’, ‘common’ and ‘links’. The disadvantage of this method is that the share of each generator in each ‘common’ (i.e. the set of buses supplied from the same set of generators) is assumed to be same. In a related work based on support vector machine techniques as given in reference [11], a dynamic voltage collapse indices is proposed using support vector machine (SVM). The SVM gives faster and more accurate results for dynamic voltage collapse prediction. The MNE methodology in this paper is based on current operating point computed by the usual load flow code and basic equations governing the load flow in the network. The method starts with partitioning of system Y-bus matrices to decompose the current of the load.
buses as a function of the generators’ current and load voltages. Then it uses the load voltages from load flow results and decomposed load currents to determine reactive power contribution from each generator to loads. The next goal of this research is to incorporate the SVM to calculate reactive power output of individual generators to system loads. The new method based on modified nodal equation has been chosen as a trainer to train the SVM. It can be expected that the application of SVM to the developed methodology will further contribute in improving the computation time of reactive power allocation methodology for deregulated system.

2. MODIFIED NODAL EQUATIONS METHOD

The derivation, to decompose the load reactive powers into components contributed by specific generators starts with basic equations of load flow. Applying Kirchhoff’s law to each node of the power network leads to the equations, which can be written in a matrix form as in equation (1) [1]:

\[ I = YV \]  

where:

- \( V \) is a vector of all node voltages in the system
- \( I \) is a vector of all node currents in the system
- \( Y \) is the Y-bus admittance matrix

The nodal admittance matrix of the typical power system is large and sparse, therefore it can be partitioned in a systematic way. Considering a system in which there are \( G \) generator nodes that participate in selling power and remaining \( L = n - G \) nodes as loads, then it is possible to re-write equation (1) into its matrix form as shown in equation (2):

\[
\begin{bmatrix}
I_G \\
I_L
\end{bmatrix} =
\begin{bmatrix}
Y_{GG} & Y_{GL} \\
Y_{LG} & Y_{LL}
\end{bmatrix}
\begin{bmatrix}
V_G \\
V_L
\end{bmatrix}
\]  

Solving equation (2) for \( I_L \), the load currents can be presented as a function of generators’ current and load voltages as shown in equation (3):

\[
I_L = Y_{LG}Y_{GG}^{-1}I_G + \left(Y_{LL} - Y_{LG}Y_{GG}^{-1}Y_{GL}\right)V_L
\]  

Now, in order to decompose the load voltage dependent term further in equation (3), into components of generator dependent terms, the following derivations are used. A possible way to deduce load node voltages as a function of generator bus voltages is to apply superposition theorem. However, it requires replacing all load bus current injections into equivalent admittances in the circuit. Using a readily available load flow results, the equivalent shunt admittance \( Y_{lj} \) of load node \( j \) can be calculated using the equation (4):

\[
Y_{lj} = \frac{1}{V_{lj}} \left(\frac{S_{lj}}{V_{lj}}\right)^*  
\]  

\( S_{lj} \) is the load complex power on node \( j \) and \( V_{lj} \) is the load bus voltage on node \( j \). After adding these equivalences to the diagonal entries of \( Y \)-bus matrix, equation (2) can be rewritten as in equation (5):

\[
\begin{bmatrix}
I_G \\
0
\end{bmatrix} =
\begin{bmatrix}
Y_{GG} & Y_{GL} \\
Y_{LG} & Y_{LL}
\end{bmatrix}
\begin{bmatrix}
V_G \\
V_L
\end{bmatrix}
\]  

where \( Y_{LL} \) is the modified sub matrices \( Y_{LL} \) in equation (2). Next, adopting the lower half of equation (5) and solving for \( V_L \) it is possible to obtain the load voltages as a function of generator voltages as in equation (6):

\[
V_L = -(Y_{LL}^{-1}Y_{LG})V_G
\]  

Now, it is a simple matter to obtain required relationship as a function of generators voltage and currents. By substituting equation (6) into equation (3), the decomposed load currents can be expressed as depicted in equation (7):

\[
I_L = Y_{LG}Y_{GG}^{-1}I_G + \left(Y_{LL} - Y_{LG}Y_{GG}^{-1}Y_{GL}\right)V_L
\]  

This equation shows that the current of each load bus consists of current contributed by individual generators. The first term relates directly the generators’ current and the second term corresponds to their voltages.

Finally the total reactive power \( Q_L \) of all loads can be expressed as in equation (8):

\[
Q_L = \text{Im}\left\{V_L^*I_L\right\}
\]

\[
= \text{Im}\left\{V_L^*\left(\left(Y_{LG}Y_{GG}^{-1}\right)^*I_G^* + V_L^*\left(Y_{LG}Y_{GG}^{-1}Y_{GL}Y_{LL}^{-1}Y_{LG}\right)V_G\right)\right\}
\]

With further simplification of equation (8), the reactive power contribution that load \( j \) acquires from generator \( i \) is as shown in equation (9):

\[
Q_{lj} = \sum_{i=1}^{nG} Q_{lj}^G + \sum_{i=1}^{nG} Q_{lj}^V
\]

where:

- \( Q_{lj}^G \): current dependent term of generator \( i \) to \( Q_{lj} \)
\[ Q_{ij}^G \] : voltage dependent term of generator \( i \) to \( Q_{ij} \)

Vector \( Q_{ij} \) is used as a target in the training process of the proposed SVM.

### 3. SUPPORT VECTOR MACHINE

Support Vector Machine (SVM), generally called as Kernel machine is a more recent powerful technique for solving classification and regression problems [12]. Unlike neural networks, which tries to define complex functions of the input feature space, SVM performs a nonlinear mapping of the data into a high dimensional feature space. Then SVM uses simple linear functions to create linear decision boundaries in the new space. The problem of choosing an architecture for a neural network is replaced by the problem of choosing a suitable kernel for the SVM. In support vector regression, the basic idea is to map the data \( \tilde{x} \) of the input space into a high dimensional feature space \( F \) via a nonlinear mapping \( \Phi \) and to perform linear regression in this space [13]:

\[
j(\tilde{x}) = <w, \Phi(\tilde{x})> + b \quad \text{with } \Phi : \mathbb{R}^n \rightarrow F, w \in F
\]  

(10)

where:
- \( j(\tilde{x}) \) : output function
- \( w \) : weight vector
- \( \tilde{x} \) : input
- \( b \) : bias threshold
- \( <, > \) : dot products in the feature space

Thus, linear regression in a high dimensional feature space \( F \) corresponds to nonlinear regression in the low dimensional input space \( \mathbb{R}^n \). Since \( \Phi \) is fixed, thus \( w \) is determined from the finite samples \( \{x_i, y_i\} \) \( (i=1,2,3,\ldots,N) \) by minimizing the sum of the empirical risk \( R_{emp}[f] \) and a complexity term \( \|w\|^2 \), which enforces flatness in feature space:

\[
R_{emp}[f] = R_{emp}[f] + \lambda \|w\|^2 = \sum_{i=1}^{l} L_{ij}(y_i, f(\tilde{x}_i, w)) + \lambda \|w\|^2
\]  

(11)

where \( l \) denotes the samples size, \( \lambda \) is regularization constant, \( L_{ij} \) is the \( \varepsilon \) - insensitive loss function which is given by,

\[
L_{ij}(y_i, f(\tilde{x}_i, w)) = \begin{cases} 0 & \text{for } |f(\tilde{x}) - y_i| < \varepsilon \\ |f(\tilde{x}) - y_i| - \varepsilon & \text{otherwise} \end{cases}
\]  

(12)

The target function (11) can be minimized by solving quadratic programming problem, which is uniquely solvable. It can be normalized as follows:

\[
\Phi(w, \xi) = \frac{1}{2} \|w\|^2 + C \sum_i \left( \xi_i^- + \xi_i^+ \right)
\]

subject to\[
\begin{align*}
y_i - <w, \Phi(\tilde{x}_i)> - b & \leq \varepsilon + \xi_i^- \\
<w, \Phi(\tilde{x}_i)> + b - y_i & \leq \varepsilon + \xi_i^+ \\
\xi_i^- & \geq 0 \\
\xi_i^+ & \geq 0
\end{align*}
\]  

(13)

where:
- \( C \) : a pre-specified value
- \( \xi_i^- \), \( \xi_i^+ \): slack variables representing upper and lower constraints on the outputs of the system

The first part of this cost function is a weight decay which is used to regulate weight size and penalizes large weights. Due to this regulation, the weight converges to smaller values. Large weights deteriorate the generalization ability of SVM because, usually, they can cause excessive variance. The second part is a penalty function which penalizes errors larger than \( \pm \varepsilon \) using a so called \( \varepsilon \) - insensitive loss function \( L_{ij} \) for each of the training points. The positive constant \( C \) determines the amount, up to which deviations from \( \varepsilon \) are tolerated. Errors larger than \( \pm \varepsilon \) are denoted with the so-called slack variables representing values above \( \varepsilon (\xi_i^+) \) and below \( \varepsilon (\xi_i^-) \), respectively. The third part of the equation represents constraints that are set to the values of errors between regression prediction \( f(\tilde{x}) \) and true values \( y_i \).

The solution is given by,

\[
\max_{\alpha, \alpha^*} W(\alpha, \alpha^*) = \max_{\alpha, \alpha^*} -\frac{1}{2} \sum_{i=1}^{l} \sum_{j=1}^{l} \alpha_i \alpha_j^* (\Phi(x_i), \Phi(x_j)) + \sum_{i=1}^{l} \alpha_i (y_i - \varepsilon) - \alpha_i^* (y_i + \varepsilon)
\]  

(14)

With constraints,

\[
0 \leq \alpha_i, \alpha_i^* \leq C, \quad i = 1, \ldots, l
\]

\[
\sum_{i=1}^{l} \alpha_i - \alpha_i^* = 0
\]  

(15)

By solving equation (14) with constraints of equation (15), the Lagrange multipliers \( \alpha, \alpha^* \) and the weight can be determine as in the regression function of equation (10), which is given by,

\[
\bar{w} = \sum_{i=1}^{l} (\alpha_i - \alpha_i^*) x_i \quad \text{and} \quad \bar{b} = -\frac{1}{2} \left[ \sum_{i=1}^{l} (\alpha_i x_i + x_i^*) \right]
\]  

(16)

The Karush-Kuhn-Tucker conditions that are satisfied by the solution are,

\[
\alpha_i \alpha_i^* = 0, \quad i = 1, \ldots, l
\]  

(17)
Therefore, the support vectors are points where exactly one of the Lagrange multipliers are greater than zero (on the boundary), which means that they fulfill the Karush-Kuhn-Tucker condition \[13\]. Training points with non-zero Lagrange multipliers are called support vectors and give shape to support vector regression. When \(\varepsilon = 0\), \(L^\varepsilon\) loss function and the optimization problem is simplified as,

\[
\min_{\beta} \frac{1}{2} \sum_{i=1}^{l} \sum_{j=1}^{l} \beta_i \beta_j \langle x_i, x_j \rangle - \sum_{i=1}^{l} \beta_i y_i \tag{18}
\]

With constraints,

\[
-C \leq \beta_i \leq C, \quad i = 1, \ldots, l
\]

\[
\sum_{i=1}^{l} \beta_i = 0
\]

and the regression function given by equation (10), where

\[
\bar{w} = \sum_{i=1}^{l} \beta_i x_i \text{ and } \bar{b} = -\frac{1}{2} \langle \bar{w}, (x_i + x_j) \rangle \tag{20}
\]

A non-linear mapping can be used to map the data into a high dimensional feature space where linear regression is performed. The Kernel approach is again employed to address the curse of dimensionality. The non-linear support vector regression solution, using an \(\varepsilon\)-insensitive loss function,

\[
\max_{\alpha, \alpha^*} \mathcal{H}(\alpha, \alpha^*) = \max_{\alpha, \alpha^*} \sum_{i=1}^{l} \alpha_i (y_i + \varepsilon) - \alpha_i (y_i - \varepsilon)
\]

\[
-\frac{1}{2} \sum_{i=1}^{l} \sum_{j=1}^{l} (\alpha_i^* - \alpha_i)(\alpha_j^* - \alpha_j) k(x_i, x_j) \tag{21}
\]

With constraints resembles as equation (15). Solving equation (21) with constraints as in equation (15), determines the Lagrange multipliers, \(\alpha, \alpha^*\) and the regression function which is given by,

\[
f(x) = \sum_{SV} (\tilde{\alpha}_i - \tilde{\alpha}_i^*) k(x_i, x) + \bar{b} \tag{22}
\]

In (22) the Kernel function, \(k(x_i, x_j) = \langle \Phi(x_i), \Phi(x_j) \rangle\).

Several Kernel functions namely, Gaussian radial basis function (RBF) Kernel, linear Kernel and multilayer perceptron Kernel are available. The commonly used Kernel function is the Gaussian RBF Kernel which is as shown in equation (23):

\[
k(x, y) = e^{-\frac{\|x - y\|^2}{2\sigma^2}} \tag{23}
\]

4. APPLICATION OF SVM TO reactive POWER ALLOCATION

The proposed allocation method is elaborated by designing an appropriate SVM for the 25-bus equivalent system of south Malaysia as shown in Fig.1.

This system consists of 12 generators located at buses 14 to 25 respectively. They deliver power to 5 loads, through 37 lines located at buses 1, 2, 4, 5, and 6 respectively. The data for training is assembled using the daily load curve and performing load flow analysis for every hour of load demand. Similarly the target vector for the training is obtained from the proposed method using MNE. Input data (D) for developed SVM contains independent variables such as reactive loads (\(Q_1, Q_2, Q_4\) to \(Q_6\)), generator reactive power (\(Q_{14}\) to \(Q_{25}\)), load bus voltage magnitude (\(V_1\) to \(V_6\)), generator bus voltage magnitude (\(V_{14}\) to \(V_{25}\)), and the target/output parameter (T) which is reactive power transfer between generators and loads placed at bus 1 to 6. This is considered as 6 outputs of SVM for reactive power transfer allocation.

a. Training

After the input and target for training data is created, it can be made more efficient to scale (preprocessing) the network inputs and targets so that they always fall within a specified range. In this case the minimum and maximum value of input and output vectors is used to scale them in the range of \(-1\) and \(+1\). The training output data of SVM is implemented separately for each target in ascending sequence of generator like generator connected with bus 14 to 25 with the same training input data of one week load pattern. Next step is to tune the regularization parameter \(\gamma\) and Kernel parameter \(\sigma^2\) through experimentation. For low value of \(\gamma\), minimizing the complexity of model is emphasized, while for large value, a good fitting of the training data points is
stressed. Initially, the number of trials with different number of $\gamma$ keeping the $\sigma^2$ constant and vice versa is set. Then, the number of $\gamma$ is taken as 15 and the number of $\sigma^2$ as 2, resulting in reasonable accuracy of the output of the SVM with the target. Fig. 2 shows the performance of the training for the RBF Kernel function estimation of SVM for selected load at bus 1.

![Fig. 2. Training input and output data for load at bus 1 keeping $\gamma = 15$ and $\sigma^2 = 2$.](image)

The attractive mean square error in this case is equal to $1.0617 \times 10^{-6}$ which is due to the estimation by SVM and the training data points having similar characteristics.

b. Pre-Testing and Simulation

After the SVM has been trained using MATLAB, next step is to simulate the SVM. The entire sample data is used in pre testing. After simulation, the obtained result from the trained SVM is evaluated with a linear regression analysis. The regression analysis for the trained network that referred to contribution of all generators to load at bus 1 is shown in Fig. 3.

![Fig. 3. Regression analysis between the SVM output and the corresponding target keeping $\gamma = 15$ and $\sigma^2 = 2$.](image)

The SVM output is indicated with line having circles whereas the target is indicated by the solid line.

## 5. Result and Analysis

The case scenario is that for each hour the real and reactive power at each load is assumed to decrement by 5% from hour 1 to 168, from the nominal trained pattern. Besides it also assumed that all generators also decrease their production proportionally according to this variation in the load demands. This assumption is being made to ensure that all reactive power generation of generator at buses 14 to 25 varies in respond to the varying daily load patterns.

The allocation of reactive power to loads using proposed SVM on hours 33 out of 168 hours is presented in Table I along with the result obtained through MNE method in Table II.

### Table I

<table>
<thead>
<tr>
<th>Supplied by SVM Output</th>
<th>Load bus no.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gen-14</td>
<td>0.3367</td>
</tr>
<tr>
<td>Gen-15</td>
<td>0.401</td>
</tr>
<tr>
<td>Gen-16</td>
<td>0.579</td>
</tr>
<tr>
<td>Gen-17</td>
<td>0.5886</td>
</tr>
<tr>
<td>Gen-18</td>
<td>0.791</td>
</tr>
<tr>
<td>Gen-19</td>
<td>0.463</td>
</tr>
<tr>
<td>Gen-20</td>
<td>0.798</td>
</tr>
<tr>
<td>Gen-21</td>
<td>0.243</td>
</tr>
<tr>
<td>Gen-22</td>
<td>0.243</td>
</tr>
<tr>
<td>Gen-23</td>
<td>0.946</td>
</tr>
<tr>
<td>Gen-24</td>
<td>0.911</td>
</tr>
<tr>
<td>Gen-25</td>
<td>0.985</td>
</tr>
<tr>
<td>Total Load</td>
<td>7.290</td>
</tr>
<tr>
<td>Actual Load</td>
<td>7.6072</td>
</tr>
</tbody>
</table>

### Table II

<table>
<thead>
<tr>
<th>Supplied by Modified Nodal Equations Method</th>
<th>Load bus no.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gen-14</td>
<td>0.278</td>
</tr>
<tr>
<td>Gen-15</td>
<td>0.278</td>
</tr>
<tr>
<td>Gen-16</td>
<td>0.630</td>
</tr>
<tr>
<td>Gen-17</td>
<td>0.628</td>
</tr>
<tr>
<td>Gen-18</td>
<td>0.818</td>
</tr>
<tr>
<td>Gen-19</td>
<td>0.495</td>
</tr>
<tr>
<td>Gen-20</td>
<td>0.829</td>
</tr>
<tr>
<td>Gen-21</td>
<td>0.236</td>
</tr>
<tr>
<td>Gen-22</td>
<td>0.236</td>
</tr>
<tr>
<td>Gen-23</td>
<td>1.000</td>
</tr>
<tr>
<td>Gen-24</td>
<td>1.041</td>
</tr>
<tr>
<td>Gen-25</td>
<td>1.073</td>
</tr>
<tr>
<td>Total Load</td>
<td>7.607</td>
</tr>
<tr>
<td>Actual Load</td>
<td>7.6072</td>
</tr>
</tbody>
</table>

Note that the result obtained by the SVM output is compared well with the result of Modified nodal equations method. The contribution from all generators to a single load at bus 4 gives the largest difference i.e. 104.431 MVAr as compared to 106.5 MVAr of actual load. This may be due to that SVM needs optimal arrangement of input and output data for training. The mean square error of SVM output is very small which are less than $4.5209 \times 10^{-6}$. In this case, the RBF Kernel
function type with $\sigma^2 = 2$ is chosen as the parameter for the SVM. Moreover, this SVM simulation computes within 31 msec whereas the MNE method took 738 msec for the calculation of same reactive transfer power allocation. Therefore it can be concluded that the SVM is more efficient in terms of computation time. The load flow results for the test system are given in Tables III.

<table>
<thead>
<tr>
<th>Bus no.</th>
<th>Voltage Magnitude (p.u)</th>
<th>Voltage Angle (p.u)</th>
<th>Real Power (MW)</th>
<th>Reactive Power (MVAr)</th>
<th>Real Power (MW)</th>
<th>Reactive Power (MVAr)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1.0343</td>
<td>6.8164</td>
<td>0</td>
<td>0</td>
<td>16.482</td>
<td>7.6072</td>
</tr>
<tr>
<td>2</td>
<td>1.0347</td>
<td>5.8345</td>
<td>0</td>
<td>0</td>
<td>155.95</td>
<td>45.643</td>
</tr>
<tr>
<td>3</td>
<td>1.0371</td>
<td>6.1067</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>4</td>
<td>1.0303</td>
<td>6.5751</td>
<td>0</td>
<td>0</td>
<td>284</td>
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</tr>
<tr>
<td>5</td>
<td>1.0103</td>
<td>2.5915</td>
<td>0</td>
<td>0</td>
<td>126.79</td>
<td>38.036</td>
</tr>
<tr>
<td>6</td>
<td>1.0079</td>
<td>1.4797</td>
<td>0</td>
<td>0</td>
<td>164.82</td>
<td>53.251</td>
</tr>
<tr>
<td>7</td>
<td>1.0366</td>
<td>7.0992</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>8</td>
<td>1.0429</td>
<td>6.6848</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>9</td>
<td>1.0377</td>
<td>7.3929</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>10</td>
<td>1.0367</td>
<td>7.1172</td>
<td>0</td>
<td>0</td>
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</tr>
<tr>
<td>11</td>
<td>1.0428</td>
<td>6.809</td>
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<td>0</td>
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</tr>
<tr>
<td>12</td>
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<td>6.5913</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>13</td>
<td>1.0357</td>
<td>5.7555</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>14</td>
<td>1.05</td>
<td>8.9033</td>
<td>60.472</td>
<td>16.894</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>15</td>
<td>1.05</td>
<td>8.9033</td>
<td>60.472</td>
<td>16.894</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>16</td>
<td>1.05</td>
<td>9.88</td>
<td>71.622</td>
<td>25.77</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>17</td>
<td>1.05</td>
<td>9.784</td>
<td>69.543</td>
<td>25.652</td>
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<td>0</td>
</tr>
<tr>
<td>18</td>
<td>1.03</td>
<td>10.063</td>
<td>45.959</td>
<td>-6.234</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>19</td>
<td>1.05</td>
<td>9.317</td>
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It can be observed that the sum of the reactive power contributed by each generator obtained from modified nodal equations is in conformity with the actual power flow.

6. CONCLUSION

In this paper, a new modified nodal equations method has been developed to identify the reactive power transfer between generators and load. The robustness of the proposed method has been demonstrated on the 25-bus equivalent system of south Malaysia. The developed SVM adopts reactive power allocation outputs determined by MNE technique as an estimator to train the SVM. Better computation time is crucial to improve online application. For this the SVM output provides the results in a faster and convenient manner with very good accuracy. In future similar allocation method can be used for both bilateral contract model and power distribution in the network.

7. ACKNOWLEDGMENT

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8. REFERENCES