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Date	: 24.06.2015

MULTI-CONTINGENCY CASCADING ANALYSIS OF SMART GRID BASED ON SELF ORGANIZING MAP (SOM)

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A report submitted in partial fulfilment of the requirements for the degree of Bachelor of Electrical Engineering (Industrial Power)

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2015

I declare that this report entitle "Multi-Contingency Cascading Analysis Of Smart Grid Based On Self Organizing Map (SOM)" is the result of my own research except as cited in the references. The report has not been accepted for any degree and is not concurrently submitted in candidature of any other degree.

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Date : 24.06. 2015

To my beloved mother and father

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Not to forget, the understanding, endless love, prayers and moral support from my beloved parents, Mr Mat Yusof Bin Abu Bakar and Mrs Sharifah Binti Yahya, were deeply appreciated. To my family members, thank you for your persevering support and encouragement. Besides that, I also would like to express my heartily gratitude to my fellow friends. Last but not least, to all parties who was involved indirectly in helping me during making this thesis. That support although small, but it means a lot to me in order to make sure this thesis will be successful.

ABSTRACT

In the investigation of power grid security, the cascading failure in multi-contingency situations has been a test because of its topological unpredictability and computational expense. Both system investigations and burden positioning routines have their limits. In this project, in view of sorting toward Self Organizing Maps (SOM), incorporated methodology consolidating spatial feature (distance)-based grouping with electrical attributes (load) to evaluate the vulnerability and cascading impact of various part sets in the force lattice. Utilizing the grouping result from SOM, sets of overwhelming stacked beginning victimized people to perform assault conspires and asses the consequent falling impact of their failures, and this SOM-based approach viably distinguishes the more powerless sets of substations than those from the conventional burden positioning and other bunching strategies. As an issue, this new approach gives a productive and solid method to study the force framework failure conduct in falling impact of basic segment failure.

ABSTRAK

Dalam penyiasatan keselamatan grid kuasa, kegagalan melata dalam situasi berbilang luar jangka telah ujian kerana ketidaktentuan topologi dan perbelanjaan pengkomputeran. Kedua-dua penyiasatan sistem dan beban rutin kedudukan mempunyai had mereka. Dalam projek ini, memandangkan jenis arah Penganjur Peta sendiri (SOM), metodologi menyatukan ciri spatial (jarak) -berdasarkan kumpulan dengan sifat-sifat elektrik (beban) untuk menilai kelemahan dan melata kesan pelbagai set bahagian dalam kekisi daya diperbadankan. Dengan menggunakan keputusan kumpulan yang SOM, set hangat disusun awal mangsa orang untuk melakukan serangan berkomplot dan kesan jatuh yang berbangkit daripada kegagalan mereka, dan pendekatan berasaskan SOM-ini maju malah membezakan set lebih berdaya pencawang daripada yang dari kedudukan beban konvensional dan strategi pencawang lain. Sebagai satu isu, pendekatan baru ini memberikan satu kaedah yang produktif dan pepejal untuk mengkaji rangka kerja kuasa kegagalan kelakuan yang jatuh kesan kegagalan segmen asas.

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LIST OF ABBREVIATIONS

SOM	–	Self Organizing Map
PI	-	Performance Index
ANN	-	Artificial Neural Network

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CHAPTER 1

INTRODUCTION

1.1 Research Background

Power system are worked with the goal that over-burdens don't happen either progressively or under any measurably likely contingency. This is regularly called keeping up framework " security". Test system is outfitted with devices for dissecting possibilities in a programmed manner. Contingency can comprise of a few activities or components that is straightforward case for blackout of a solitary transmission line and intricate for blackout of single of a few lines, various generators, and the conclusion of typically open transmission line. The Power grid security is one of the huge perspectives, where the correct move needs to be made by the operational specialists for the unseen contingency. In this way the contingency investigation is key for the power grid security. The contingency positioning utilizing the execution list is a strategy for the line blackouts in a power grid, which positions the most noteworthy execution record line first and returns in a plummeting way focused around the computed PI for all the line blackouts. This serves to make the former move to keep the grid secure. In the present work the Newton Raphson burden stream strategy is utilized for the power grid contingency positioning for the line blackout focused around the active power and voltage performance index [1]. The positioning is given by considering the general execution record, which is the summation of Active power and voltage performance index.

The self organizing map is a standout between the most mainstream neural network models. A self organizing map (SOM) is a sort of artificial neural network (ANN) that is prepared utilizing unsupervised figuring out how to create a low-dimensional (ordinarily two-dimensional), discretized representation of the information space of the preparation examples, called a map. "Self Organizing" is on the grounds that no supervision is needed. SOMs learn all alone through unsupervised aggressive learning. "Maps" is because they attempt to map their weights to conform to the given input data [2] . The nodes in SOM network attempt to become like the inputs presented to them. Holding guideline "Features Maps" of the info information is a crucial standard of SOMs, and one of the things that makes them so important. Particularly, the topological connections between data information are saved when mapped to a SOM system. "Training" forms the guide utilizing info samples (a focused procedure, likewise called vector quantization), while "mapping" naturally orders another data vector.

Smart grid is system made through the blend of data engineering, correspondence innovation and electrical power framework. Smart grid is conveys electrical power to the shoppers utilizing two way computerized engineering. Monitors is the supply to the customers and estimations. Numerous nations and power markets are taking a gander at Smart Grid as progressive arrangements in conveying blend of upgraded qualities going from higher security, dependability and power quality, lower expense of conveyance, interest streamlining and vitality productivity. Smart grid arrangements empower utilities to build vitality profit and power dependability while permitting the clients to deal with the use and expenses through on going data trade. It affects all the parts of the power grid like generation, transmission and distribution [3].

A self organizing map is portrayed by the arrangement of a topographic map of the info designs in which the spatial areas (i.e. directions) of the neurons in the cross section are characteristic of inherent factual features contained in the info designs. The inspiration for the improvement of this model is because of the presence of topologically requested computational maps in the human mind. A computational map is characterized by an exhibit of neurons speaking to somewhat diversely tuned processors, which work on the tangible data motions in parallel. Hence, the neurons change information signals into a spot coded likelihood dispersion that speaks to the figured estimations of parameters by locales of most extreme relative movement inside the guide. The objective of adapting in the self organizing map is to cause distinctive parts of the system to react correspondingly to certain information designs. This is somewhat spurred by how visual, sound-related or other tangible data is taken care of in divided parts of the cerebral cortex in the human mind [4]. Schematically the Kohonen models are shown below:

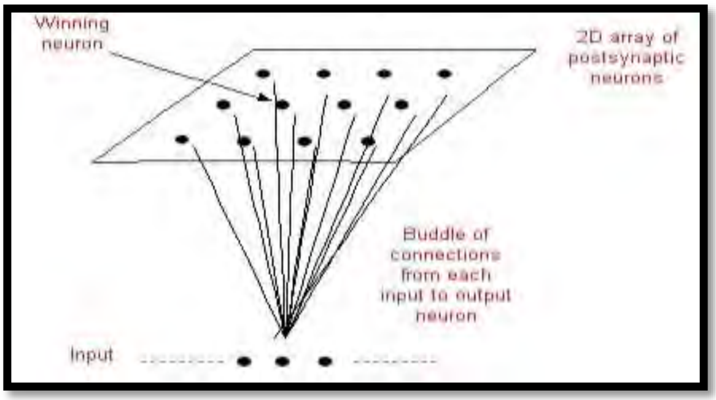


Figure 1.1 : Schematically of the Kohonen model [4].

1.2 Motivation

Nowadays, the power grid is a standout amongst the most basic base in cutting edge society. With a great many substations and transmission lines, the power grid is currently a complex grid comprises of numerous levels of territorial power sub grid whose group examples differ significantly crosswise over distinctive ranges. With this complex structure worked at diverse levels and by distinctive managers, the power grid are inexorably helpless against failures and face numerous security challenges. Among the difficulties to the power grid, vindictive assaults are attracting becoming consideration because of the expanding multifaceted nature of helplessness to shield. As the industry is moving towards the redesign of customary power grid to the most recent era of smart grid with more canny control from the communication system, it is additionally confronting the expanding dangers to keen smart grid security because of the heft of data and access looked for by the potential aggressors.

1.3 Problem Statement

Nowadays, there are many researchers study about design and concepts of self organizing maps in smart grid. The analysis also focus on the cascading failure analysis in multi-contingency scenarios has been a challenge due to its topological complexity and computational cost. The contingencies are chosen by computing a sort of seriousness indices known as Performance Indices (PI). These indices are ascertained utilizing the conventional power flow algorithms for individual possibilities in a logged off mode. In view of the qualities acquired the contingencies are positioned in a way where the most noteworthy estimation of PI is positioned first. The analysis is carried out beginning from the contingency that is positioned one and is proceeded till no severe contingencies are found. There are two sort of performance index which are of extraordinary utilize, these are active power performance index (PI_p) and reactive power performance index (PI_v). Hence, modern computers are furnished with possibility investigation programs which show the power system and are utilized to study blackout occasions and alarm the administrators of potential over-burdens and voltage infringement. The most troublesome methodological issue to adapt inside contingency investigation is the exactness of the strategy and the rate of arrangement of the model used.

1.4 Objectives

The objectives of this research are :

1) Define contingency cascading analysis for power system.
2) Utilize of ability Self Organizing Map (SOM) method using smaller and bigger data.
3) Apply Self Organizing Map (SOM) to contingency analysis.

1.5 Scope of work

Scope of these projects is only focus on multi-contingency cascading analysis of smart grid based on Self-Organizing Map (SOM). In this project, analysis and simulation there were using MATLAB software based SOM Toolbox to determine the analysis. The data mining from IEEE 14 Bus System and IEEE 57 Bus System will used for this project. U-matrix algorithm were used in order to find cluster in the nodes of the SOM.

CHAPTER 2

LITERATURE REVIEW

2.1 Theory and Basic Principles

2.1.1 Load Contingency Analysis

Contingency analysis is the investigation of the blackout of components, for example, transmission lines, transformers and generators, and examination of the ensuing impacts on line force streams and transport voltages of the remaining framework. It speaks to a vital device to study the impact of components blackouts in power framework security amid operation and arranging. Contingency alluding to unsettling influences, for example, transmission component blackouts or generator blackouts may cause sudden and expansive changes in both the setup and the condition of the framework [5]. Contingencies may bring about extreme infringement of the working imperatives. Thusly, getting ready for contingencies structures an essential part of secure operation.

Contingency investigation permits the framework to be worked protectively. The administrator normally needs to know whether the present operation of the framework is secure and what will happen if a specific blackout happens. Inexact models can be utilized as the DC burden stream as for megawatt streams. At the point when voltage is concern, full AC burden stream investigation is needed. The writing audits in contingency investigation gave data about numerous strategies that can be utilized to perform the contingency investigation. For look for of exactness, full AC burden stream examination is performed post every blackout utilizing the blackout reenactment to get post-blackout line streams and transport voltages. Operations staff must perceive which line or generator blackouts will result in force streams or voltages to go out of their breaking points. So as to anticipate the impacts of blackouts, contingency investigation system is utilized. Contingency investigation strategies demonstrate a solitary gear disappointment occasion, that is one line or one generator blackout, or various supplies disappointment occasions, that is two transmission lines, a transmission line and a generator, one after an alternate in arrangement until all dependable blackouts have been examined. For every blackout tried, the contingency examination system checks all force streams and voltage levels in the system against their individual breaking points [6].

Electric power designers utilize their judgment and past experience for selecting and examining extreme contingency. Thusly, the change of a contingency situating figuring which would rank contingencies based upon their relative reality is alluring. The possibilities can be situated based upon their trappings in light of line stacking or transport voltages. A blended pack of figuring are created which can be gathered into two social occasions. One is the execution file (PI) based framework which utilizes a wide system scalar execution rundown to assess the earnestness of every one case by finding out their PI values and situating them properly. The other is the screening framework which is concentrated around vague force stream answer for discard those non-basic contingencies. With the progress of modernized thinking, expert structures and cushy theory are proposed to gage the reality of distinctive contingency. In like manner reenacted neural frameworks procedures execution record (PI) have been proposed for contingency determination [7]. In this study contingencies are situated using a PI based system. Framework execution records are not special and obtain differing structures depending upon the parameters that are of most basics to the specialist. The most generally perceived sort of structure execution records give a measure of the deviation from assessed estimations of system variables, for instance, line streams, bus voltages and bus power infusions. The ranking method used in this paper is a fast and accurate method to rank the contingencies according to their severity on the power system. The ranking technique utilizes a system wide scalar PI to quantify the severity of each contingency with actually calculating the post contingency line flows and bus voltages using full AC load flow analysis. Contingencies are ranked in the order of their performance index values and processed starting with the most severe contingency at the top of the list proceeding down the ranking to the less severe ones [8]. The performance indices are calculated for contingency cases with real flow violations and voltage violations. The masking problem is successfully addressed by changing the exponent of the performance index from 2 to higher values. The post contingency line flows and bus voltages are obtained from the load flow solution after the application of the outage simulation. The exponent (m) of the performance index is changed in the range from 2 to 30 to avoid masking errors. Outages are then ranked on the basis of their corresponding performance indices. In this study the contingencies are ranked on the basis of line loading in equation 2.1 :

$$APLPI = \sum_{t=1}^{NL} W_{pi} \left(\frac{P_{tpc}}{P_{tLim}}\right)^{2\,m} \tag{2.1}$$

Where:

P_{tpc} :The post-contingency active power flow on line (i).

P_{tLim} :The active power flow limit on line (i).

W_{pi} :The weight factor of active power flow on line (i).

NL :Number of transmission lines.

m :Is a positive integer.

2.1.2 Smart Grid Network

The Smart Grid is the mix of electrical and digital technologies, information and communication which offices coordination methodology and framework to yield genuine measurable esteem over the power conveyance chain. It is a savvy future power grid that unites all supply, network and interest components through a correspondence grid. Brilliant network conveys power to purchasers utilizing two-way advanced innovation that empower the effective administration of shoppers, productive utilization of the grid to distinguish and remedy supply that is interest awkward nature [22]. Keen matrix arrangements empower utilities to expand vitality benefit and force dependability while permitting the clients to deal with the utilization and expenses through constant data trade. It affects all the segments of the power grid like generation, transmission and dispersion [9].

2.1.3 Self Organizing Maps (SOM)

The Self-Organizing Map is a standout between the most mainstream neural system models. A sorting toward oneself out guide (SOM) is a sort of simulated neural system (ANN) that is prepared utilizing unsupervised figuring out how to create a low-dimensional (ordinarily two-dimensional), discretized representation of the information space of the preparation examples, called a map. "Self Organizing" is on the grounds that no supervision is needed. SOMs learn all alone through unsupervised aggressive learning. "Maps" is on the grounds that they endeavor to guide their weights to fit in with the given info information. The hubs in a SOM system endeavor to wind up like the inputs displayed to them. Holding guideline "Features Maps" of the info information is a crucial standard of SOMs, and one of the things that makes them so important. Particularly, the topological connections between data information are saved when mapped to a SOM system. "Training" forms the guide utilizing info samples (a focused procedure, likewise called vector quantization), while "mapping" naturally orders another data vector [10]. A self-organizing map consists of components called nodes or neurons. Associated with each node is a weight vector of the same dimension as the input data vectors and a position in the map space. The usual arrangement of nodes is a two-dimensional regular spacing in a hexagonal or rectangular grid. The self-organizing map describes a mapping from a higher-dimensional input space to a lower-dimensional map space.

The structure of a SOM is genuinely basic, and is best comprehended with the utilization of an outline in figure 1 is a 4x4 SOM organize (4 hubs down, 4 hubs over). It is not entirely obvious this structure as being trifling, however there are a couple of key things to take note. In the first place, each one guide hub is joined with each one info hub. For this little 4x4 hub organize, that is 4x4x3=48 associations. Also, perceive that guide hubs are not joined with one another. The hubs are composed in this way, as a 2- D network makes it simple to picture the results. This representation is additionally valuable when the SOM calculation is utilized. In this setup, each one guide hub has an exceptional direction. This makes it simple to reference a hub in the system, and to compute the separations between hubs. Due to the associations just to the information hubs, the guide hubs are unaware in respect to what values their neighbors have. A guide hub will just redesign its weights (clarified next) focused around what the data vector lets it know [11].

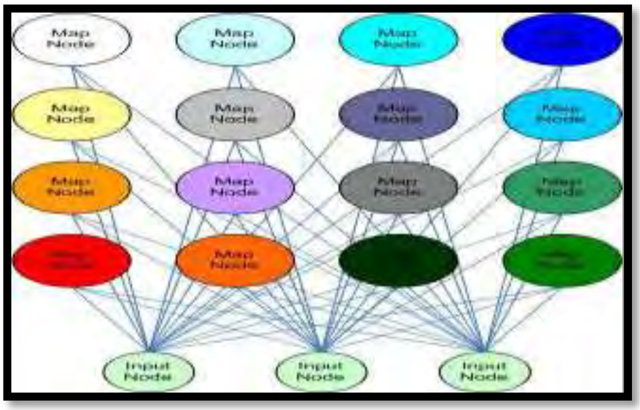


Figure 2.1: The structure of a SOM [11].

While it is characteristic to consider this sort of system structure as identified with feed forward systems where the hubs are pictured as being joined, this kind of structural planning is in a general sense diverse in plan and inspiration. Helpful augmentations incorporate utilizing Toroidal Grids where inverse edges are joined and utilizing extensive quantities of hubs. It has been demonstrated that while self organizing maps with a little number of hubs carry on in a manner that is like K-means, bigger organizing toward oneself maps adjust information in a manner that is on a very basic level topological in character. It is likewise basic to utilize the U-Matrix. The U-Matrix estimation of a specific hub is the normal separation between the hub and its closest neighbors. In a square framework, case in point, we should seriously think about the closest 4 or 8 hubs (the Von Neumann and Moore neighborhoods, separately), or six hubs in a hexagonal matrix. Extensive SOM show rising properties. In maps comprising of a large number of hubs, it is conceivable to perform bunch operations on the guide itself [11].

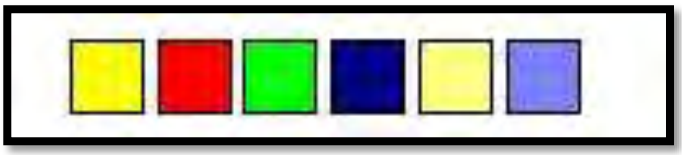


Figure 2.2: Colors are represented in 3D [11].

The principal piece of a SOM is the information. Above are a few illustrations of 3 dimensional information which are normally utilized when trying different things with SOMs. Here the colors are spoken to in three measurements (red, blue, and green.) The thought of the self organizing maps is to extend the n-dimensional information (here it would be shades and would be 3 measurements) into something that be better seen outwardly (for this situation it would be a 2 dimensional picture map). For this situation one would expect the dim blue and the grey hairs to wind up close to one another on a decent guide and yellow near both the red and the green [11].

The second segment to SOMs are the weight vectors. Each one weight vector has two parts to them which I have here endeavored to show in the picture beneath. The principal piece of a weight vector is its information. This is of the same measurements as the example vectors and the second piece of a weight vector is its common area. The fortunate thing about colors is that the information can be indicated by showing the color, so for this situation the shade is the information, and the area is the x, y position of the pixel on the screen [12].

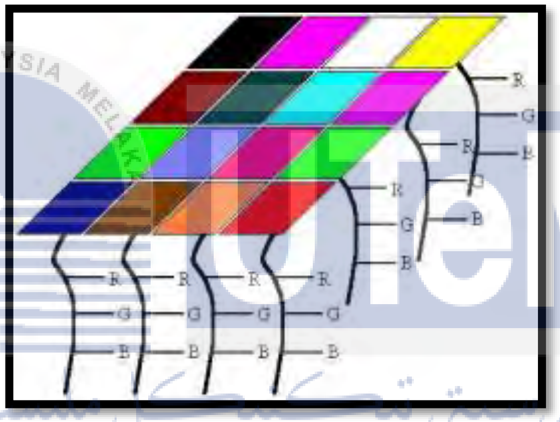


Figure 2.3: 2D array of weight vector [12].

In this case, to show what a 2D cluster of weight vectors would look like. This picture is a skewed perspective of a matrix where you have the n-dimensional exhibit for each one weight and each one weight has its own particular extraordinary area in the lattice. Weight vectors don't essentially must be masterminded in 2 measurements, a considerable measure of work has been carried out utilizing SOMs of 1 measurement, yet the information a piece of the weight must be of the same measurements as the example vectors. Weights are in some cases alluded to as neurons since SOMs are really neural systems [12].

Utilizing the bunching result from SOM, we pick sets of overwhelming stacked beginning victimized people to perform assault conspires and assess the consequent falling impact of their disappointments, and this SOM-based approach viably distinguishes the more defenseless sets of substations than those from the customary burden positioning and other grouping strategies. As an issue, this new approach gives a productive and solid method to study the force framework disappointment conduct in falling of Kohonen's self organizing map(SOM) is an unique scientific model of topographic mapping from the (visual) sensors to the cerebral cortex. Demonstrating and dissecting the mapping are paramount to seeing how the cerebrum sees, encodes, perceives and forms the examples it gets and therefore, if to a degree in a roundabout way, are valuable to machine-based pattern gratitude [13].

Calculate the BMU in equation 2.2 :

$$Distance\ From\ Input^2 = \sum_{i=0}^{i=n}(I_i - W_i)^2 \tag{2.2}$$

$Where$:

$I = current\ input\ vector$

$W = node's\ weight\ vector$

$n = number\ of\ weights$

Radius of the neighborhood in equation 2.3:

$$\sigma\ (t) = \sigma_0 e^{\left(-\frac{t}{\lambda}\right)} \tag{2.3}$$

$Where$

$t = current\ iteration$

$\lambda = time\ constant$

$\sigma_0 = radius\ of\ the\ map$

Time constant in equation 2.4:

$$\lambda = number\ of\ iterations/map\ radius \tag{2.4}$$

New weight of a node in equation 2.5:

$$W(t+1) = W(t) + \theta(t)L(t)\big(I(t) - W(t)\big) \tag{2.5}$$

Learning rate in equation 2.6:

$$L(t) = L_0 e^{\left(-\frac{t}{\lambda}\right)} \tag{2.6}$$

Distance From Best Matching Unit (BMU) in equation 2.7:

$$\theta(t) = e^{\{-distFromBMU^2/2\sigma^2(t)\}} \tag{2.7}$$

There are a few things to note about these equations. Mathematical equation 2.2 is just the Euclidean distance formula, squared. It is squared on the grounds that we are not concerned with the genuine numerical separation from the data. We recently require an uniform scale to contrast every hub with the data vector. This comparison gives that, taking out the requirement for a computationally lavish square root operation for each hub in the system. Mathematical equations 2.3 and 2.6 use exponential rot. At t=0 they are at their max. As t (the current cycle number) expands, they approach zero. In equation 2.3, the span should to begin as the range of the grid, and methodology zero, at which time the sweep is essentially the BMU hub [13].

Equation 2.4 is practically self-assertive. Any fixed value can be picked. This gives a decent esteem, however, as it depends specifically on the guide size and the quantity of emphases to perform [13].

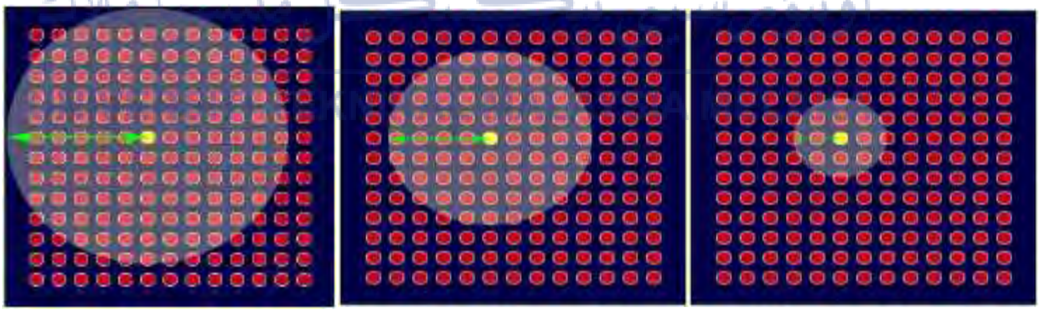


Figure 2.4: The map size and the number of iterations to perform [13].

Equation 2.5 is the principle learning capacity. W(t+1) is the new "taught" weight estimation of the given hub. About whether, this mathematical statement basically makes a given hub weight more like the right now chose information vector, I. A hub that is altogether different from the current info vector will take in more than a hub very much alike to the current data vector. The distinction between the hub weight and the information vector are then scaled by the current learning rate of the SOM, and by Θ(t). Mathematical equation 2.7, is utilized to make hubs closer to the BMU take in more than hubs on the edge of the current neighborhood sweep. Hubs outside of the nine area sweep are skipped totally [13].

2.1.4 SOM Algorithm

I. Size and Shape

In the original SOM, the number of neurons and topological relations are predetermined from the start. There are four main value which need to be selected: number of neurons, map grid dimension, map lattice and shape.

The number of neurons should be selected as big as possible, with the neighborhood size controlling the smoothness and generalization of the mapping. It will not become a hitch even number of neurons are exceeding the number of input vectors, if the neighborhood size are determine properly. However, as the map size increases up to several thousand of neurons the training phase becomes impractical and computationally heavy for most application.

If possible, the shape of the map grid should correspond to the shape of the data manifold. Therefore, toroidal and cylindrical shapes only take place if known that the data is circular. For default shaped map sheet, it is recommended that side length along one dimension is longer than the others, (e.g. : msize = [15 10]) so that the map can orientate itself properly. It is also possible to use the eigenvalues of the training data set as guideline in setting the map grids side lengths [20].

Hexagonal lattice are more preferable because all six sides of hexagon will interact with all six neighbors of a neurons at the same distance. This will allow smoother and cleaner maps.

II. Initialization

Before the training , initial values are preset for the prototype vectors. The SOM is very robust with respect to the initialization, but properly archive that allow the algorithm to converge faster to form a solution. Three of initialization procedures used:

- Random initialization, where the weight vectors are initialized with small random values
- Sample initialization, where the weight vectors are initialized with random samples drawn from the input data set.
- Linear initialization, where the weight vectors are initialized in an orderly fashion along the linear subspace spanned by the two principal eigenvectors of the input data set. The eigenvalues can be calculated using Gram-Schmidt procedure.

In SOM Toolbox it is employing random and linear initialization. Random initialization is done by taking randomly values from the d-dimensional cube definedby the maximum and minimum values of the variables. Linear initialized is done by selecting a mesh point from the d-dimensional minimum-maximum cube of the training data. The axis of the mesh eigenvectors corresponding to the m greatest eigenvalues of the training data (m referred as the map grid dimension). Notice that the shape (e.g. toroidal) of the map is not taken into account in initialization and it is constantly presumed to be a sheet.

2.1.5 SOM Visualization

I. U-Matrix

The U-matrix or unified distance matrix that visualizes the distance between adjacent units in the SOM. Instead of the color representing the value of the unit for a particular variable, we instead showed the average distance of that unit to other units. The U-Matrix is an important clue when determine how many natural clusters the SOM is covering.

The U-Matrix visualizes distances between neighboring map units, thus shows the cluster structure of the map : high values of the U-matrix indicates the cluster border, uniform areas of low values indicates cluster themselves. Each component plane shows the values of one variable in each map unit.

2.2 Review of Previous Relates Works

2.2.1 Clustering of Self Organizing Map (SOM)

Clustering data is a substitute extraordinary accommodation for neural system and this strategy incorporates gathering data by likeness. Case in point, Data mining by distributing data into related subsets. For clustering issues, the self organizing map (SOM) is the most generally used framework, after the framework has been readied, there are various visualization gadgets that can be used to break down the resulting groups. The clustering is carried out using a two-level approach, where the data set is at first bunched using the SOM, and after that, the SOM is clustered. The most discriminating benefit of this system is that computational trouble decreases widely, making it possible to cluster far reaching data sets and to consider a couple of unique preprocessing frameworks in a confined time. Normally, the procedure is considerable simply if the groups found using the SOM are similar to those of the first data. In the trials, a connection between the results of quick bunching of data and grouping of the model vectors of the SOM is performed, and the correspondence is found to be satisfactory [14].

2.2.2 Topological analysis of cascading failures

The power grid system are unprotected against distinctive strikes which may provoke cascading failures. Genuine cascading failures can bring about gigantic scale power outage and neutralizing them is acknowledged to be one of the best troubles in force framework. In this paper, cascading failures using the Bay Area power grid data. Two topology based models, which portray the importance of trouble and the reaction of the framework upon substation failures or over-troubling. Usually, it is much of the time acknowledged that the attacker will pound down the center (i.e. substation) with the most hoisted trouble, which addresses the strongest ambush system. In any case, that the ampleness of the routine trouble based attack procedure varies under unique framework models. Especially, the load based system is not the strongest strike in the framework show that expect the over-trouble substations completely disregard to limit. Under an interchange framework show in which the over-trouble substations still limit however with reduced capability in energy movement, ambushing the center with the high load can bring about amazing falling disillusionment. In the most hindering plausibility, striking a singular center with the second most astonishing load can achieve 44% loss of framework efficiency [15].

2.2.3 Self organized formation of topologically correct feature maps.

This work contains a hypothetical study and machine reenactments of an self organizing maps (SOM). The chief exposure is that in a fundamental arrangement of adaptable physical parts which gets signals from a vital event space, the sign representations are thus mapped onto a set of yield responses in such a course, to the point that the responses secure the same topological demand as that of the crucial events. As it were, a rule has been observed which supports the modified course of action of topologically right maps of peculiarities of perceivable events. The key planning to oneself system is an one or two-dimensional show of changing units taking after an arrangement of edge reason units, and depicted by short-augment sidelong enter between neighboring units. A couple of sorts of machine recreations are used to demonstrate the asking for procedure and furthermore the conditions under which it falls level [16].

2.3 Summary and Discussion of The Review

The SOM model is neurobiological spurred and it catches the imperative features contained in an information space of investment. The SOM known as a vector quantize. It upholds the type of realizing which is called unsupervised as in no target data is given with the presentation of the information. This paper proposes a topological strategy to analyse the weakness of subsets of substations in power grids focused around SOM grouping. While the physical attributes is considered as the premise in the assessment of power grid security, partner falling investigation with spatial feature based grouping demonstrates that the consolidated methodology has the capacity place the more discriminating segments in a huge scale power grid than customary strategies, giving an effective device to the contingency analysis. In our methodology, the potential victimized people are handled by the hearty SOM bunching with the goal that the competitors of inquiry are refined to a restricted reach, which altogether diminishes the computational expense while keeping the capacity to distinguish the absolute most helpless sets or assault conspires in the framework. This methodology shows better execution for cascading analysis in correlation to the conventional burden positioning based and the K-means based grouping technique, and the result will give astute data to choice help and power grid defensive system.

Therefore it will be critical to go beyond the topological analysis and consider the physical laws of the power systems. One possible extension on this is to integrate our approach with the extended topological model as discussed to analyse how our proposed method will perform with the consideration of several key features in power flow analysis. Furthermore, we can enhance our falling model by presenting overcurrent transfers and era inclining to surmised power grid failure practices. Finally, critical temporal features during the procedure of cascading can also be analysed, so that we can simulate different strategies with limited strength and resource to optimize defence mechanism against smart grid attacks.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Principles of the methods or techniques used in the previous work

Previous research shows analysis and simulation there were using MATLAB software to determine the analysis. The analysis not only focus on power grid security, the cascading failure analysis in multi-contingency scenarios has been a challenge due to its topological complexity and computational cost. Both network analysis and load ranking methods have their own limitations. From the analysis, based on self-organizing map (SOM), integrated approach combining spatial feature (distance)-based clustering with electrical characteristics (load) are proposed to assess the vulnerability and cascading effect of multiple component sets in the power grid.

3.2 Selected Methodology

For first phase, only study about literature review on multi-contingency cascading analysis of smart grid based on self organizing map (SOM). Starting to understand about objectives and scopes of this project. Secondly, designing and hence simulation study about load contingency analysis using self organizing map (SOM). Self organizing map (SOM) parameter setup will produce different clustering results in different experiments, the power factor curve proves that this small sampling will be able to identify some more vulnerable victim sets, according to our cascading analysis model. For self organizing map (SOM) performances, access the performance of a simple SOM-based attack where the size of SOM neurons is 2 2, namely 4 victim nodes are chosen in the initial attack [17].

Based on performance comparison, in the following part, two different approaches are compared for the initialization of the SOM weights. For both linear and random initialization, a few independent experiments are performed to compare the strongest attack schemes found in each type.

Next phase, only focus on analysis of the design this project. The outputs of the simulation being observe and analyze. The challenges of multi-contingency analysis for smart grid attacks can be concluded in the following perspectives that is the restricted scalability of many N-k contingency analyses which are validated mostly on relatively small power system benchmarks. Then, the limited knowledge of attackers on the complex dynamics in real-time power systems, in contrast to the power system managers, that restricts their strength in modeling the power system and the estimation of the impact of their attacks.

Based on theoretical, the best value of Quantization error must nearly „0‟, Topographic error also must nearly „0‟ and Training time must be „5‟ and below. The recreation of SOM programming comprises of the mix between the different normalization methods ($'var','range','\log' \; or \; 'logistic'$) and the optimum number of neurons. The $'var'$ data input will normalize the variance variable to unity and the means to zero. For the $'range'$ input data will scale the variable values between zero and one. The $'\log'$ is a logarithmic change and the $'logistic'$ softmax change scales all feasible values somewhere around zero and one[18].

3.3 Description of the work to be undertaken

The flowchart as shown in Figure 3.1 describes all the activities or tasks to be done at each stage of the project. It is important to make sure the project complete at the specific time.

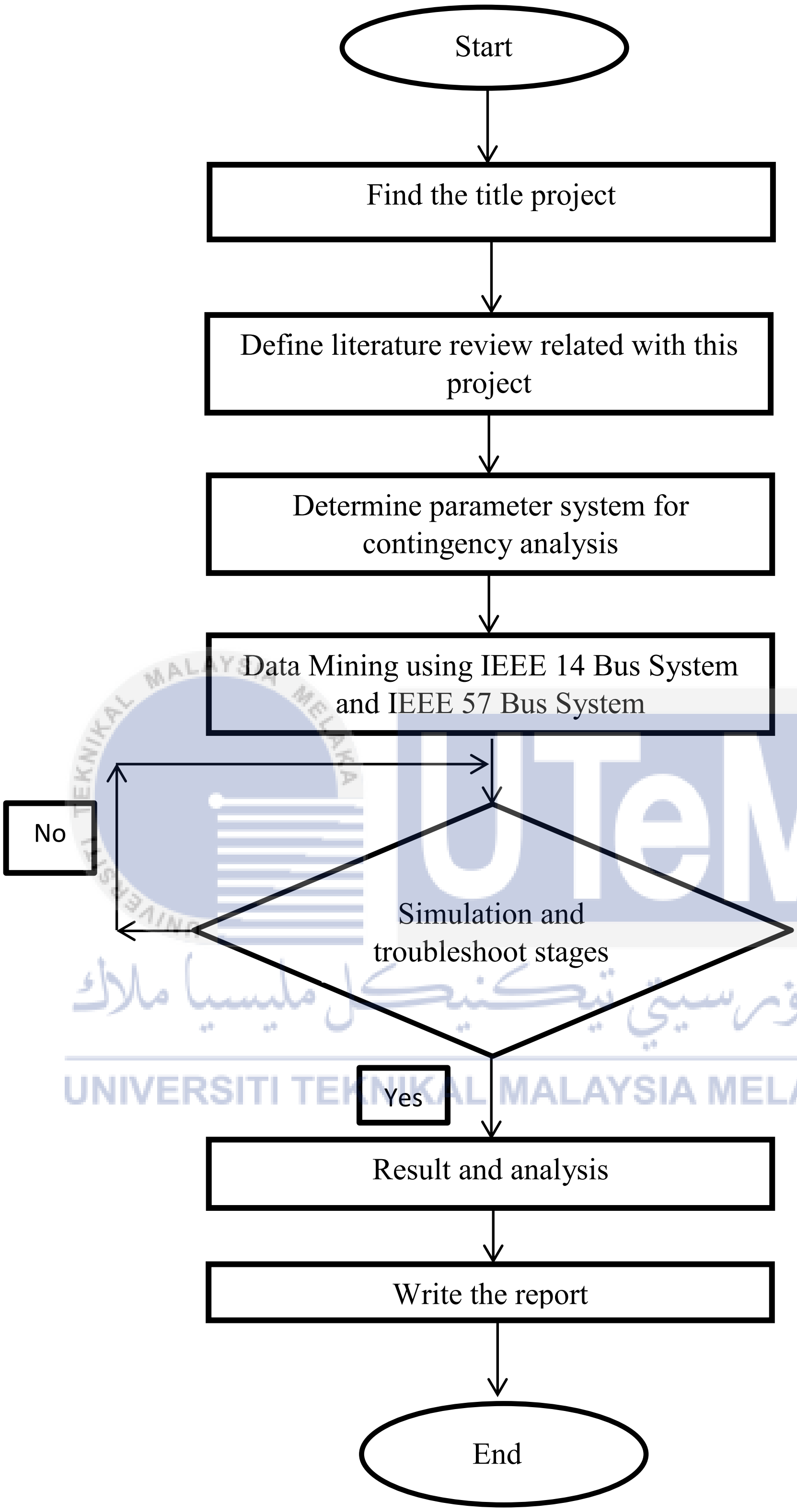


Figure 3.1: Flow Chart of Methodology

3.4 Project Gantt chart and key milestones

3.4.1 Gantt chart

Table 3.2: Table of Project Gantt chart

Tasks	September	October	November	December	March	April	May	June
Search and Register for Supervisor and Project Title								
Literature Review								
Ready PSM I Report								
Send PSM I Report								
Seminar and Alter of Commented Report								
Send altered PSM I Report								
Software Development								
Experiment								
Data mining from IEEE paper								
Analysis of result								
Ready PSM II Report								
Send PSM II Report								
Seminar and Alter of Commented Report								
Send Final Report								

3.4.1 Key Milestones

Table 3.2: Table of Project Key Milestones

Project Movement	Period
Assortment of Article and Literature Review	September 2014
Determine contingency parameter	October 2014
Prepare PSM I Report	October 2014
Send PSM I Report	November 2014
First seminar	November 2014
Data mining from IEEE paper	December 2014 – March 2015
Simulation stage	April 2015 – May 2015
Analysis of result	April 2015 – May 2015
Prepare final report	May 2015
Send final report	June 2015
Final seminar	June 2015

3.5 Data Organization

Data are divided into two main groups the IEEE 14 Bus and 57 Bus System parts. For this data, IEEE paper will use for load data 14 Bus System and 57 Bus System [21]. The parameters will use magnitude, angle, active power, reactive power and apparent power. For IEEE 14 Bus System, load data bus can be classify that B1, B2, B3, B6 and B8 have generator and carry high power bus that is B4, B5 and B9. This load bus also can be categorize as important bus. Another bus will assume as less important bus that is B7, B10, B11, B12, B13 and B14. For IEEE 57 Bus System, load data bus can be classify that B1, B2, B3, B6, B8, B9 and B12 have generator and carry high power bus that is B16 and B17. This load bus also can be categorize as important bus. Another bus will assume as less important bus.

3.5.1 IEEE 14 Bus System and IEEE 57 Bus System

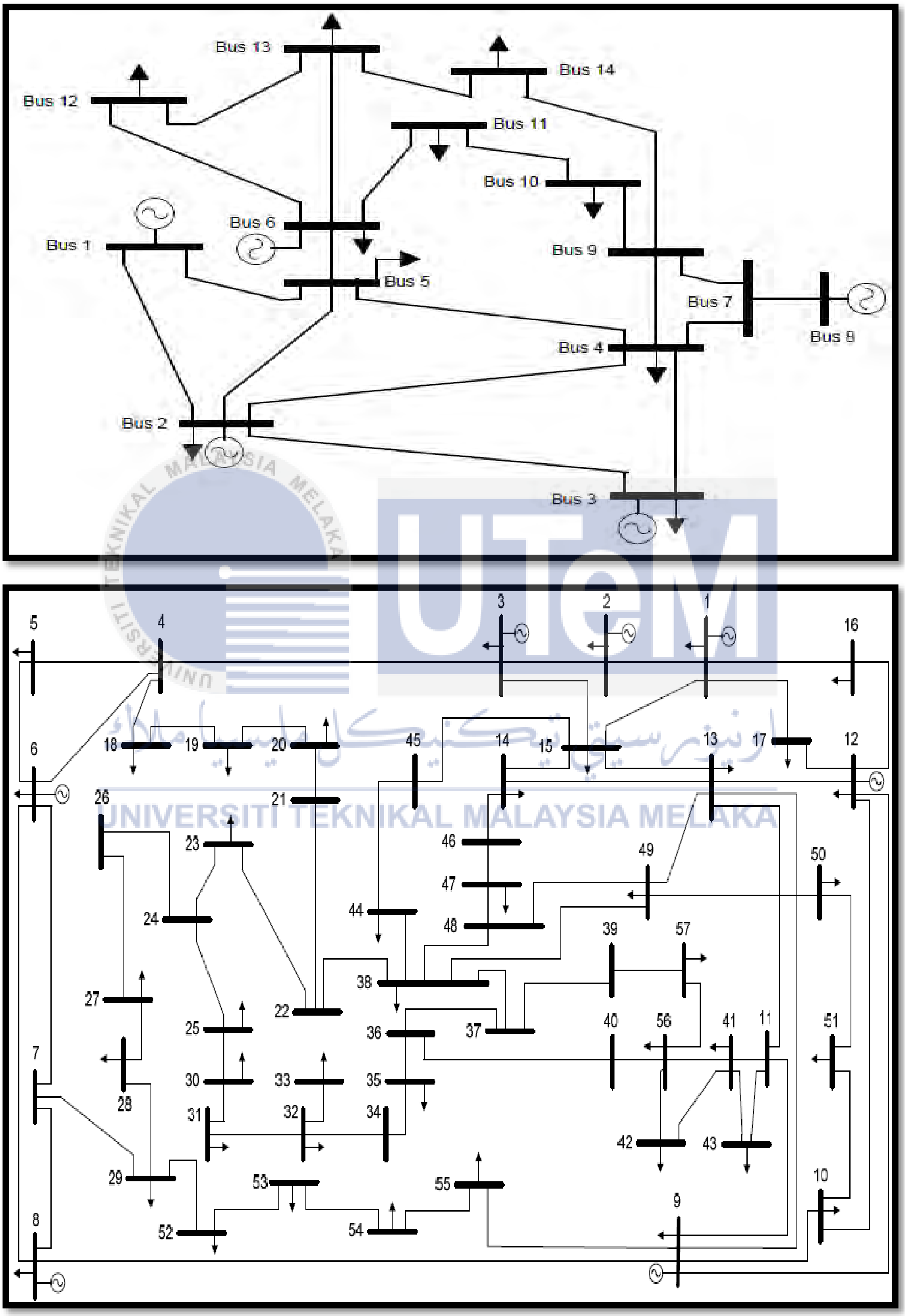
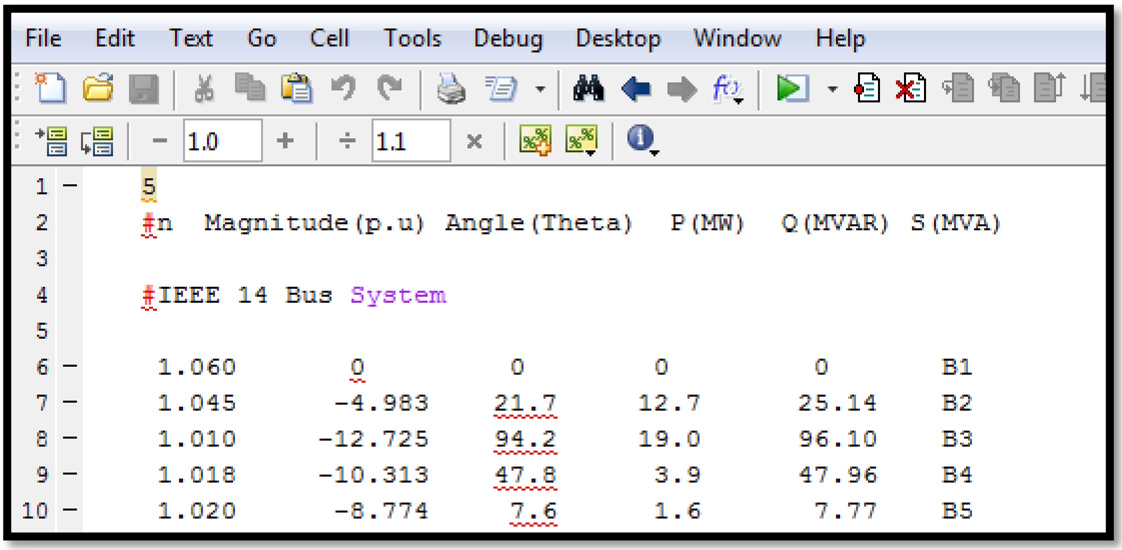


Figure 3.3 : IEEE 14 Bus and 57 Bus System [21]

Figure 3.4 : Load Data IEEE 14 Bus System [21]

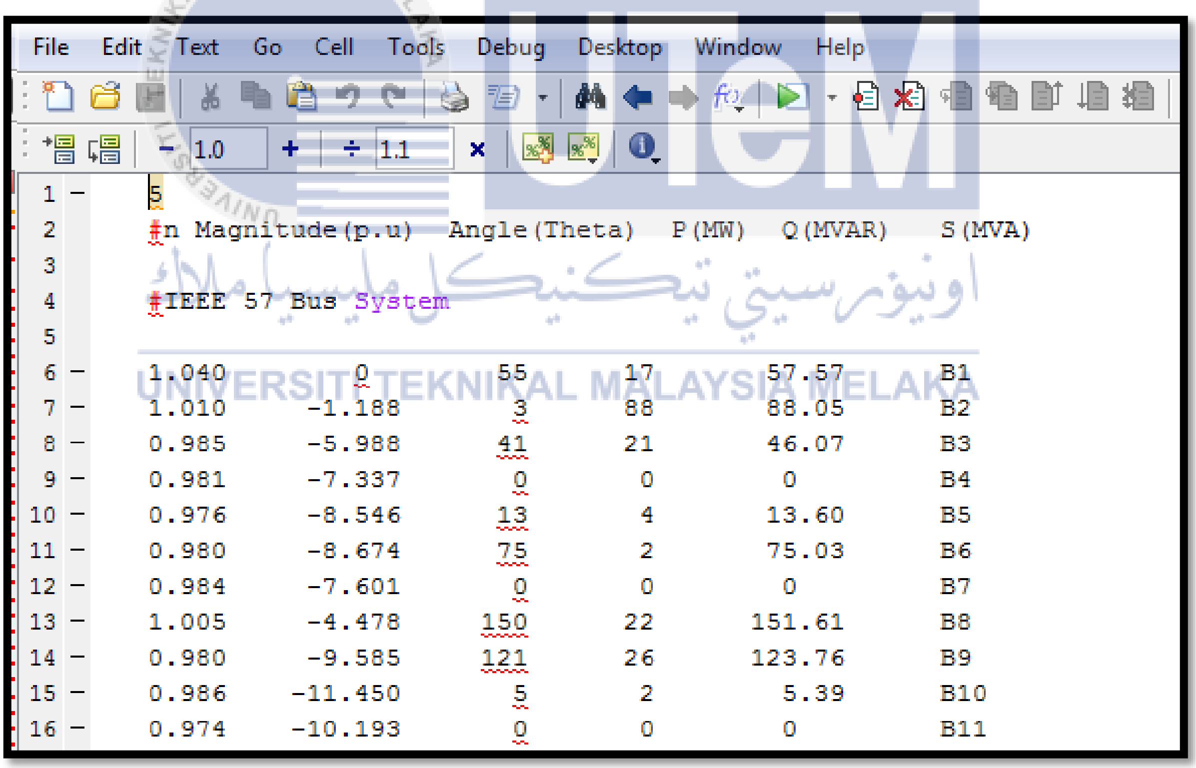


```
5
#n  Magnitude(p.u) Angle(Theta)  P(MW)  Q(MVAR) S(MVA)

#IEEE 14 Bus System

 1.060        0        0       0        0       B1
 1.045    -4.983     21.7    12.7    25.14      B2
 1.010   -12.725     94.2    19.0    96.10      B3
 1.018   -10.313     47.8     3.9    47.96      B4
 1.020    -8.774      7.6     1.6     7.77      B5
```

Figure 3.5 : Load Data IEEE 57 Bus System [21]



```
5
#n Magnitude(p.u)  Angle(Theta)  P(MW)  Q(MVAR)   S(MVA)

#IEEE 57 Bus System

1.040       0        55     17    57.57     B1
1.010    -1.188       3     88    88.05     B2
0.985    -5.988      41     21    46.07     B3
0.981    -7.337       0      0     0        B4
0.976    -8.546      13      4    13.60     B5
0.980    -8.674      75      2    75.03     B6
0.984    -7.601       0      0     0        B7
1.005    -4.478     150     22   151.61     B8
0.980    -9.585     121     26   123.76     B9
0.986   -11.450       5      2     5.39     B10
0.974   -10.193       0      0     0        B11
```


Other data, refer to Appendix B1 and B2 (pages 51 and 52).

CHAPTER 4

RESULT AND ANALYSIS

4.0 Introduction

In this Section after implementation of MATLAB commands function and numerical features input SOM performances are analyzed in Section 4.1 and best combination are continue with mapping process through Unified Matrix (U-Matrix). The results are presented in next Section 4.1.2 for detailed. From the analysis, based on the Self Organizing Map, U-matrix is shown and easy to see that the top three rows of the SOM form a very clear cluster. For this results, IEEE paper will use for load data 14 Bus System and 57 Bus System [21].

4.1 SOM Classification Performances

Performance evaluation for each 14 Bus and 57 Bus system in terms of topographic, quantization error and training time are detailed in this subsection.

4.1.1 IEEE 14 Bus System

In this part, further analysis on SOM Classification performance especially 14 Bus system are presented and explained. Hexagonal form of topology selected for this classification.

Refer Table 4.1, topographic error zero for 120 neurons until 200 neurons. However, for 200 neurons shown zero quantization error compare to 120 neurons until 180 neurons. Time for training took for 120 neurons until 200 neurons are the same that is zero seconds. Observed that the value of that the value of quantization error and topographic error is achieve zero. The 200 neurons is the best selection for „*log*" normalization method according to topographic and quantization error value.

Table 4.1 : SOM Results Using Hexagonal Topology with „*log*" Normalization Method (IEEE 14 Bus System)

No. of Neurons	Classification Result			
	Map Size	Quantization Error	Topographic Error	Training Time (sec)
100	[17, 6]	0.055	0.071	0
120	[20, 6]	0.017	0.000	0
140	[20, 7]	0.010	0.000	0
160	[23, 7]	0.004	0.000	0
180	[26, 7]	0.001	0.000	0
200	[25, 8]	0.000	0.000	0
220	[28, 8]	0.000	0.143	0
240	[27, 9]	0.000	0.143	1
260	[29, 9]	0.000	0.286	1
280	[31, 9]	0.000	0.143	1
300	[30, 10]	0.000	0.143	1
320	[32, 10]	0.000	0.071	1
340	[34, 10]	0.000	0.071	1
360	[36, 10]	0.000	0.000	1
380	[35, 11]	0.000	0.143	2
400	[36, 11]	0.000	0.143	2

If refers to Table 4.2, topographic error value achieve zero during 100 until 220 neurons. But for quantization error, 180 until 220 neurons produce zero quantization error compare to 100 until 160 neurons even though the training it took zero second. Therefore, 180 until 220 neurons is the best choice in „*logistic*" nomalization method.

Table 4.2 : SOM Results Using Hexagonal Topology with „*logistic*" Normalization Method (IEEE 14 Bus System)

No. of Neurons	Classification Result			
	Map Size	Quantization Error	Topographic Error	Training Time (sec)
100	[14, 7]	0.008	0.000	0
120	[15, 8]	0.005	0.000	0
140	[16, 9]	0.002	0.000	0
160	[18, 9]	0.002	0.000	0
180	[18, 10]	0.000	0.000	0
200	[20, 10]	0.000	0.000	0
220	[20, 11]	0.000	0.000	0
240	[22, 11]	0.000	0.071	1
260	[22, 12]	0.000	0.071	1
280	[23, 12]	0.000	0.143	1
300	[23, 13]	0.000	0.071	1
320	[25, 13]	0.000	0.000	1
340	[26, 13]	0.000	0.071	1
360	[26, 14]	0.000	0.000	2
380	[27, 14]	0.000	0.143	2
400	[29, 14]	0.000	0.071	2

As shown in Table 4.3, topographic achieve zero by using 100, 140, 160, 180, 200, 220, 240, 280, 300, 360, and 380 neurons. For 200 and 220 neurons, the quantization error achieve value zero and the training time is zero second. Classification with 200 and 220 neurons is prefer to be the best for $'range'$ nomalization.

Table 4.3 : SOM Results Using Hexagonal Topology with $'range'$ Normalization Method (IEEE 14 Bus System)

No. of Neurons	Classification Result			
	Map Size	Quantization Error	Topographic Error	Training Time (sec)
100	[14, 7]	0.011	0.000	0
120	[15, 8]	0.004	0.071	0
140	[18, 8]	0.002	0.000	0
160	[18, 9]	0.001	0.000	0
180	[18, 10]	0.001	0.000	0
200	[20, 10]	0.000	0.000	0
220	[20, 11]	0.000	0.000	0
240	[22, 11]	0.000	0.000	1
260	[24, 11]	0.000	0.143	1
280	[23, 12]	0.000	0.000	1
300	[25, 12]	0.000	0.000	1
320	[25, 13]	0.000	0.071	1
340	[26, 13]	0.000	0.071	1
360	[28, 13]	0.000	0.000	2
380	[27, 14]	0.000	0.000	2
400	[29, 14]	0.000	0.071	2

For 14 Bus System data classification with regard of $'var'$ normalization method as in Table 4.4 again 200 neurons are portraying the best in term of quantization error and normalization error even though 220 neurons is the least in term of quantization error and normalization error because mapping result display not good at U Matrix. Both topographic and quantization values are 0.001 and zero with training time is also zero second. Value of 200 neurons again selected for $'var'$ normalization.

Table 4.4 : SOM Results Using Hexagonal Topology with $'var'$ Normalization Method (IEEE 14 Bus System)

No. of Neurons	Classification Result			
	Map Size	Quantization Error	Topographic Error	Training Time (sec)
100	[14, 7]	0.036	0.000	0
120	[15, 8]	0.016	0.000	0
140	[18, 8]	0.013	0.000	0
160	[18, 9]	0.004	0.000	0
180	[20, 9]	0.002	0.000	0
200	[20, 10]	0.001	0.000	0
220	[22, 10]	0.000	0.000	0
240	[22, 11]	0.000	0.000	1
260	[24, 11]	0.000	0.000	1
280	[23, 12]	0.000	0.071	1
300	[25, 12]	0.000	0.071	1
320	[25, 13]	0.000	0.071	1
340	[26, 13]	0.000	0.071	1
360	[28, 13]	0.000	0.000	1
380	[27, 14]	0.000	0.071	2
400	[29, 14]	0.000	0.000	2

In Table 4.7, best neurons value with different normalization method according to their SOM Classification performance are listed and detailed. Observed in Table 4.7 all log , $logistic$, $range$ and var method produce zero value in topographic error. If we comparing based on quantization error only var method not produce zero value that is 0.001. All selected combination are finished on their phase in zero second, proved that this value is considerably good and satisfactory. From the performance evaluation, neurons value at 180, 200 and 220 have the ability to produced good classification result. All listed neurons value in Table 4.5 is visualized using U Matrix in Section 4.5.2.

Table 4.5 : Results Summary of Classification Performance for Different Method of Normalization for 14 Bus System

Normalization Method	No. of Neurons	Map Size	Quantization Error	Topographic Error	Training Time (sec)
log	200	[25, 8]	0.000	0.000	0
$logistic$	180	[18, 10]	0.000	0.000	0
	200	[20, 10]	0.000	0.000	0
	220	[20, 11]	0.000	0.000	0
$range$	200	[20, 10]	0.000	0.000	0
	220	[20, 11]	0.000	0.000	0
var	200	[20, 10]	0.001	0.000	0

4.1.2 IEEE 57 Bus System

In this part, further analysis on SOM Classification performance especially for 14 Bus System are presented and explained. Hexagonal form of topology selected for this classification.

According to Table 4.6, topographic error produced zero by using 340 value of neurons. Quantization error value reaching near zero (0.025) during 340 neurons. For 100 until 400 neurons with zero of training time consider to be fast and fine. As a result, 340 neurons is preferred value of neurons for „*log*" method.

Table 4.6 : SOM Results Using Hexagonal Topology with „*log*" Normalization Method (IEEE 57 Bus System)

No. of Neurons	Classification Result			
	Map Size	Quantization Error	Topographic Error	Training Time (sec)
100	[20, 5]	0.200	0.018	0
120	[24, 5]	0.163	0.018	0
140	[28, 5]	0.136	0.035	0
160	[27, 6]	0.113	0.018	0
180	[30, 6]	0.101	0.053	0
200	[33, 6]	0.086	0.053	0
220	[31, 7]	0.076	0.123	0
240	[34, 7]	0.072	0.018	0
260	[37, 7]	0.056	0.035	0
280	[35, 8]	0.050	0.053	0
300	[38, 8]	0.039	0.070	0
320	[40, 8]	0.031	0.035	0
340	[43, 8]	0.025	0.000	0
360	[40, 9]	0.029	0.053	0
380	[42, 9]	0.021	0.018	0
400	[44, 9]	0.018	0.018	0

From Table 4.7, topographic error achieve zero when apply 140, 160, 200, 240, 260, 280, 320, 360 and 400 neurons value. In aspect of quantization error, neurons value at 400 produces the least value at 0.012. When facing multiple neurons value that are producing near integer, the best combination of less topographic error, a smaller amount of quantization error and low training time are considered as the frontrunner for the best performance. In this case 300 neurons is the selected neurons value for „*logistic*“ method with zero second training time.

Table 4.7 : SOM Results Using Hexagonal Topology with „*logistic*“ Normalization Method (IEEE 57 Bus System)

No. of Neurons	Classification Result			
	Map Size	Quantization Error	Topographic Error	Training Time (sec)
100	[13, 8]	0.065	0.018	0
120	[15, 8]	0.062	0.018	0
140	[16, 9]	0.050	0.000	0
160	[16, 10]	0.047	0.000	0
180	[18, 10]	0.046	0.018	0
200	[18, 11]	0.041	0.000	0
220	[20, 11]	0.035	0.018	0
240	[20, 12]	0.031	0.000	0
260	[22, 12]	0.027	0.000	0
280	[22, 13]	0.023	0.000	0
300	[23, 13]	0.025	0.088	0
320	[23, 14]	0.020	0.000	0
340	[24, 14]	0.019	0.035	0
360	[26, 14]	0.015	0.000	0
380	[25, 15]	0.015	0.018	0
400	[27, 15]	0.012	0.000	0

Referring at $'range$" normalization method at Table 4.8, it is obvious that neurons value at 100, 140, 200, 220, 240, 260, 300 and 400 attain zero in topographic error with zero training time. This indicates 240 neurons are selected even though 260, 300 and 400 neurons is least quantization error and topographic error again because mapping result show not good at U Matrix. In conclusion, 240 neurons is the selected neurons value for $'range$" normalization with quantization error (0.028) , topographic error (0.000) and training time (0 second).

Table 4.8 : SOM Results Using Hexagonal Topology with $'range$" Normalization Method (IEEE 57 Bus System)

No. of Neurons	Classification Result			
	Map Size	Quantization Error	Topographic Error	Training Time (sec)
100	[13, 8]	0.068	0.000	0
120	[13, 9]	0.062	0.018	0
140	[16, 9]	0.050	0.000	0
160	[16, 10]	0.044	0.018	0
180	[16, 11]	0.040	0.018	0
200	[18, 11]	0.038	0.000	0
220	[18, 12]	0.030	0.000	0
240	[20, 12]	0.028	0.000	0
260	[20, 13]	0.022	0.000	0
280	[22, 13]	0.019	0.018	0
300	[21, 14]	0.019	0.000	0
320	[23, 14]	0.015	0.018	0
340	[24, 14]	0.013	0.018	0
360	[24, 15]	0.012	0.018	0
380	[25, 15]	0.012	0.018	0
400	[25, 16]	0.011	0.000	0

For $'var'$ normalization method in Table 4.9, topographic error accomplished the slightest amount through 160, 200, 240, 300, 360 and 380 neurons value at zero. Look at result generate by 380 neurons its quantization error value at 0.057 are the lowest. Hence, 380 neurons are chosen as the best option available for this method.

Table 4.9 : SOM Results Using Hexagonal Topology with $'var'$ Normalization Method (IEEE 57 Bus System)

No. of Neurons	Classification Result			
	Map Size	Quantization Error	Topographic Error	Training Time (sec)
100	[13, 8]	0.321	0.018	0
120	[15, 8]	0.301	0.018	0
140	[16, 9]	0.268	0.018	0
160	[16, 10]	0.241	0.000	0
180	[18, 10]	0.182	0.035	0
200	[18, 11]	0.158	0.000	0
220	[20, 11]	0.148	0.018	0
240	[20, 12]	0.130	0.000	0
260	[22, 12]	0.111	0.018	0
280	[22, 13]	0.106	0.018	0
300	[23, 13]	0.099	0.000	0
320	[23, 14]	0.079	0.018	0
340	[24, 14]	0.076	0.035	0
360	[24, 15]	0.064	0.000	0
380	[25, 15]	0.057	0.000	0
400	[27, 15]	0.044	0.018	0

In Table 4.10, all selection of neurons value for different normalization method are listed and detailed. For 57 Bus System classification, neurons value of best selection for each method are not consistent and result for topographic error are excellent where four methods get zero error for log , $logistic$, $range$ and var method. If we observed in quantization error perspective, $logistic$ method resulting the lowest that value at 0.012. All best option for every method is visualized by U Matrix in Section 4.5.2.

Table 4.10 : Results Summary of Classification Performance for Different Method of Normalization for 57 Bus System

Normalization Method	No. of Neurons	Map Size	Quantization Error	Topographic Error	Training Time (sec)
log	340	[43, 8]	0.025	0.000	0
$logistic$	400	[27, 15]	0.012	0.000	0
$range$	240	[20, 12]	0.028	0.000	0
var	380	[25, 15]	0.057	0.000	0

4.2 U Matrix (Unified Distance Matrix)

Refer Section 4.1, there are four maps that being analyzed based on previous finding. These maps are plotted using SOM U Matrix and result analyses are discussed further in this Section. As mentioned in Section 3, hexagonal lattice topology selected for the classification for faster ang good mapping quality. Classifications done are separated by type of winding part either 14 Bus or 57 Bus System.

4.2.1 Results for IEEE 14 Bus System

In Figure 4.1, using $'log'$ normalization with 200 neurons has detected deviation at B8, B1, B5, B6, B2, B3, B9 and B4 according to clustered SOM Map in red boxes. For this clustered as shown very important bus because this bus have generator and carry high active power, reactive power and apparent power. Other than that, another bus is less important because it is carry lower power that is B7, B10, B11, B12, B13 and B14 in black box.

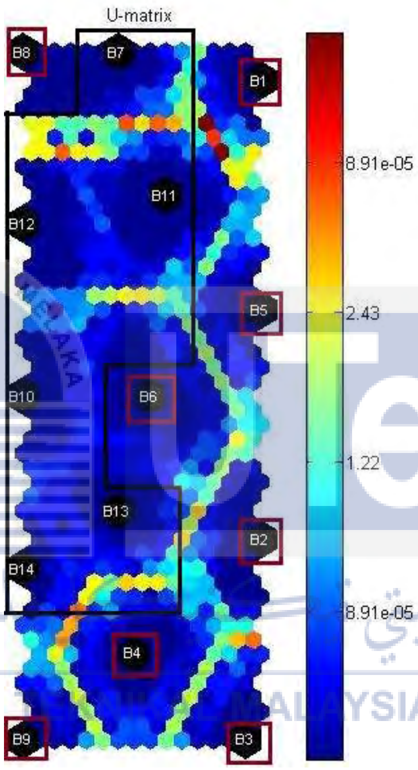


Figure 4.1 : U Matrix for $'log'$ normalization using 200 Neurons

In figure 4.1, using $'logistic'$ normalization with 180, 200 and 220 neurons has detected deviation at B1, B5, B2, B4, B3, B8, B6 and B9 in red boxes. According to clustered SOM Map, it is shown important bus that have generator and also carry higher active power, reactive power and apparent power while another bus shown not important in black box.

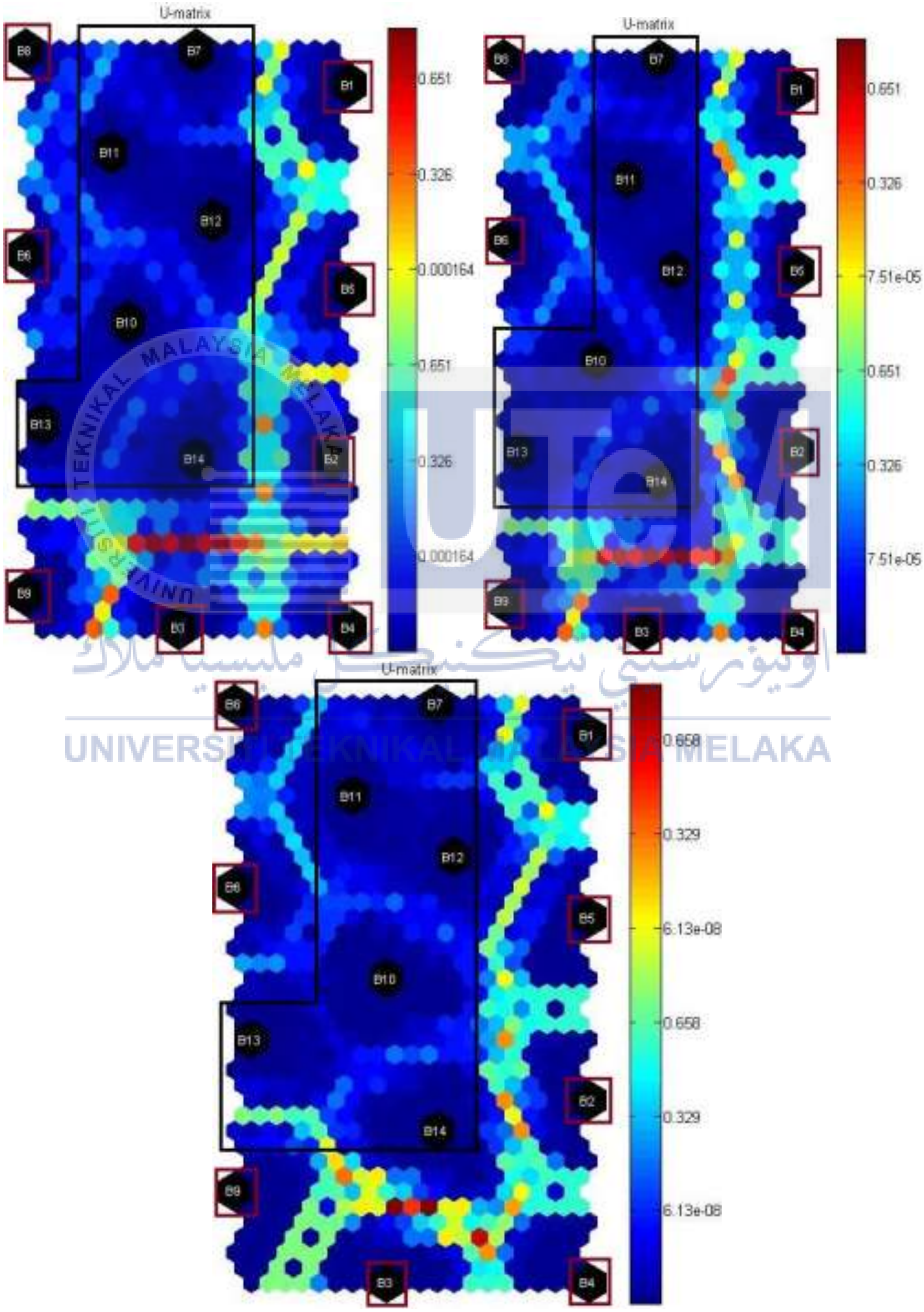


Figure 4.2 : U Matrix for $'logistic'$ normalization using 180, 200 and 220 Neurons

In Figure 4.3, using $'range'$ normalization with 200 and 220 neurons has detected difference at B1, B5, B2, B4, B3, B8, B6 and B9 in red boxes. As the result, this clustered as proved very important bus because this bus have generator and carry high active power, reactive power and apparent power. Other than that, another bus is less important because it is carry lower power in black box.

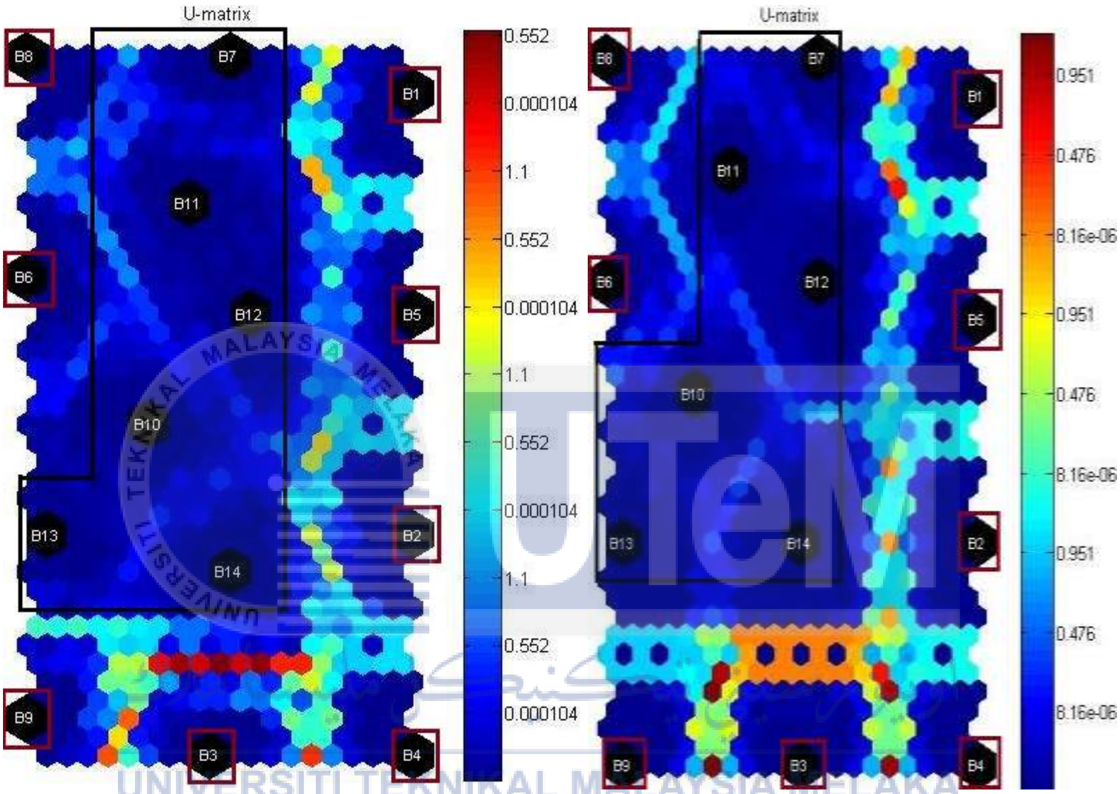


Figure 4.3 : U Matrix for $'range'$ normalization using 200 and 220 Neurons

In figure 4.4, using $'var'$ normalization with again 200 neurons has detected difference cluster at B1, B5, B2, B4, B3, B8, B6 and B9 in red boxes. For this clustered as shown very important bus because this bus have generator and carry high active power, reactive power and apparent power. Furthermore, another bus is less important because it is carry less active power, reactive power and apparent power in black box.

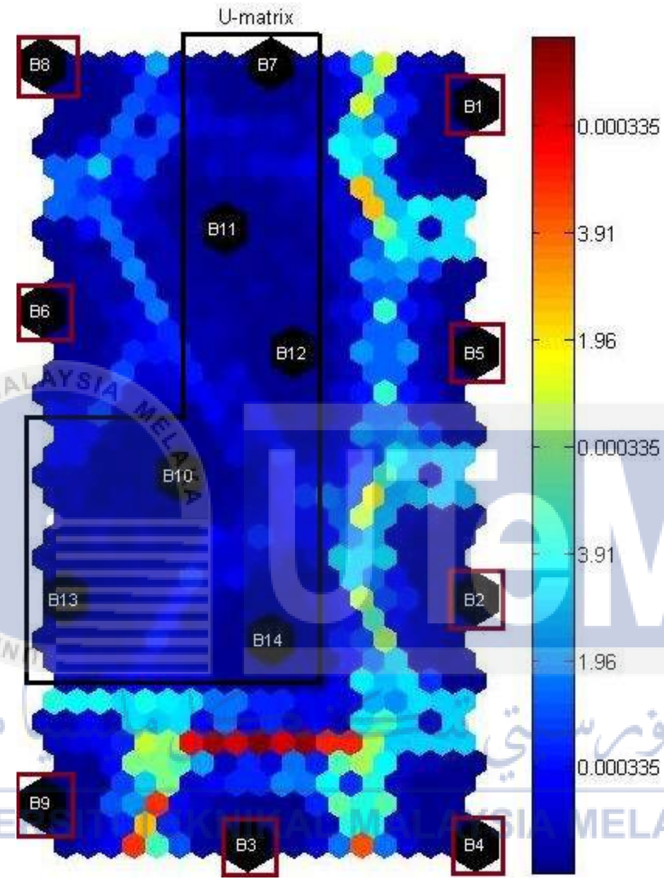


Figure 4.4 : U Matrix for $'var'$ normalization using 200 Neurons

From Table 4.11, $'logistic'$, $'range'$ and $'var'$ method producing identical result with minor different in form of U Matrix mapping. For $'log'$ normalization method result indicate that location of B6 is different than other method. In conclusion, the good result shown is $'logistic'$, $'range'$ method.

Table 4.11: U Matrix Results Summary by Different Methods of Normalization for 14 Bus System

Normalization Method	No. of Neurons	Topographic Error	Location and Condition of Abnormality
log	200	0.000	• Important Bus- red boxes (B1, B5, B2, B4, B3, B8, B6 and B9). • Less Important Bus- black box.
$logistic$	180	0.000	• Important Bus- red boxes (B1, B5, B2, B4, B3, B8, B6 and B9). • Less Important Bus- black box.
	200	0.000	
	220	0.000	
$range$	200	0.000	• Important Bus- red boxes (B1, B5, B2, B4, B3, B8, B6 and B9). • Less Important Bus- black box.
	220	0.000	
var	200	0.000	• Important Bus- red boxes (B1, B5, B2, B4, B3, B8, B6 and B9). • Less Important Bus- black box.

4.2.2 Results for IEEE 57 Bus System

In Figure 4.5, using $'log'$ normalization with 340 neurons has detected deviation at red box. In the red box representations for the important bus that is carry higher active power, reactive power and apparent power and also have generator. The result in red box indicates that bus display clustered with overlap pattern and overlap bus. It is difficult to determine which are the important bus.

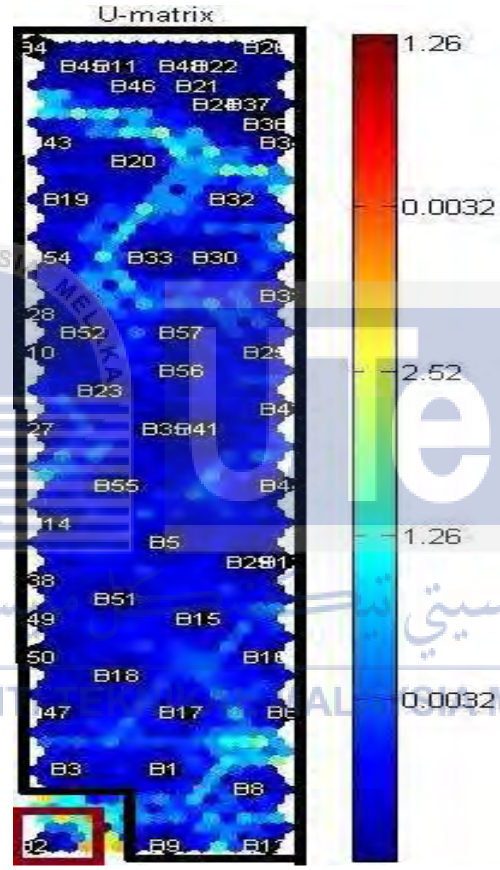


Figure 4.5 : U Matrix for $'log'$ normalization using 340 Neurons

From Figure 4.6, using $'logistic'$ normalization with 400 neurons has detected variation at B1, B2, B3, B6, B8, B9, B12, B16 and B17 in red boxes. For this clustered as shown very important bus because this bus have generator and carry high active power, reactive power and apparent power. Besides , another bus is less important in black box because it is carry less active power, reactive power and apparent power. For this clustered as shown good pattern and easy to determine important bus.

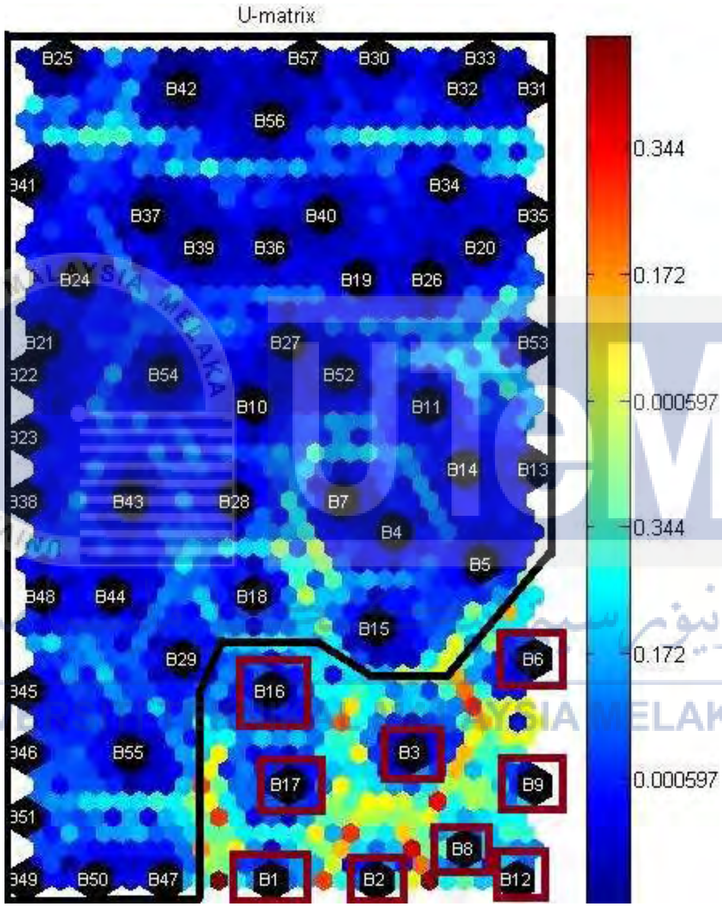


Figure 4.6 : U Matrix for $'logistic'$ normalization using 400 Neurons

Refer to Figure 4.7, using $'range'$ normalization with 240 neurons has detected variation at B1, B2, B3, B6, B8, B9, B12, B16 and B17 in red boxes. For this clustered as presented a few bus that important because this bus have generator and carry high active power, reactive power and apparent power. In addition, another bus in black box is less important that is carry less active power, reactive power and apparent power.

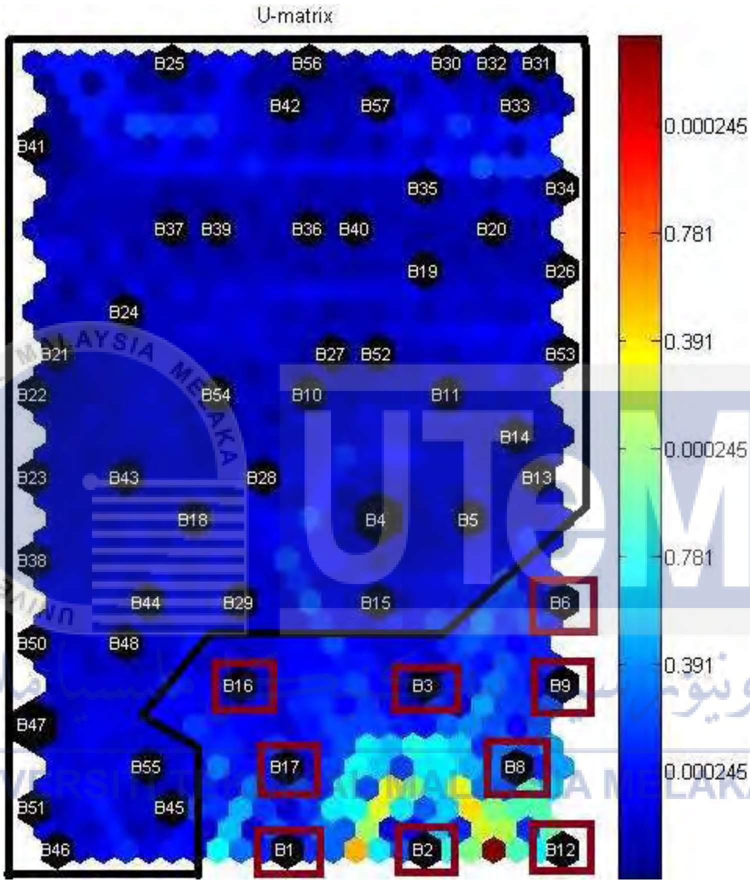


Figure 4.7 : U Matrix for $'range'$ normalization using 240 Neurons

Refer to Figure 4.8, using $'var'$ normalization with 380 has detected B1, B2, B3, B6, B8, B9, B12, B16 and B17 in red boxes. As the conclusion, this clustered is verified that a few important bus as be represented. Another bus in black box is shown as less important because it is carry lower active power, reactive power and apparent power.

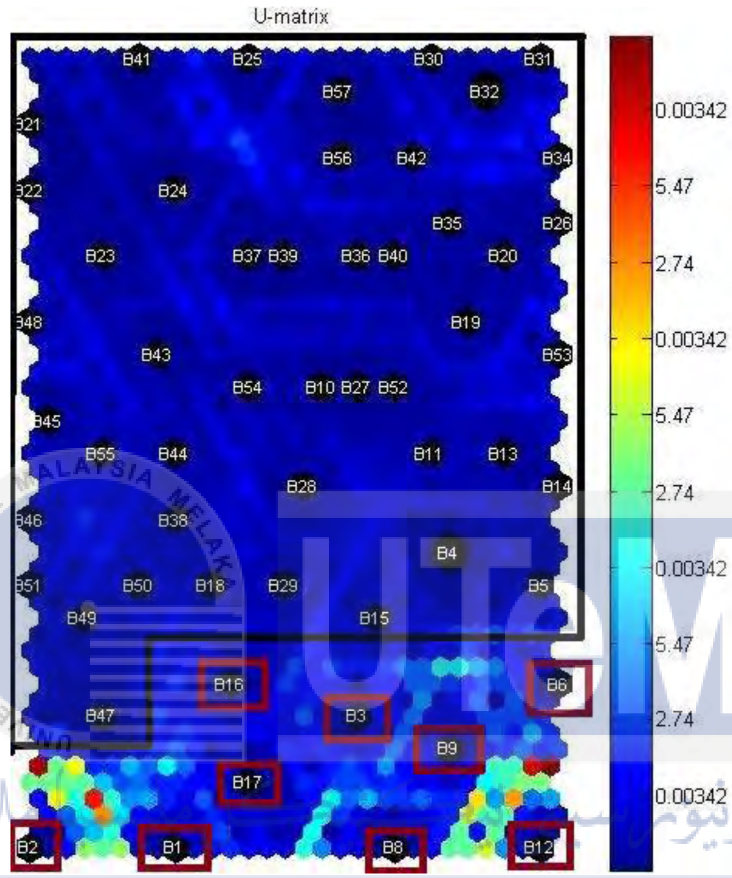


Figure 4.8 : U Matrix for $'var'$ normalization using 380 Neurons

From Table 4.12, $'logistic'$, $'range'$ and $'var'$ method producing the same result with a bit dissimilar form of U Matrix mapping. Referred to $'log'$ methods that sharing the same classification result with different form of U Matrix mapping and also the result in red boxes indicates that bus display clustered with overlap pattern and overlap bus. It is difficult to determine which are the important bus. As the result, the best cluster presented was $'logistic'$ method.

Table 4.12: U Matrix Results Summary by Different Methods of Normalization for 57 Bus System

Normalization Method	No. of Neurons	Topographic Error	Location and Condition of Abnormality
log	340	0.000	• Important Bus- red box (bus display clustered with overlap pattern and overlap bus). • Less Important Bus- black box.
$logistic$	400	0.000	• Important Bus- red boxes (B1, B2, B3, B6, B8, B9, B12, B16 and B17). • Less Important Bus- black box.
$range$	240	0.000	• Important Bus- red boxes (B1, B2, B3, B6, B8, B9, B12, B16 and B17). • Less Important Bus- black box.
var	380	0.000	• Important Bus- red boxes (B1, B2, B3, B6, B8, B9, B12, B16 and B17). • Less Important Bus- black box.

CHAPTER 5

CONCLUSION

5.1 Conclusion

This paper proposes a topological technique to study the vulnerability of subsets of substations in power grids focused around SOM clustering. While the physical attributes is considered as the premise in the assessment of power grid security, partner falling investigation with spatial feature based clustering demonstrates that the joined methodology has the capacity spot the more basic segments in a substantial scale power lattice than conventional routines, giving a proficient device to the contingency analysis. In our methodology, the potential victimized people are prepared by the powerful SOM clustering so the applicants of pursuit are refined to a restricted extent, which essentially decreases the computational cost while keeping the capacity to recognize the absolute most powerless sets or assault conspires in the lattice. This methodology shows better execution for cascading analysis in comparison to the traditional load ranking based and the K-means based clustering system, and the result will give wise data to decision support and power grid protective component. SOM is a compelling stage for visualization of high-dimensional information [23][24]. However, to have the capacity to completely comprehend substance of an information set, it is basic to see whether the information has cluster structure. In the event that this is the situation, the clusters need to be concentrated to have the capacity to completely abuse the properties of the information set by delivering synopsis data.

5.2 Recommendation

First, although the SOM related methods are finding wide application in more and more fields, to make the methods more efficient, robust and consistent is a key challenge, especially for large-scale and real-world applications. To adapt the SOM methods is saiz of network can be use bigger data mining. Secondly, suggestion is to increase the samples and put more relevant features for classification. Lastly, more features will also ease on the classification process and procedure more accurate and also have to consider current trend in power networks. The suitable amount of features can procedure the best classification results.

5.3 Achievement

Table 5.0: Table of Achievement

No.	Author	Title	Conference / Journal	Status
1	Z.H.Bohari, M.A.M.Yusof, M.H.Jali, M.F.Sulaima and M.N.M.Nasir.	Feature Combination Analysis in Smart Grid Based using SOM for Sudan National Grid	International Conference on Mechanical Engineering Research (ICMER) 2015	Accepted
2	Z.H.Bohari, M.A.M.Yusof, M.H.Jali, M.F.Sulaima and M.N.M.Nasir.	Multi-Hybridization Feature Analysis of Smart Based Via Self Trained Neural Network in Sudan National Grid.	International Conference of Advances in Mechanical Engineering (ICAME) 2015	Accepted
3	Z.H.Bohari, M.A.M.Yusof, M.H.Jali, M.F.Sulaima and M.N.M.Nasir.	Multi-Hybridization Feature Analysis of Smart Grid Based Using Self Organizing Maps	International Journal of Engineering & Technology	Submitted

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APPENDIX A

Coding for U Matrix

```
%sD=som_read_data('Load_Data_Bus14.m');
%sD=som_read_data('Load_Data_Bus57.m');

%sD=som_normalize(sD,'log');
%sD=som_normalize(sD,'logistic');
%sD=som_normalize(sD,'range');
%sD=som_normalize(sD,'var');
sM=som_make(sD,'munits',100,'lattice','hexa');
sM=som_autolabel(sM,sD,'vote');
sM;
som_show(sM,'umat','all')
som_show_add('label',sM.labels,'TextSize',8,'TextColor','w')
som_hits(sM,sD)
som_show_add('hit',som_hits(sM,sD));
figure;
som_show(sM,'umat','all','comp',1:5);

%validation
%SD2=som_read_data('transformer_asle_testsample.m');
%SD2=som_normalize(SD2,sD);
%som_show_clear('lab')
%sM = som_autolabel(sM,SD2);
%som_show(sM,'umat','all')
%som_hits(sM,SD2)
%som_show_add('hit',som_hits(sM,SD2))
%som_show_add('label',sM.labels,'TextSize',12,'TextColor','w')
%figure
%som_show(sM,'umat','all','comp',1:17)
```

APPENDIX B1

Load Data IEEE 14 Bus System

```
 5
 %n  Magnitude(p.u) Angle(Theta)   P(MW)   Q(MVAR)  S(MVA)

 %IEEE 14 Bus System

  1.060        0          0        0         0        B1
  1.045      -4.983     21.7     12.7      25.14      B2
  1.010     -12.725     94.2     19.0      96.10      B3
  1.018     -10.313     47.8      3.9      47.96      B4
  1.020      -8.774      7.6      1.6       7.77      B5
  1.070     -14.221     11.2      7.5      13.48      B6
  1.062     -13.360      0        0         0        B7
  1.090     -13.360      0        0         0        B8
  1.056     -14.939     29.5     16.6      33.85      B9
  1.051     -15.097      9.0      5.8      10.71      B10
  1.057     -14.791      3.5      1.8       3.94      B11
  1.055     -15.076      6.1      1.6       6.31      B12
  1.050     -15.156     13.5      5.8      14.69      B13
  1.036     -16.034     14.9      5.0      15.72      B14
```

APPENDIX B2

Load Data IEEE 14 Bus System

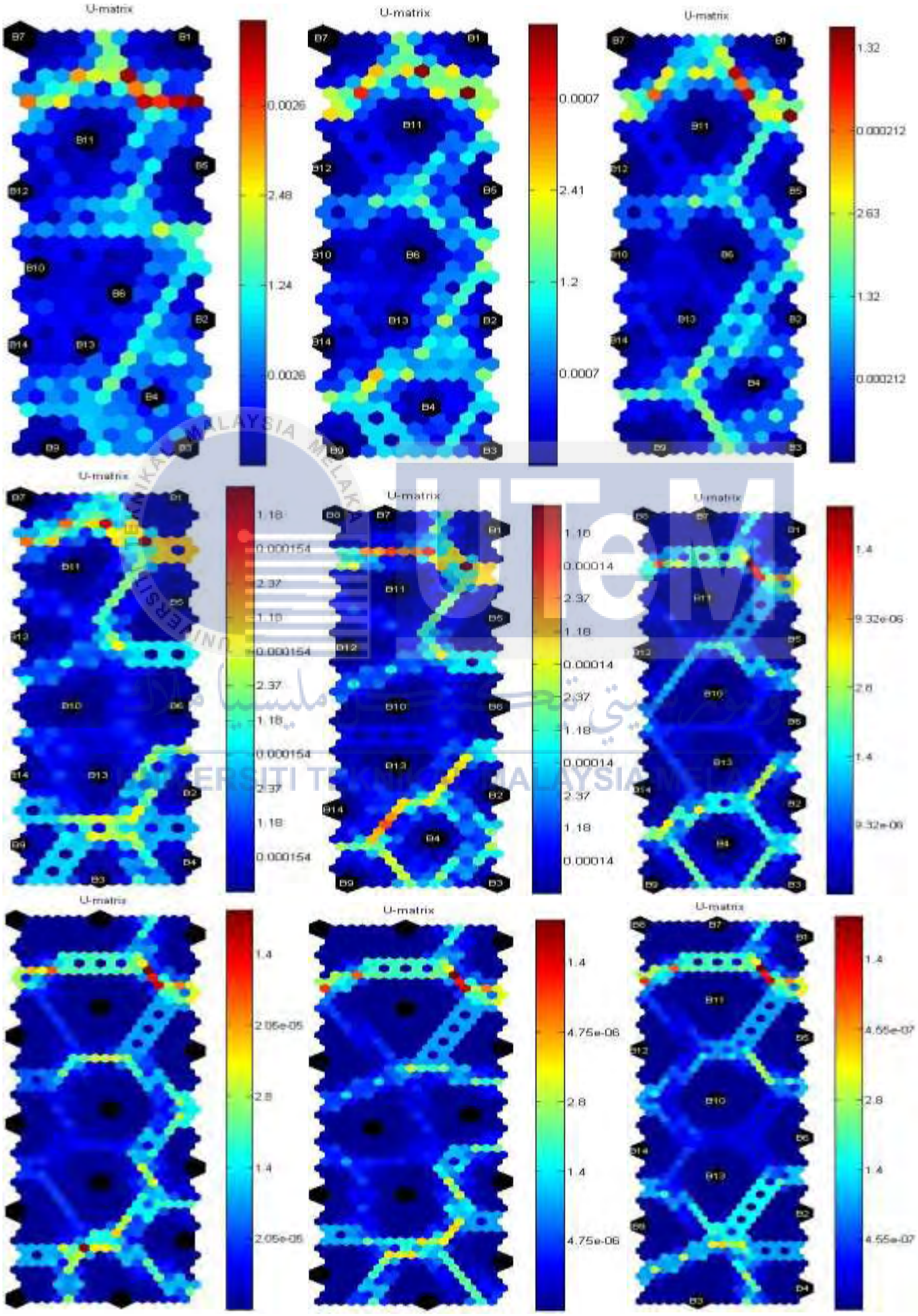
```
%
%n Magnitude(p.u)   Angle(Theta)   P(MW)   Q(MVAR)     S(MVA)

%IEEE 57 Bus System

   1.040         0          55       17       57.57      B1
   1.010    -1.188           3       88       88.05      B2
   0.985    -5.988          41       21       46.07      B3
   0.981    -7.337           0        0        0         B4
   0.976    -8.546          13        4       13.60      B5
   0.980    -8.674          75        2       75.03      B6
   0.984    -7.601           0        0        0         B7
   1.005    -4.478         150       22      151.61      B8
   0.980    -9.585         121       26      123.76      B9
   0.986   -11.450           5        2        5.39      B10
   0.974   -10.193           0        0        0         B11
   1.015   -10.471         377       24      377.76      B12
   0.979    -9.804          18        2.3     18.15      B13
   0.970    -9.350          10.5      5.3     11.76      B14
   0.988    -7.190          22        5       22.56      B15
   1.013    -8.859          43        3       43.10      B16
   1.017    -5.396          42        8       42.76      B17
   1.001   -11.730          27.2      9.8     28.91      B18
   0.970   -13.227           3.3      0.6      3.35      B19
   0.964   -13.444           2.3      1        2.51      B20
   1.008   -12.929           0        0        0         B21
   1.010   -12.874           0        0        0         B22
   1.008   -12.940           6.3      2.1      6.64      B23
   0.999   -13.292           0        0        0         B24
   0.983   -18.173           6.3      3.2      7.07      B25
   0.959   -12.981           0        0        0         B26
   0.982   -11.514           9.3      0.5      9.31      B27
   0.997   -10.482           4.6      2.3      5.14      B28
```

```
   0.997   -10.482           4.6      2.3      5.14      B28
   1.010    -9.772          17        2.6     17.20      B29
   0.963   -18.720           3.6      1.8      4.03      B30
   0.936   -19.384           5.8      2.9      6.49      B31
   0.950   -18.512           1.6      0.8      1.79      B32
   0.948   -18.552           3.8      1.9      4.25      B33
   0.959   -14.149           0        0        0         B34
   0.966   -13.906           6        3        6.71      B35
   0.976   -13.635           0        0        0         B36
   0.985   -13.446           0        0        0         B37
   1.013   -12.735          14        7       15.65      B38
   0.983   -13.491           0        0        0         B39
   0.973   -13.658           0        0        0         B40
   0.996   -14.077           6.3      3        6.98      B41
   0.967   -15.533           7.1      4.4      8.35      B42
   1.010   -11.354           2        1        2.24      B43
   1.017   -11.856          12        1.8     12.13      B44
   1.036    -9.270           0        0        0         B45
   1.060   -11.116           0        0        0         B46
   1.033   -12.512          29.7     11.6     31.89      B47
   1.027   -12.611           0        0        0         B48
   1.036   -12.936          18        8.5     19.91      B49
   1.023   -13.413          21       10.5     23.48      B50
   1.052   -12.533          18        5.3     18.76      B51
   0.980   -11.498           4.9      2.2      5.37      B52
   0.971   -12.253          20       10       22.36      B53
   0.996   -11.710           4.1      1.4      4.33      B54
   1.031   -10.801           6.8      3.4      7.60      B55
   0.968   -16.065           7.6      2.2      7.91      B56
   0.965   -16.584           6.7      2        6.99      B57
```

IEEE 14 Bus System

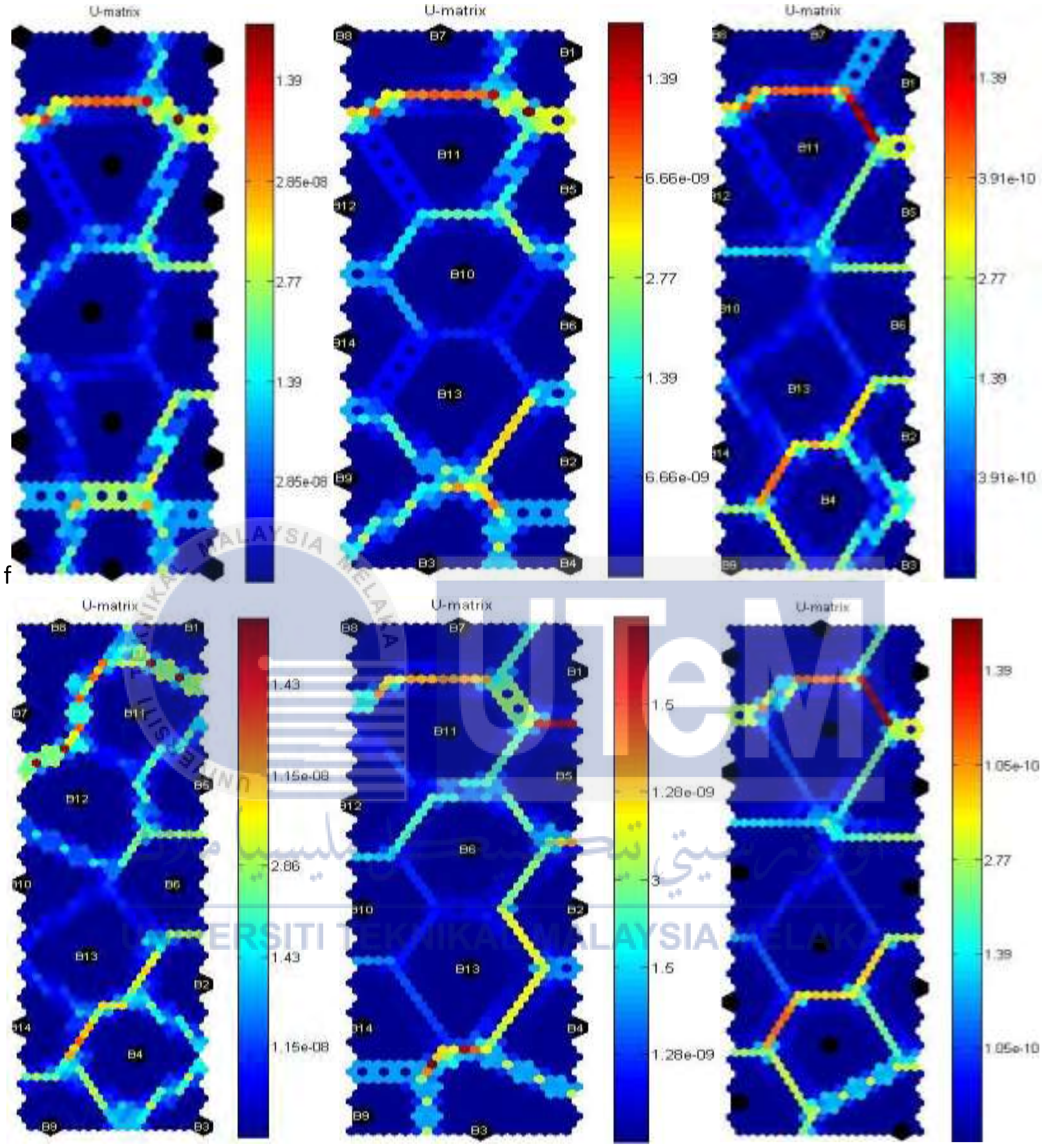
APPENDIX C1

U Matrix for $'log'$ Method using 100, 120, 140, 160, 180, 220, 240, 260 and 280 Neurons



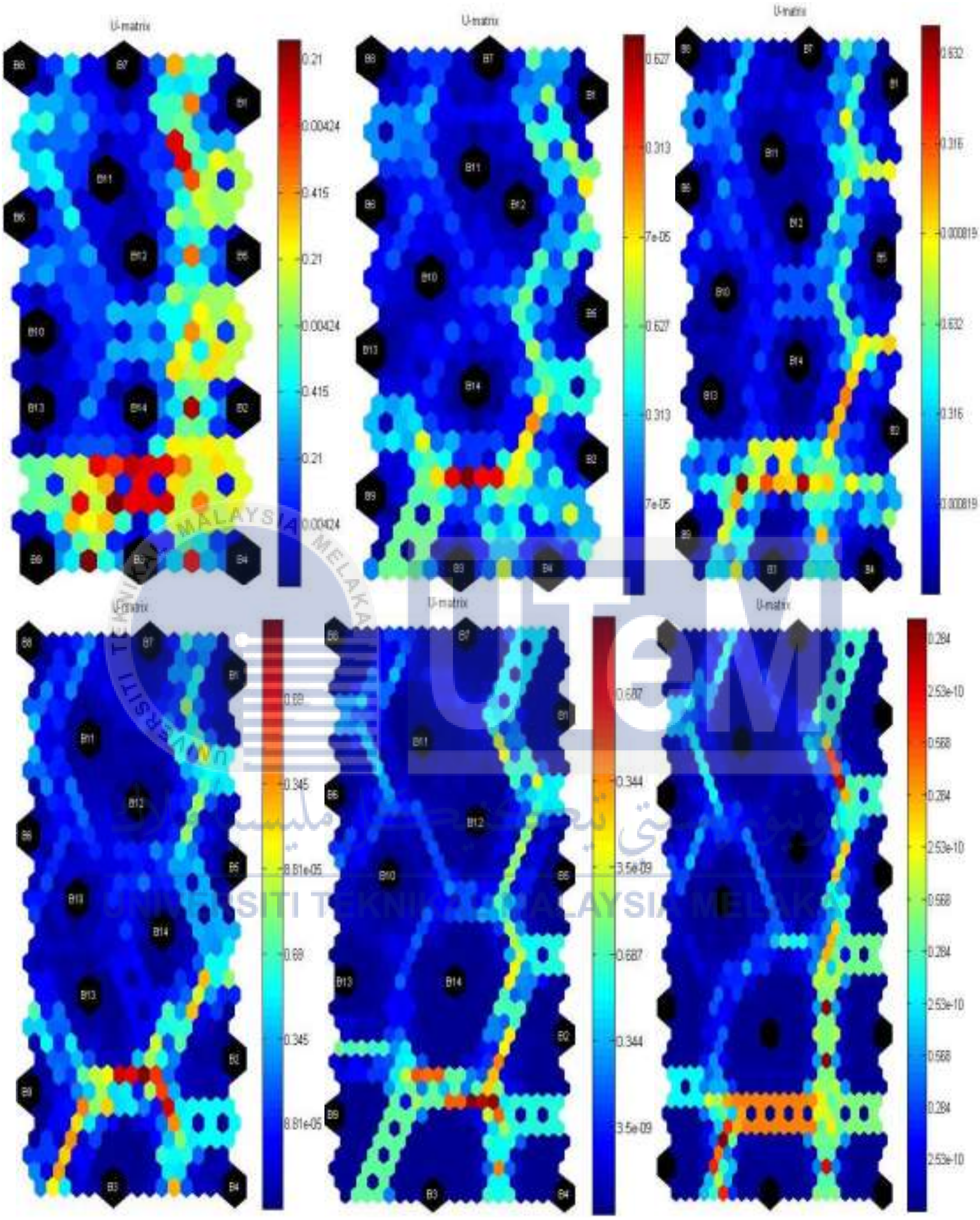
APPENDIX C2

U Matrix for $'log'$ Method using 300, 320, 340, 360, 380 and 400 Neurons



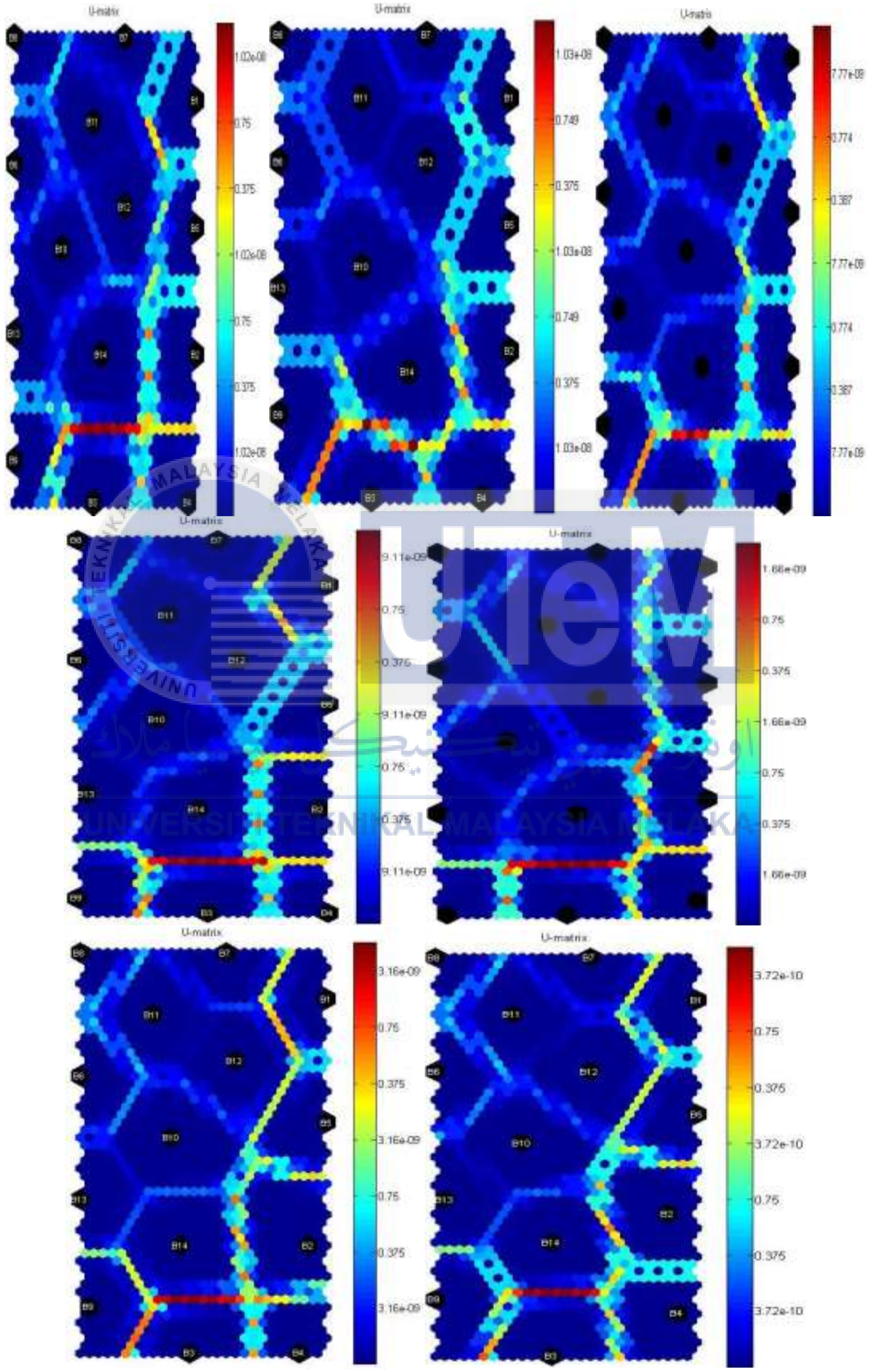
APPENDIX C3

U Matrix for $'logistic'$ Method using 100, 120, 140, 160, 240 and 260 Neurons



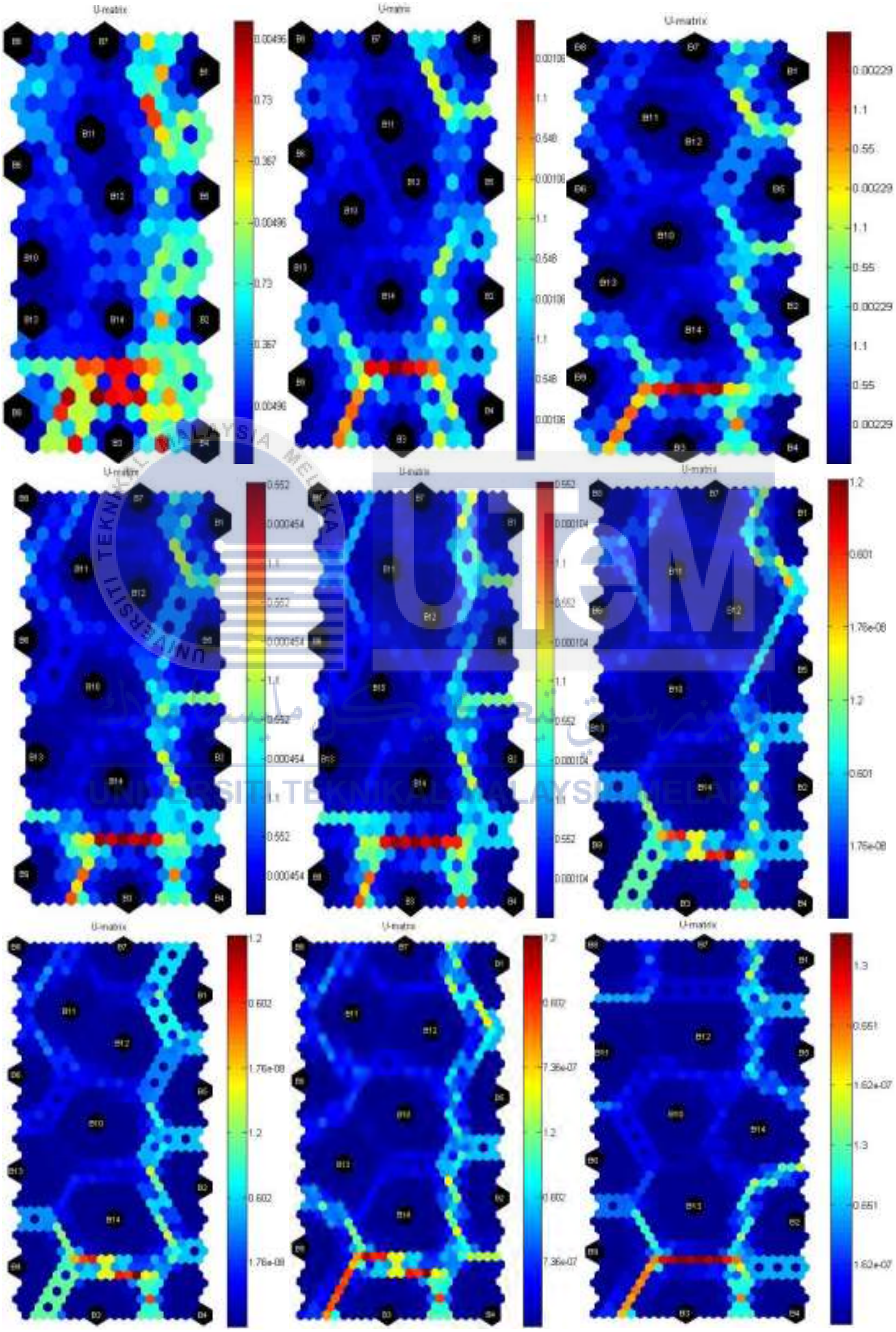
APPENDIX C4

U Matrix for $'logistic'$ Method using 280, 300, 320, 340, 360, 380 and 400 Neurons



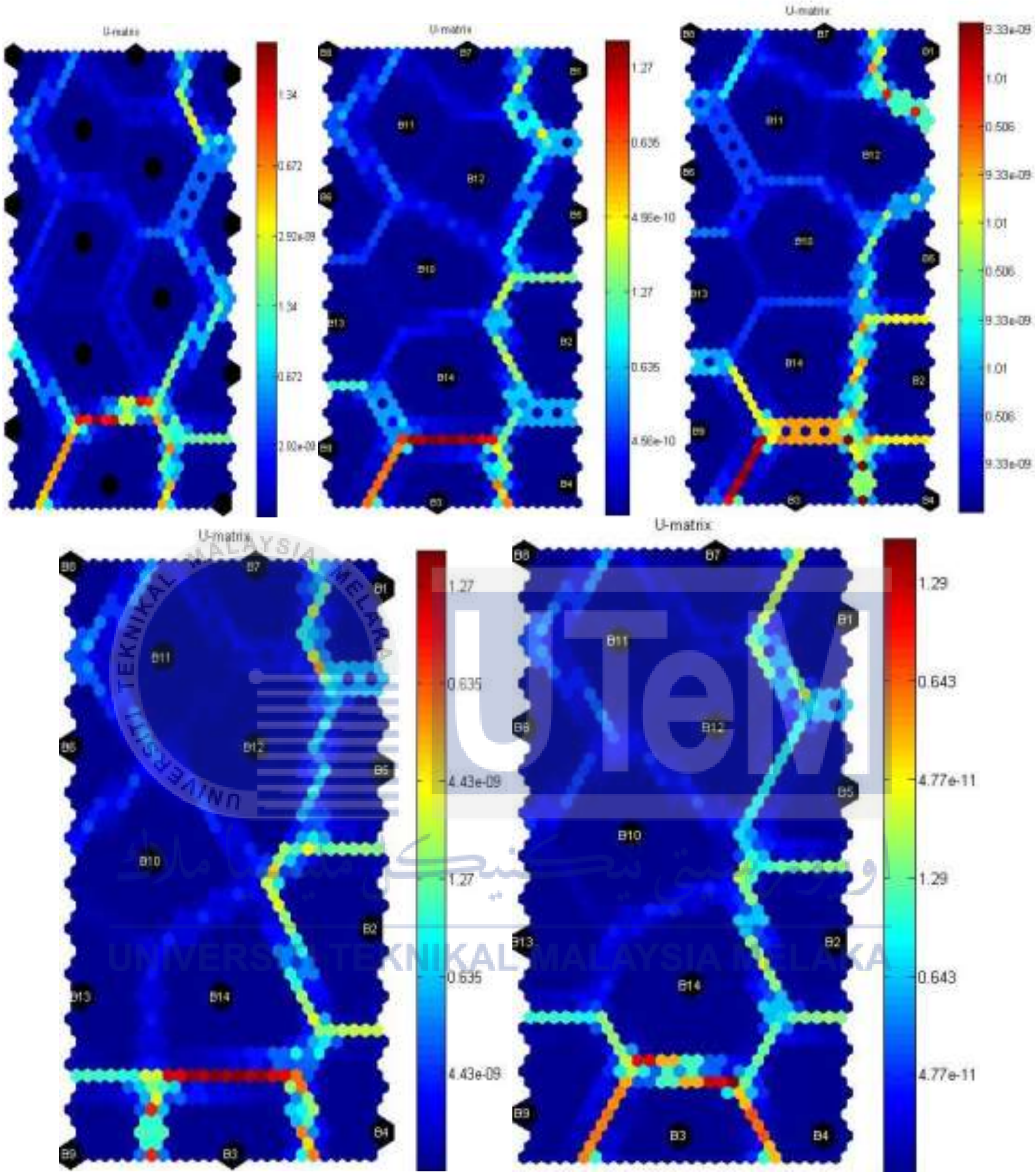
APPENDIX C5

U Matrix for $'range'$ Method using 100, 120, 140, 160, 180, 240, 260, 280 and 300 Neurons



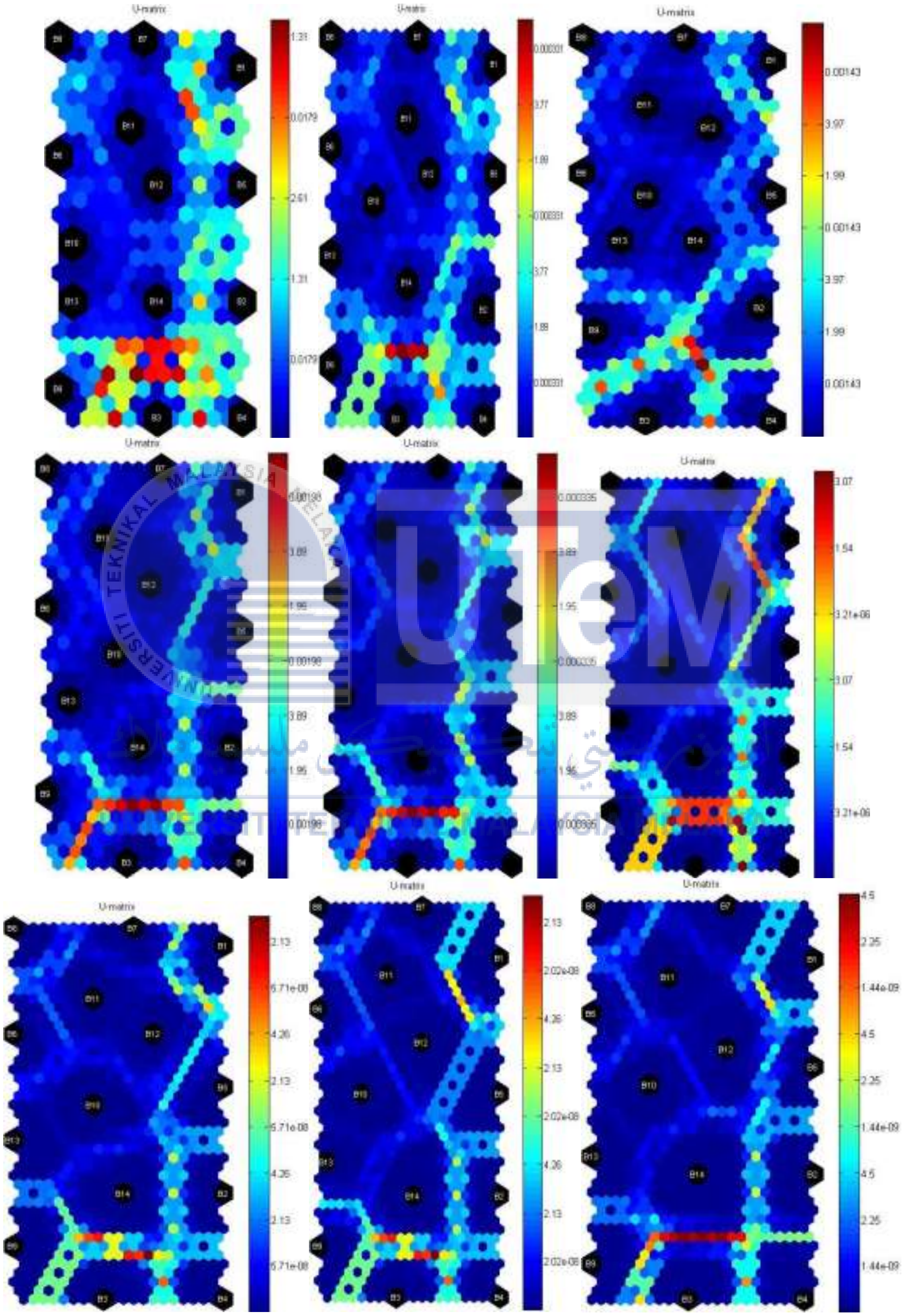
APPENDIX C6

U Matrix for $'range'$ Method using 320, 340, 360, 380 and 400 Neurons



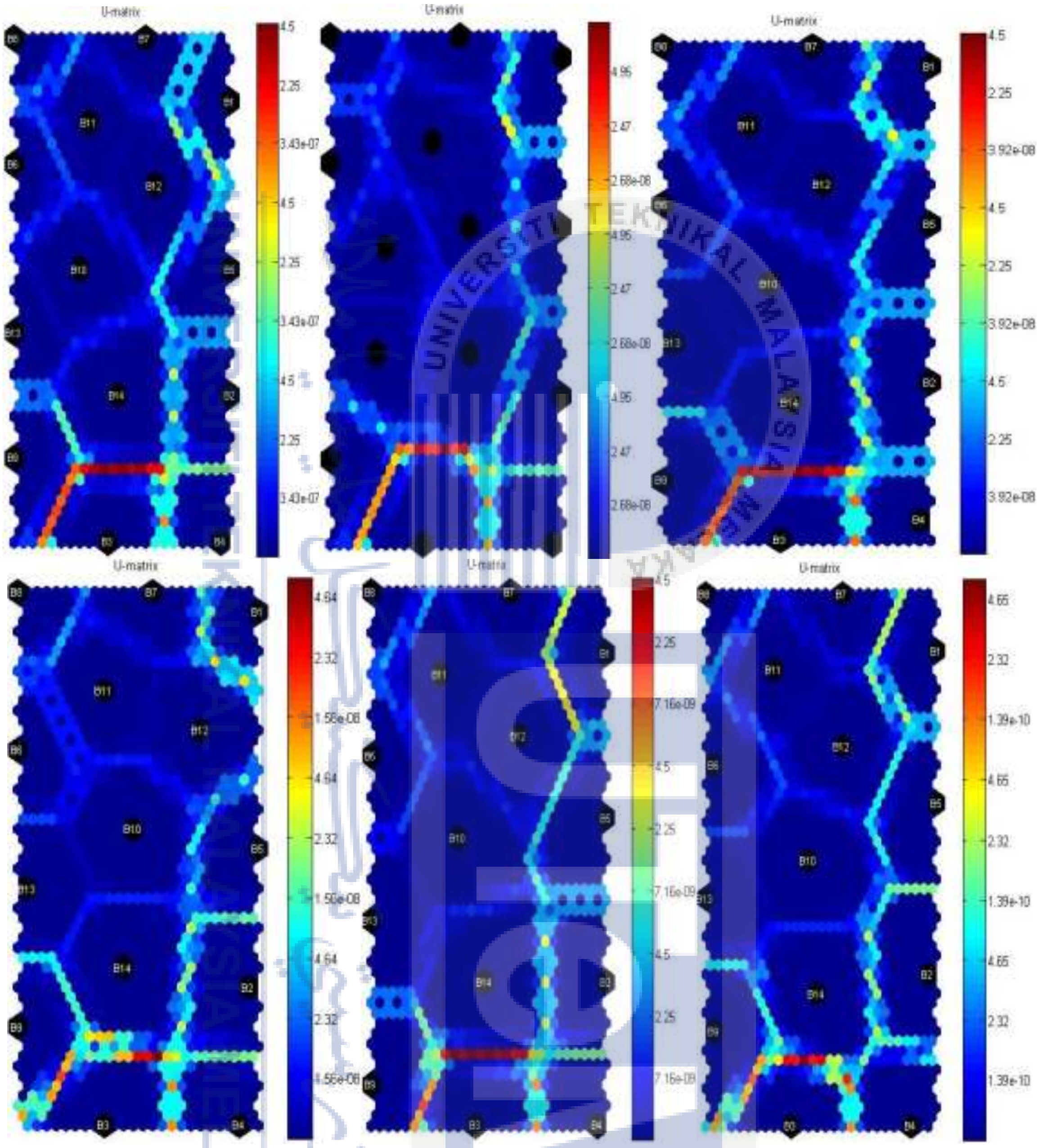
APPENDIX C7

U Matrix for $'var'$ Method using 100, 120, 140, 160, 180, 220, 240, 260, and 280 Neurons



APPENDIX C8

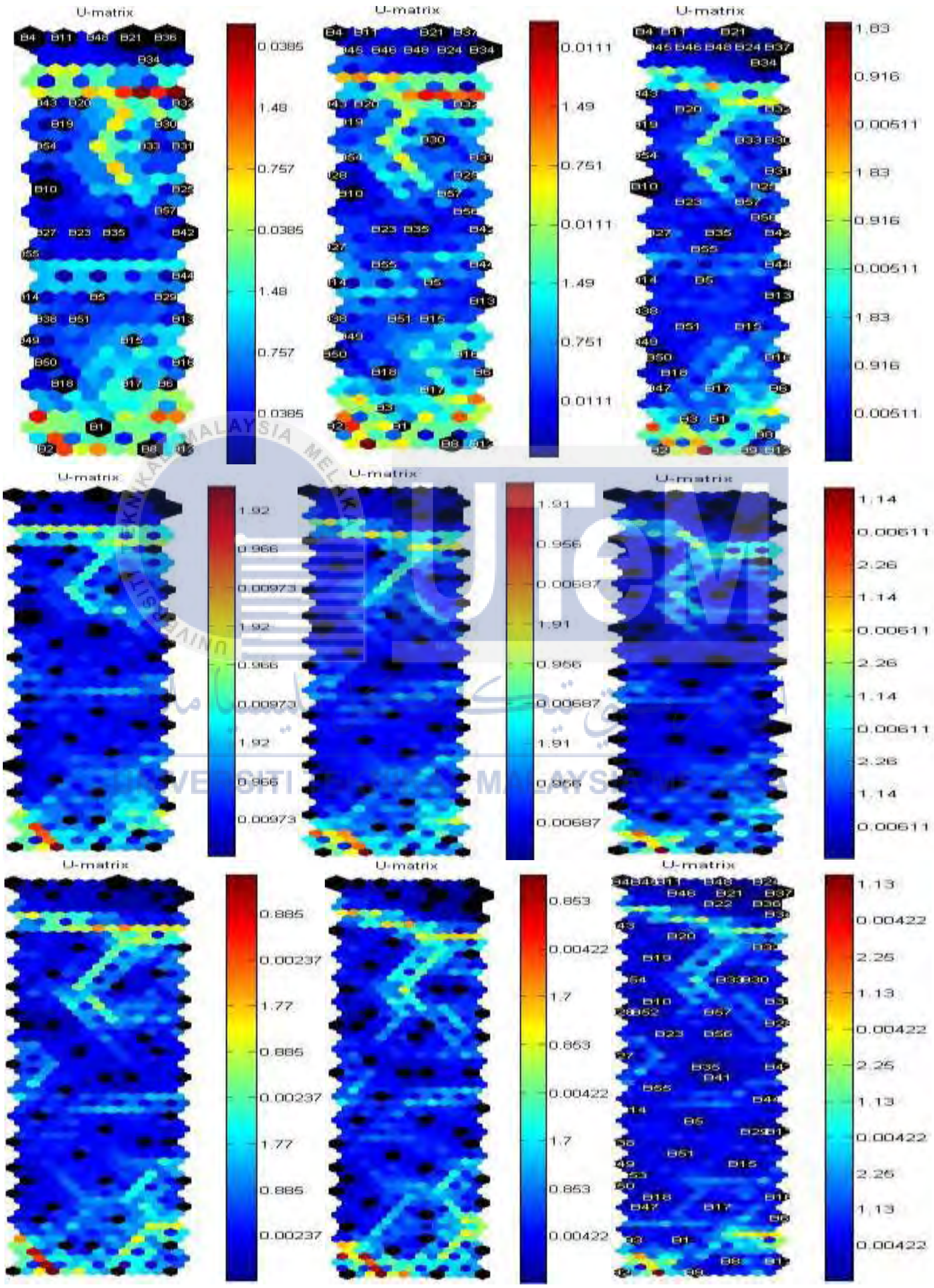
U Matrix for $'var'$ Method using 300, 320, 340, 360, 380 and 400 Neurons



<u>IEEE 57 Bus System</u>

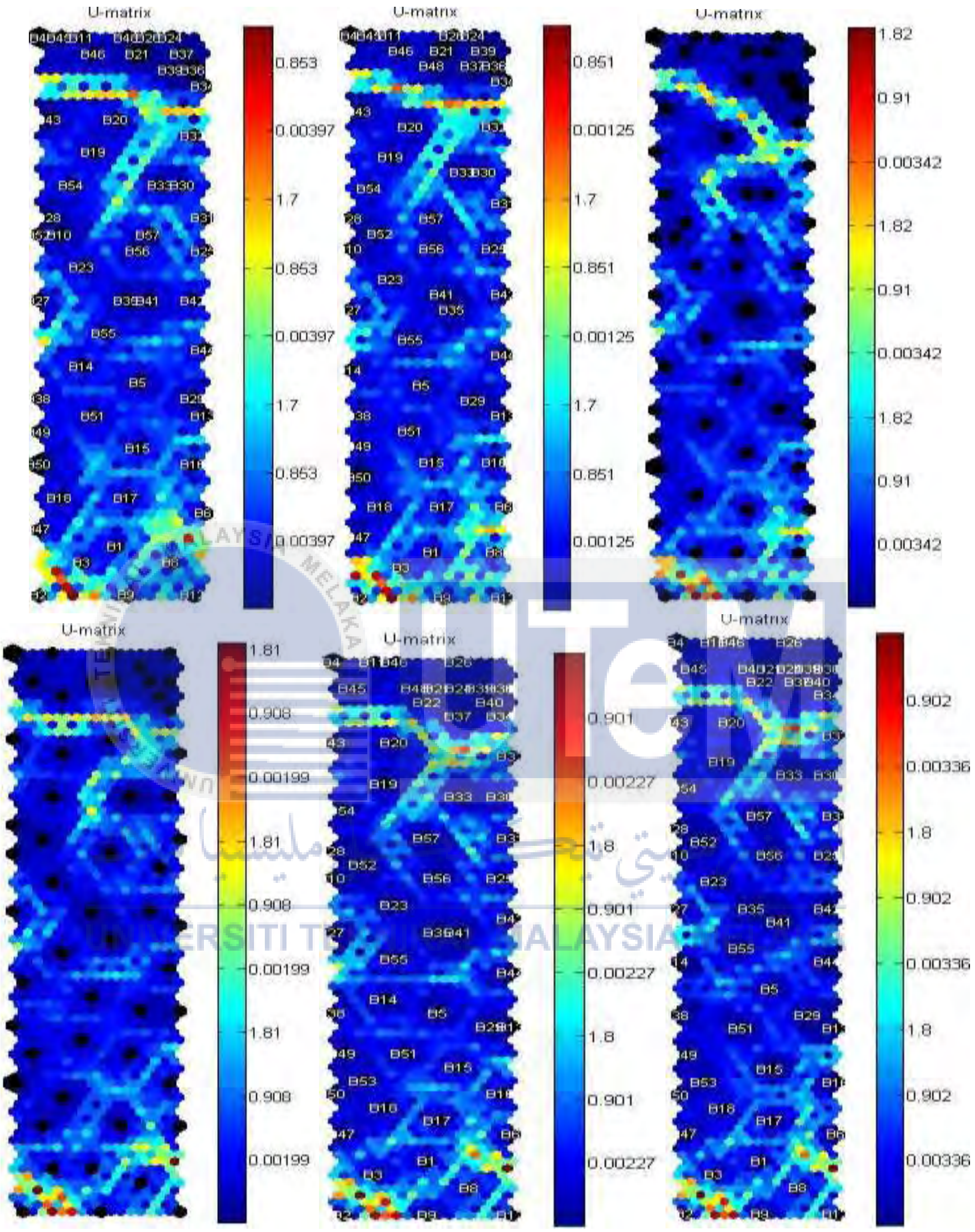
APPENDIX D1

U Matrix for $'log'$ Method using 100, 120, 140, 160, 180, 200, 220, 240, and 260 Neurons



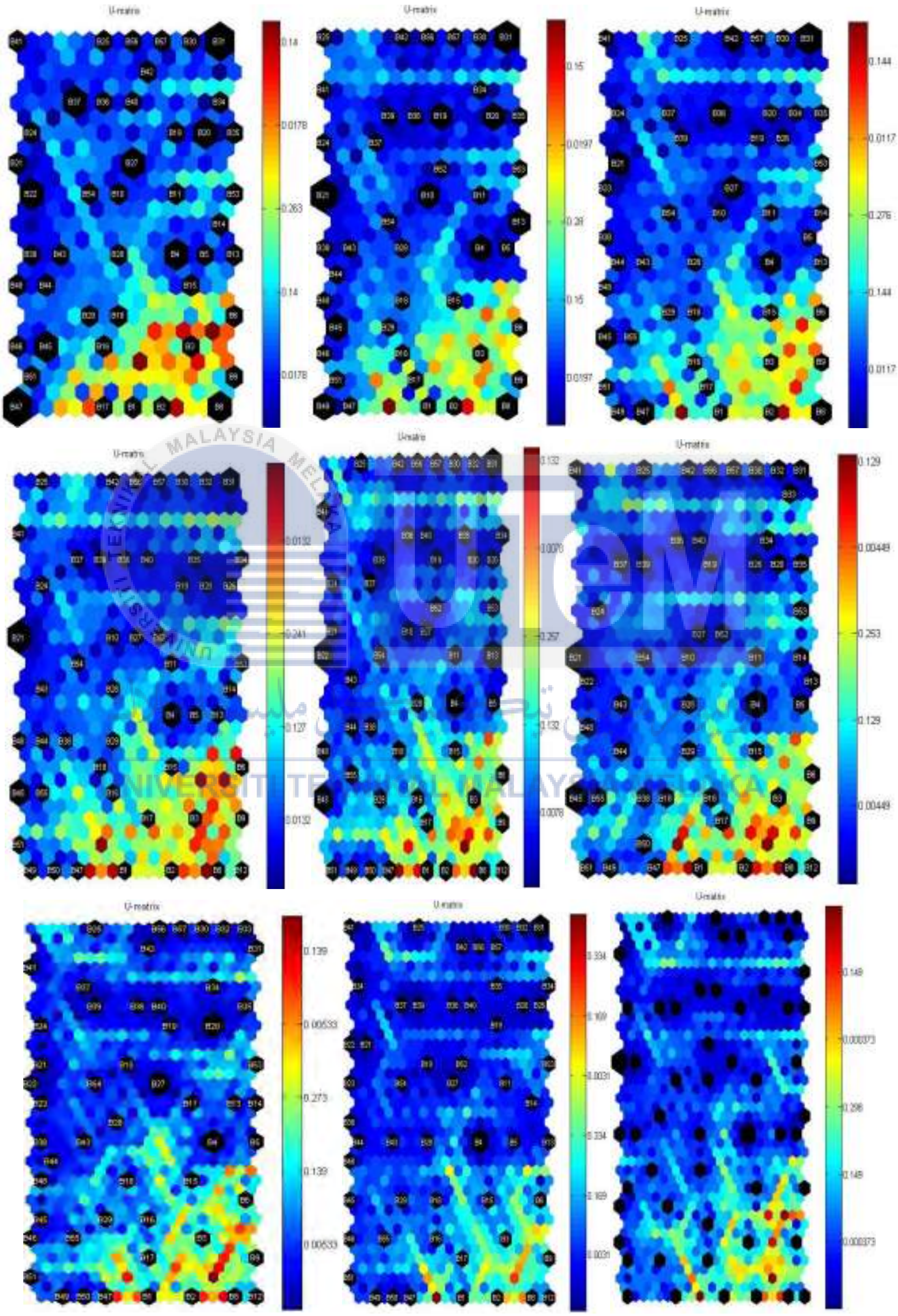
APPENDIX D2

U Matrix for $'log'$ Method using 280, 300, 320, 360, 380 and 400 Neurons



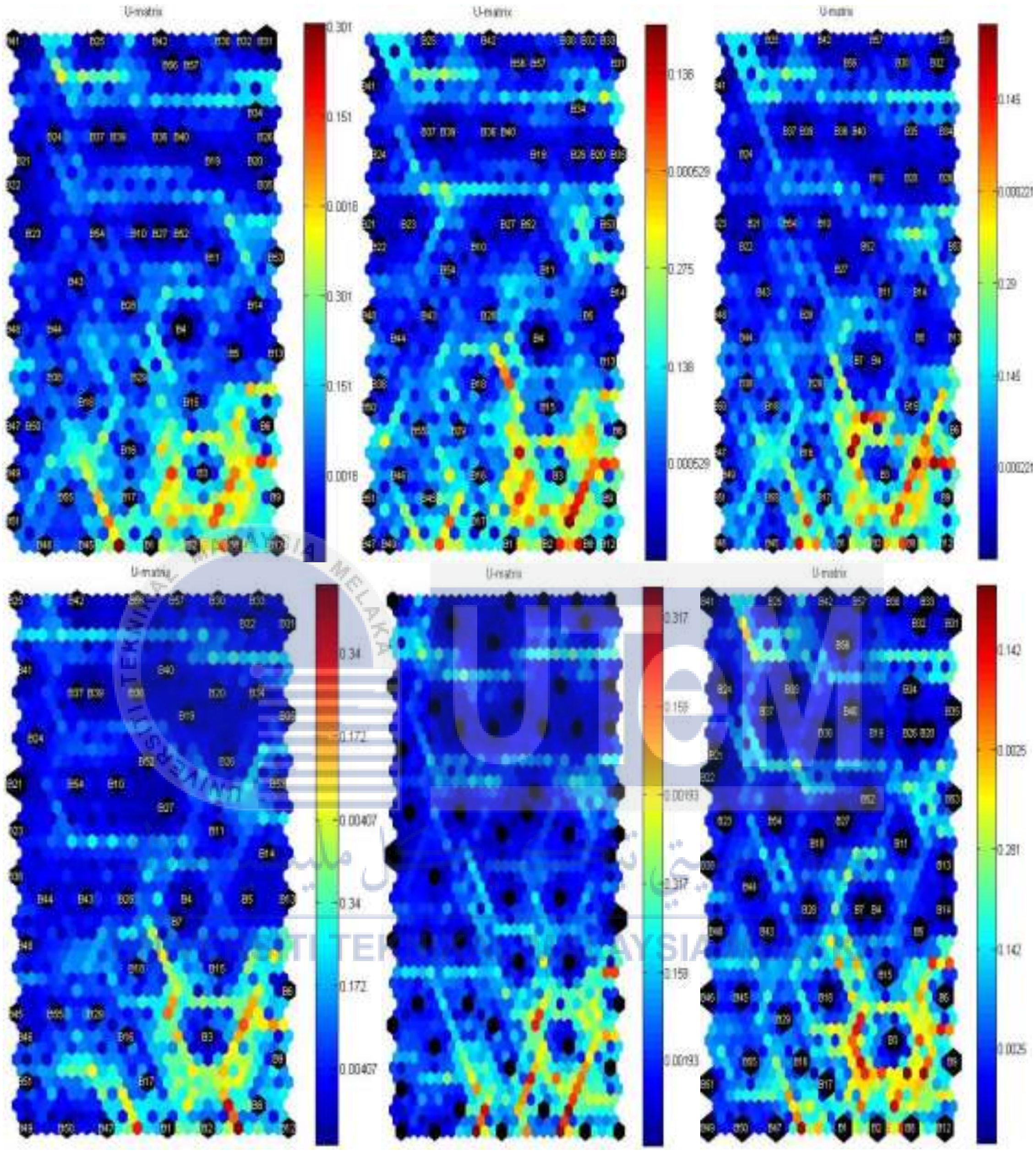
APPENDIX D3

U Matrix for $'logistic'$ Method using 100, 120, 140, 160, 180, 200, 220, 240, and 260 Neurons



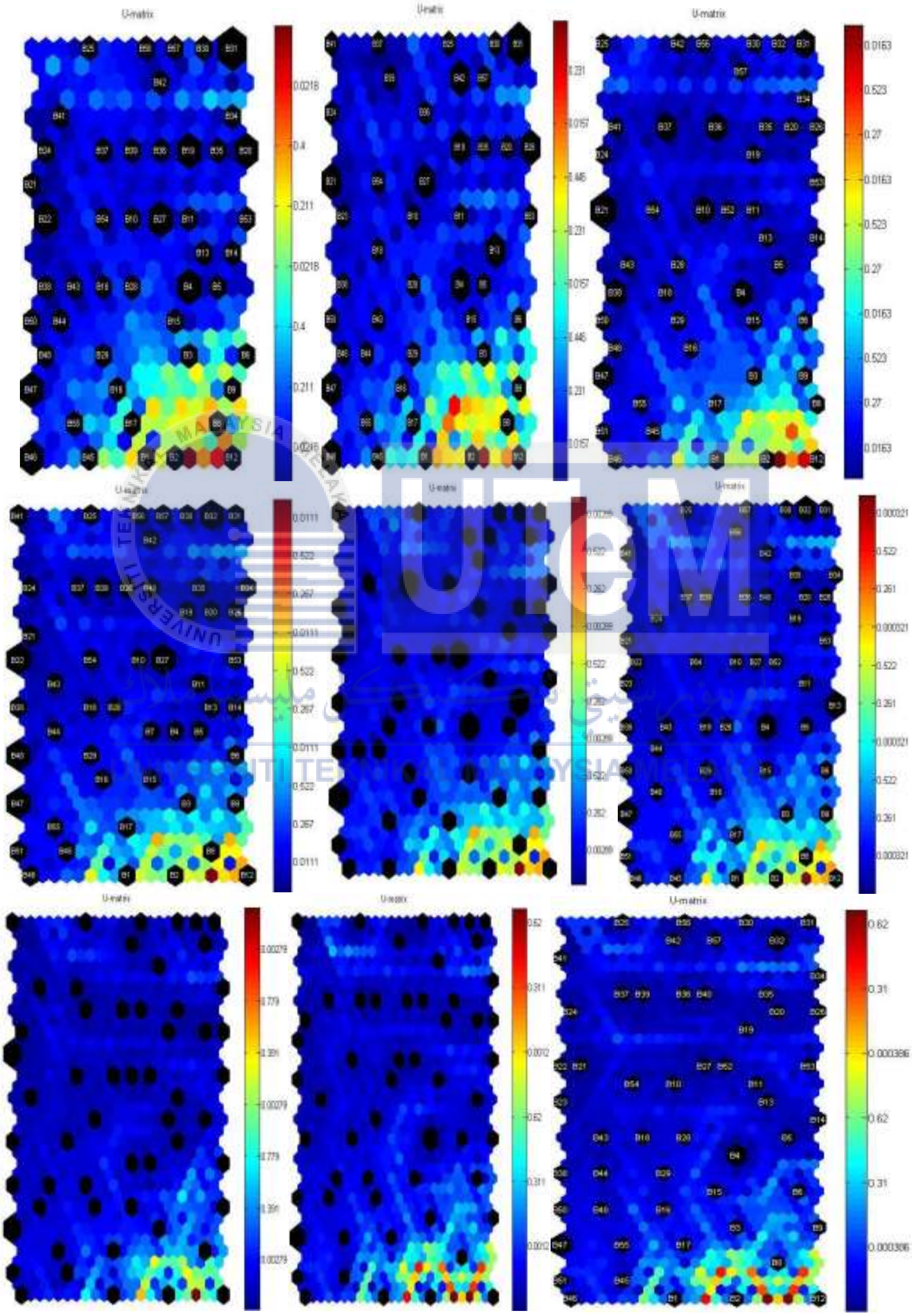
APPENDIX D4

U Matrix for $'logistic'$ Method using 280, 300, 320, 340, 360 and 380 Neurons



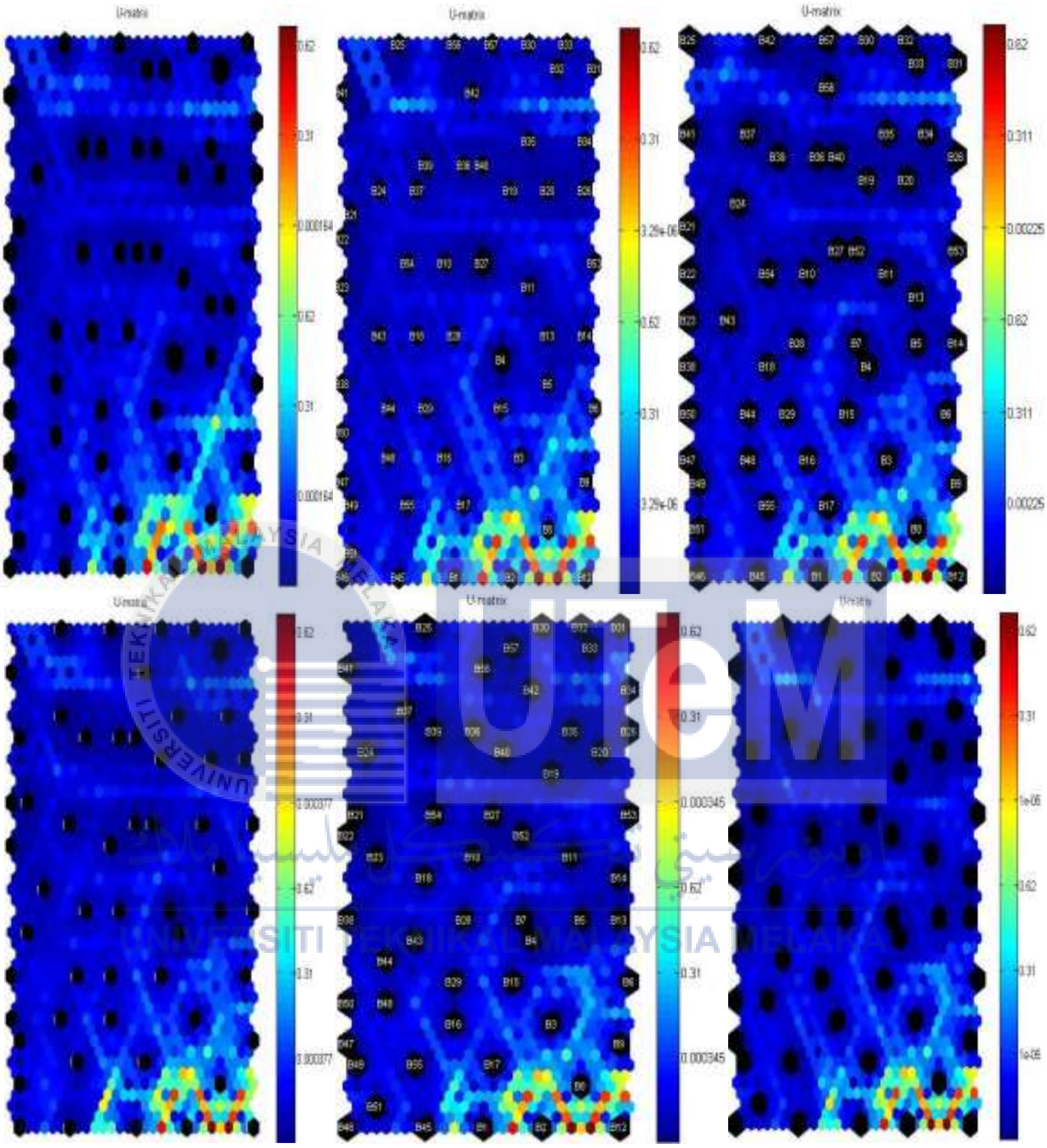
APPENDIX D5

U Matrix for $'range'$ Method using 100, 120, 140, 160, 180, 200, 220, 260 and 280 Neurons



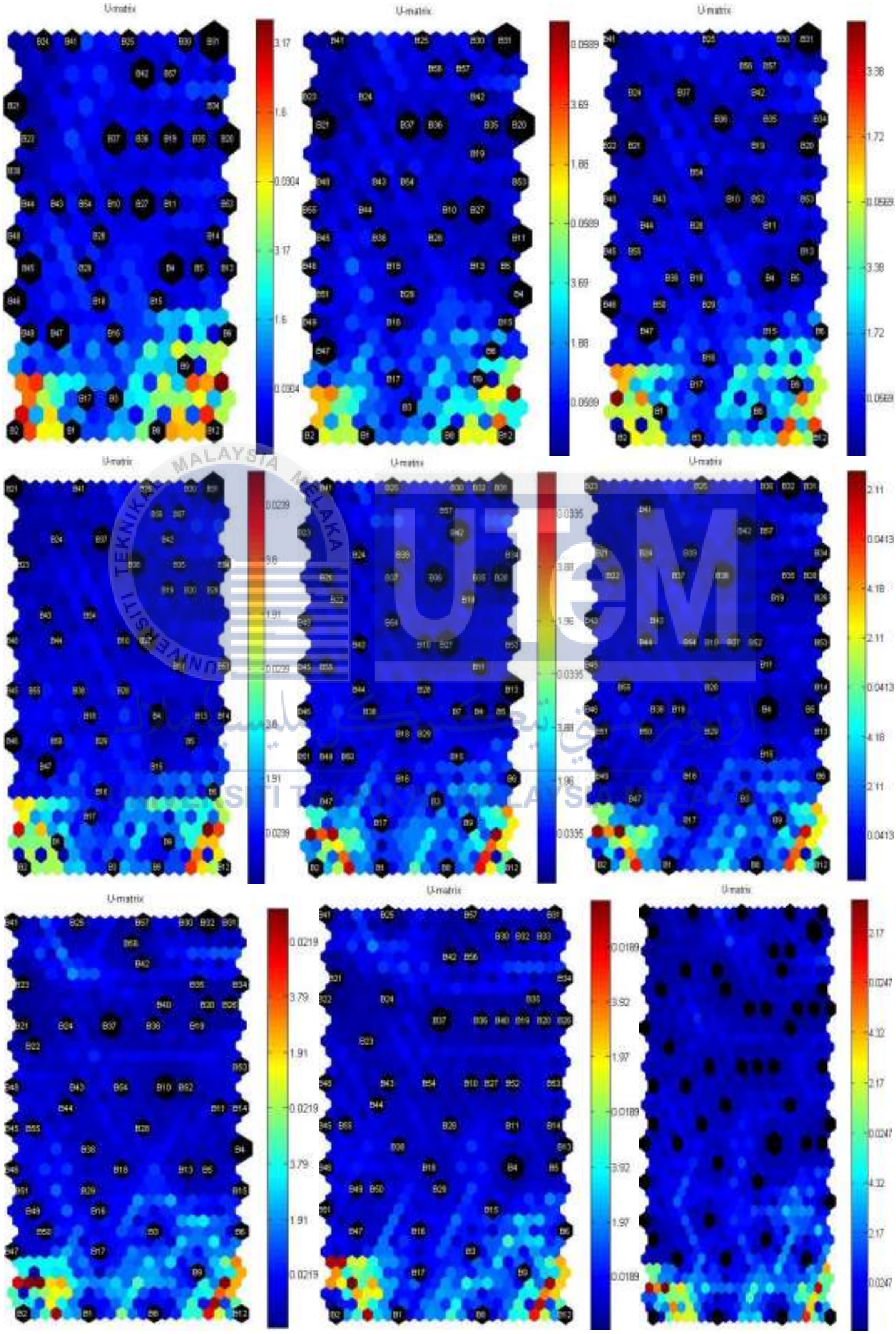
APPENDIX D6

U Matrix for $'range'$ Method using 300, 320, 340, 360, 380 and 400 Neurons



APPENDIX D7

U Matrix for $'var'$ Method using 100, 120, 140, 160, 180, 200, 220, 240, and 260 Neurons



APPENDIX D8

U Matrix for $'var'$ Method using 260, 300, 320, 340, 360and 400 Neurons