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Analysis of Motor Valve Operations in Fukuoka City Water Supply Network Using Self-Organizing Map

by

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Abstract

The water distribution regulation system of Fukuoka City is a system in which motor valves are operated by remote control while pressure gauges and flow meters attached to distribution pipes are monitored. One of the main objectives of this system is to regulate pressure in all the network nodes between lower and upper target values.

With the ever-increasing complexity of the city-wide distribution pipe network, motor valve operations to regulate pressure and flow came to depend more and more on the experience and skills of operators. For this reason, an improvement of valve operations support should be done based on valve operation planning for flow and pressure regulation, and the operation knowledge database which is constructed on the basis of past experience in order to prevent the events of pressure regulation falls outside the required target pressure range and also to reduce the effort of operators.

Therefore in this study and with the assistance of three years of telemetry data, an analysis of the existing valve operation of a certain block within the city district is performed using both correlation analysis and an unsupervised class of Artificial Neural Networks (ANN) named Self-Organizing Maps (SOM). Results show that correlation analysis has successfully classified the operation types of different valves attached to the studied network into three categories while SOM is an efficient tool in clustering the different complicated operational patterns of valves, visualizing the huge amount of telemetry valves data, detecting the patterns which need future improvement and could present good alternative solutions for improving future valve operational support.

Keywords: Water distribution networks, Motor valve control, Correlation analysis, Pressure regulation, Self-Organizing Maps (SOM), Artificial Neural Networks (ANN)

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1. Introduction

Fukuoka City is poor in water resources with no large rivers within the city district. For this reason it has taken various measures towards the creation of a "water-saving city", a city in which valuable water will not be wasted. One such measure has been the installation of the water distribution regulation system; one of the leading systems of its type in Japan[1]. With this system, round-the-clock centralized monitoring of data from pressure gauges and flow meters attached to distribution pipes is carried out, while on the basis of this data, pressure and flow within the entire city district is regulated by the remote operation of motor valves. By putting this system into operation, it has been possible not only to supply water evenly to consumers, but because water pressure can be regulated appropriately it has also been possible to reduce excess pressure and conserve water.

The purpose of a water supply network is to convey water to consumers in the required quantity at appropriate pressure, of acceptable quality, as economically as possible. Therefore in order to improve the existing system operation and management of Fukuoka City water supply network, the Water Distribution Control Center which is responsible for operation and management of the whole city water distribution network has introduced several operational support functions to further the reliability of water supply and distribution. **Table 1** shows a summary of the used operational support functions used in Fukuoka City water supply system, their purposes and factors affecting the formulation of those functions. By centralizing the city network control and using the operational support functions, the center seeks to achieve several objectives like regulating flow between water purification plants, reducing manpower required for valve operations during water shortages, making early discovery of distribution pipe abnormalities and respond rapidly by remote control; and gathering and analyzing information to make water distribution more efficient[2]. The ultimate goal of water supply operations is to make all facilities function work at the peak of efficiency. Toward this end, work has continued up to present day to improve all the functions of the Water Distribution Control Center, but various kinds of problems are still encountered during operations.

As one of those problems, is the problems related to the motor valve operations which

Table 1 Operational support functions used in Fukuoka City water distribution network.

Function	Brief Purpose	Affected factors
Demand Estimation Support	- Estimate total water demand of the City water supply network. - Time period and amount of water from each purification plant.	- Weather Conditions. - Factors affecting the day (working day, holiday, Month, etc...). - Past data for that particular day.
Trouble-Shooting Support	- Suggest recommended scenario in case of pipe breakage caused by accident or fire, suspension of water supply, pipe cleansing and restoration of supply	- Hydraulic conditions of the studied part of the City water network. - Duration of the recommended scenario.
Schedule Control	- Carried out the additional operations for valves aperture setting.	- Changing the stage of electric motor valve apertures.
Valve Operations Support	- Suggested set of electric motor valve openings.	- Required water demand. - Pressure regulation constraints.

aim to find the optimal electric openings of different motor valves to achieve two targets; feed consumers with their requirements of water demand and try to regulate water pressure in the entire water supply network between upper and lower values. Approximately the lower and upper target values in the Fukuoka City water supply network are set to 24 m and 32 m, respectively. The lower pressure target value is assigned because consumers want to receive water with adequate pressure while the upper target value is introduced for the purpose that higher pressures cause an increase of the amount of leaked water from the network. By controlling the distribution of hydraulic pressures in the network, pipe breaking could be lessened and water could be conserved.

Available models that explore pressure regulation problem through optimal control valve settings could be divided into two categories. In the first type, a mathematical statement is used as an objective function to be minimized. This mathematical statement could be presented in the form of network pressure regulation[3,4] or as the total amount of leaked water from the network[5]. The main drawback of using this category of models is its computational time. The objective function of all available models of that class deal directly with the pressure regulation problem from an optimization point of view which required a computational time depending on the water network size, the number of variables to be optimized and the used optimization method and in most cases required a network simplification method which is consider as another optimization problem.

The second category of the pressure regulation models are based on extracting several useful operational rules based on the previous knowledge and experience, analyzing past recorded data and the present experience and skills of operators. Existing valve operation support functions applied in Fukuoka City are from this type. The main advantage of this kind of models that it could be used as on-line operational model providing us with the most recommended values for electric motor valves set and providing us with the system response for those recommended values.

In this study an analysis of the existing motor valve operations of Block 12 of Fukuoka City water supply network is presented. We start to classify the different operations of electric motor valves attached to the pipes of Block 12. This classification has been performed using three years of continuous telemetry data with one hour interval. Then we tried to use an unsupervised class of Artificial Neural Networks (ANN) named Self-Organizing Maps (SOM) in order to expand the analysis of existing valve operations used in this block.

ANN are already quite commonly used in several applications of water resources engineering as an alternative for conventional computational models. ANN used an ensemble of input-output patterns to model a map from an input layer to an output layer, which is considered in this case a supervised type of ANN. SOM are considered also a class of ANN, but trained in an unsupervised way. That means SOM do not require an associated output (target) for each input pattern during training. The process of SOM classify the input patterns to different groups based on measuring similarity between input patterns, with no or little knowledge about the structure of used data.

The purpose of using SOM in this study is to test its ability of clustering the different complicated operational groups of valves, visualizing the huge amount of telemetry valve data and detecting the groups which need future improvement. Finally, using the results obtained from the SOM, we could suggest good alternative solutions for improving future valve operations.

2. Self-Organizing Maps (SOM)

The SOM is relatively a simple unsupervised neural network used for the categorization of input patterns into a finite number of classes. SOM consists of two layers units, the input units are a one-dimensional array which provides simulation to a usually two-dimensional array of map space units (output units) and all units in the input layer are fully connected with the units in the output layer (**Fig. 1**). The neurons of the output layer which is preferable to be arranged in two dimensional grids for better visualization are connected to adjacent neurons by a neighborhood relation dictating the structure of the map. The arrangement of the output layer neurons are usually distributed in rectangular or hexagonal arrangement. Generally it is preferable to use the hexagonal lattice, because it does not favor horizontal and vertical directions as much as rectangular array[6].

When an input vector x is sent through the network, each neuron k of the output network, which is also called competitive layer computes the distance between the weight vector w and the input vector x. Among all the output neurons, the so-called winning unit or Best-Matching Unit (BMU) is determined by the similarity between the weight vector w on that unit and the input vector x. For an input vector x, the BMU is determined by

$$\|x-w_c\|=\min_i\{\|x-w_i\|\} \tag{1}$$

in which the subscript c refers to the winning unit (BMU), $\|\ldots\|$ is the distance measure and i refers to all units in the competition layer, in Eq. 1 each unit in the two-dimensional output layer is identified by a single subscript for simplicity. Accordingly, a second winning unit will be determined with respect to the second input vector, and so forth. At the end of competition only one unit in the competitive layer wins in corresponding to one input vector.

For the BMU and its neighborhood neurons, the weight vectors w are updated by the SOM learning rule.

$$w_i(t+1)=\begin{cases} w_i(t)+\alpha(t)h_{ci}(t)(x(t)-w_i(t)) \rightarrow \mathit{if} \quad i\in N_c(t) \\ w_i(t) \qquad\qquad\qquad\qquad\qquad\quad \rightarrow \mathit{else} \end{cases} \tag{2}$$

where α is the learning rate at time t; h_{ci} so-called neighborhood function that is valid for the neighborhood N_c. The value of α varies from 0.0 to 1.0, and it controls the rate of learning. An α of 1.0 means it learns a new example as soon as it is presented. However, it forgets

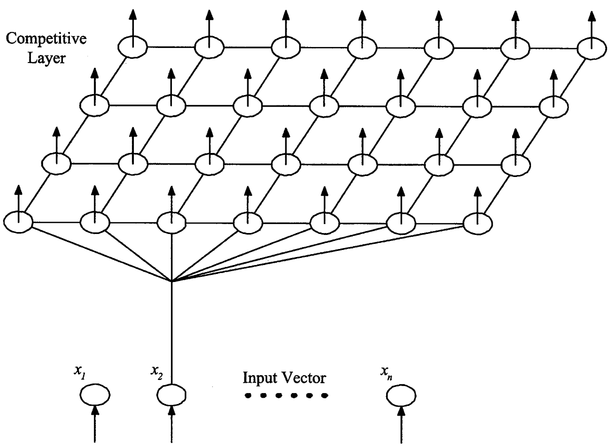

Fig. 1 Structure of SOM network.

all previous examples of that class. Similarly, an α of 0.0 means that the network does not learn at all, but classifies new examples based on previous experiences only. The neighborhood function $h_{ci}(t)$ is a time-variable and a decreasing function [$h_{ci}(t) \rightarrow 0$ when $t \rightarrow \infty$]. It is often represented by a Gaussian function as follow

$$h_{ci}(t) = e^{-d_{ci}^2/2\sigma(t)^2} \tag{3}$$

where σ is the neighborhood radius at time t and $d_{ci} = \|r_c - r_i\|$ is the distance between map units c and i on the map grid.

The training is usually performed in two phases. In the first phase, relatively large initial learning rate and neighborhood radius are used. In the second phase both learning rate and neighborhood radius are small right from the beginning. This procedure corresponds to first tuning the SOM approximately to the same space as the input data and then fine-tuning the map.

There are two different styles of training strategies. In sequential training the weights are updated each time when an input vector is presented. In batch training the weights are only updated after the presentation of all input vectors. In many applications, batch training type is the preferred option, as it forces the search to move in the direction of the true gradient at each weight update. However, several researchers suggest using the sequential type, as it requires less storage and "...makes the search path in the weight space stochastic... which allows for a wider exploration of the search space and, potentially, leads to better quality solutions"[7,8].

After some training steps, the SOM will arrange high-dimensional input data along its two-dimensional output space such that similar inputs are mapped onto neighboring regions of the map which means that the similarity of the input data is preserved within the representation space of the SOM. Usually, in the SOM application, in order to ensure that all variables of any input vector x receive equal attention during the training process, it is important to normalize the input vector to unit length before the training steps.

To measure the ability of SOM to arrange the different input vectors through its two-dimension grid, usually two evaluation criteria could be applied to measure the quality of SOM; resolution and topology preservation. For identifying and measuring the resolution of the SOM, we compute the quantization error[6] which is the average distance between each data vector and its winning unit (BMU). The topographic error which used to present the accuracy of the training map in the preserving topology is also calculated. This error represents the proportion of all input data vectors for which first and second BMUs are not adjacent for the measurement of topology preservation. The topographic error can be calculated as follows[9]:

$$\varepsilon_t = \frac{1}{N}\sum_{k=1}^{N} u(x_k) \tag{4}$$

where N is the number of input vectors; $u(x_k)$ is 0.0 if the first and second BMU's of x_k are next to each other, other wise $u(x_k)$ is 1.0.

In recent times, a variety of applications have used the SOM in several water resources management problems. The Following represent some successful applications in this field: (i) Evaluation of water quality in reservoirs[10], (ii) Data division for water resources models[11], (iii) Optimization of water application under trickle irrigation[12], (iv) River flow forecasting[13]; and (v) Classification of flood data into classes defined by representative regional catchments[14]. Review the literature show also that SOM has never been used in the field of water distribution network which provide a rich future area of research in the application of SOM in this field.

In this paper we used SOM to classify different electric motor valve operations, each represented by one vector representing the actual recorded set of valves setting. After classification we used two methods to cluster the obtained SOM to several main groups. First, we applied the method of unified distance matrix[6] (U-matrix) which is based on calculating the distance between adjacent SOM units. After calculated the U-matrix it could be visualized on a special color map size and then we could detect the different clusters using a color scale display on the map.

Another method that we have applied to select the best number of groups is computing the Davies-Bouldin Index (DBI)[15]. The smallest value of DBI represents the best number of groups which indicate the best clustering. Small DBI values occur for a solution with low variance within groups (Clusters) and high variance between clusters. Therefore, a choice is made concerning the number of clusters at which the DBI attains its minimum value.

After clustering the different groups of motor valve operations with the methods of U-matrix and DBI, we make a comparative analysis of the characteristics of different operation groups and their effect on the real measured pressure at the different pressure gauges. With the results obtained we could detect the well operated groups and the groups that need future improvement.

3. Case Study and Data Used

The water supply network of Fukuoka city is divided into 21 blocks and the area served by each block takes into consideration separate water distribution areas, differences in land elevation, location of rivers and railroads, as well as local differences in water usage. Fukuoka City is the first Japanese City that has established a Water Distribution Control Center in 1981. In this system motor valves are operated by remote control while pressure gauges and flow meters attached to distribution pipes are monitored. The values of flow rate passing each flow meter, the opening percentage of each motor valve and the pressure intensity at each pressure gauge are recorded every minute. As in April 2001, the system includes 120 water pressure gauges, 68 flow meters, and 149 electric motor valves at all important points along the water distribution pipes.

Block 12 as one of the main blocks of the city network is selected as a case study due to its location in the center of the city. Our case study (Block 12) is surrounded from the north by Hakata Bay, from the east by the Naka River and Block 9, from the west by the Hii River and Block 15; and from the south by an elevated area (Block 50) and also by Block 13. In Block 12 the original number of nodes and pipes are 1133 and 1645, respectively, considering pipes with diameters more than 100 mm. A skeletonized figure of Block 12 containing 57 nodes and 83 pipes is shown in **Fig. 2**. In this block, there are 20 motor valves, 7 flow meters, and 11 pressure gauges. It is noticed from the figure that flow meters are connected to the main inlets and outlets and a valve is connected adjacent to each flow meter in order to control the flow entering or leaving the block (e.g., M1, V1; M4, V6; ...). The remaining motor valves are connected to the main junctions of this network (e.g., V3; V5; V7; ...) to make water distribution more efficient and also play an important role to change the direction of water flow at any pipe in order to prevent the occurrence of red water. Pressure gauges are located at different zones in the important end flow points to maintain an acceptable value of pressure and get a good idea about the water pressure status in this zone.

The analyzed data in this study are based on hourly data for all flow meters, pressure gauges, and motor valves since 1st April 1998 to 31st March 2001. This makes the total

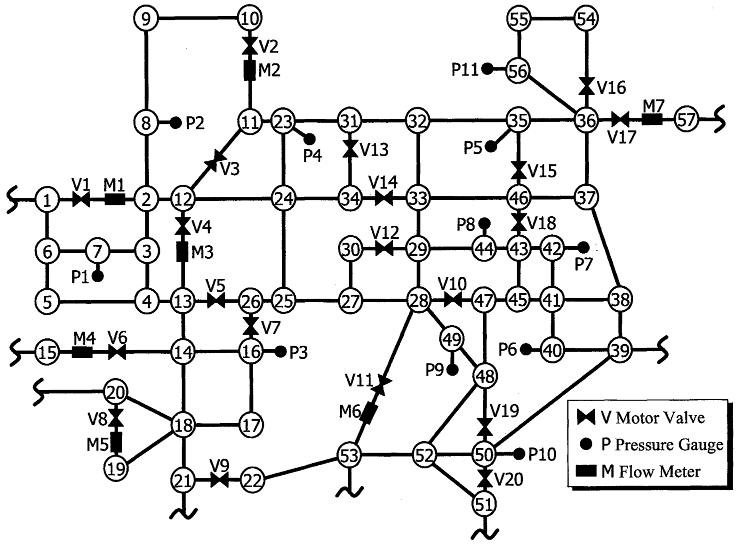

Fig. 2 Block 12 of the Fukuoka City water supply.

number of data for each telemeter 26304 (total number of hours during this period). The analysis of motor valve operations is based on 24799 vectors out of the 26304 vectors because there are 1505 vectors of valves data set which are completely missing.

4. Correlation Analysis

Each motor valve of Block 12 has its own time series operation during which the valve opening varies between a minimum and maximum values. To get an idea about the different valves operation we plot the box-whisker plot for the different 20 motor valves of Block 12 (see **Fig. 3**). In this figure, the box-whisker plot shows the median, upper and lower quartiles, upper and lower 5% of events and the maximum and lower motor valve opening recorded for the three years of valves telemetry data set. In this figure, some motor valves are continually

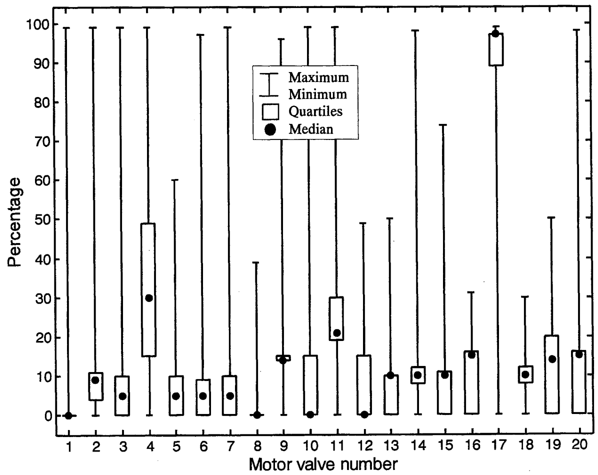

Fig. 3 Box-whisker plots for the 20 electric motor valve of Block 12.

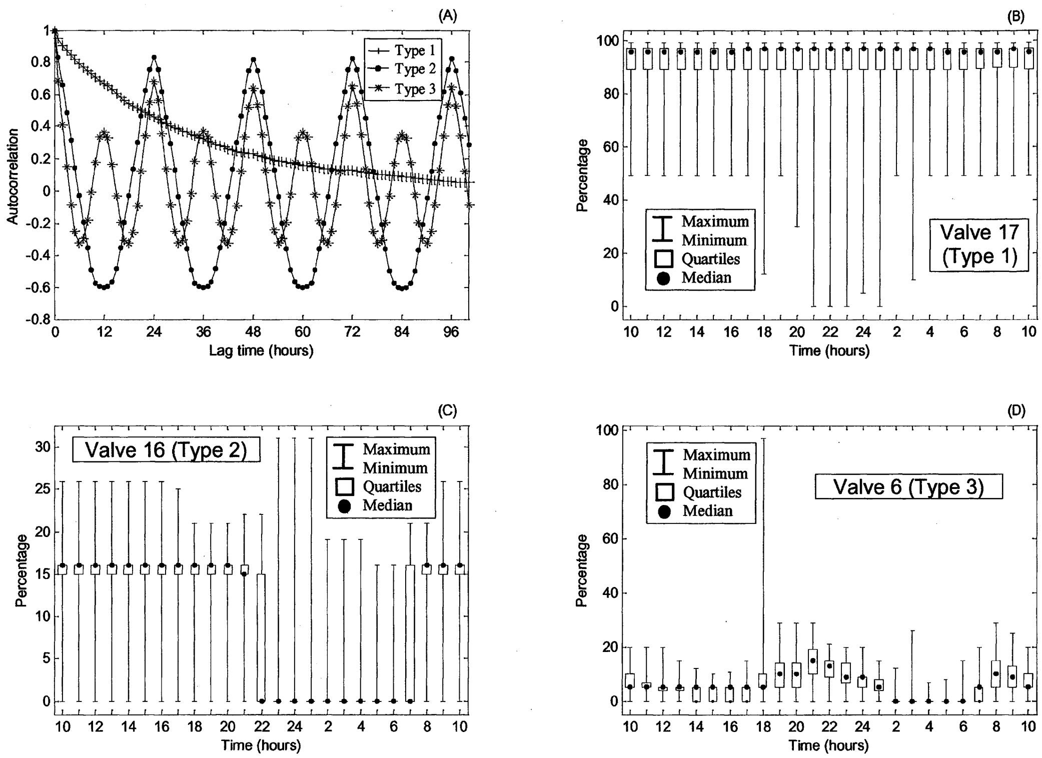

Fig. 4 (A) statistically classification of electric motor valves using autocorrelation function, (B) Valve 17 as an example of type 1, (C) Valve 16 as an example of type 2 ; and (D) Valve 6 as an example of type 3.

operated (e.g., V2, V3 and V4) while other motor valves are operated occasionally (see V1, V8 and V9).

To classify the different operational types of motor valves, we compute a collection of correlation coefficient calculated for various lags which is named autocorrelation function (ACF) for each motor valve of Block 12. **Figure 4A** shows an example of ACF plotted for the typical three types of valve operations in this network while **Figs. 4B**, **4C** and **4D** show a box-whisker plot of the statistical distribution of hourly degree of valve opening for the classified three types of valve operations in Block 12. The box-whisker plot shows the median, upper and lower quartiles and also the maximum and minimum valve opening recorded for each type of the motor valves. V17, V16 and V6 are selected as representative of type 1, type 2 and type 3 respectively.

The followings are the main characteristics of the three types of valves.

-***Type 1*:** Six valves of this network falls in this type and they are Valves 1, 4, 8, 9, 11 and 17. All these valves are connected to the main entrances of the network and have approximately constant percentage of opening during the different hours of the day (**Fig. 4B**).

-***Type 2*:** Valves 13, 15, 16 and 20 are classified under this type. Those valves have only one main change during daily operation; they are completely closed during night time (from 10.00 p.m. to 6.00 a.m.) and they have approximately constant percentage of opening during the remaining hours of the day. This type is connected to the internal pipes of the block to reduce pipe-leakage through the network; and also to decrease the pressure during the night time when the water demand is at minimum (**Fig. 4C**).

-***Type 3***: The remaining 10 valves are considered of this type. This type of valves has two main changes during daily operation and they are used to maintain the pressure value between 24 m and 32 m. Therefore those valves are slightly opened around the rush-hours (at 7.00 a.m. and 8.00 p.m.) and they are completely closed during the late night hours (**Fig. 4D**).

The classification of valves is important for future improvement of motor valve operations according to the time horizon on which they are considered. For long-term operation, the valves of *Type 1* are responsible for supplying the different nodes of Block 12 with the required water demand. Any future improvements of those valve settings should be done in conjunction with other valves connected to the main inlets and outlets of adjacent blocks. For example, any change occurs in motor valve (V1) will affect directly the operation of Block 15 which is located in the west of the studied Block 12. From another point of view, electric motor valve (V1) could be considered as a common valve between both blocks 12 and 15.

For middle-term operation or daily management, the four valves of *Type 2* is completely affect this time horizon management and in a lesser degree the 10 valves of *Type 3*. Those valves take into consideration the main daily change in consumption. Therefore, they are completely closed during the night time when the water demand at different network nodes is at its minimum. On the other hand, they are partially opened during the remaining hours of daily operation. When considering the rough tuning of pressure regulation problem both valves of *Type 1* and *2* should be involved in this operation to regulate pressure at different network nodes between the desired upper and lower target values.

For short-term operation or hourly management, *Type 3* valves take the complete responsibility of regulating the pressure at different network nodes. Those valves have no effect on the adjacent blocks and could be considered as fine-tuning operational valves. According to the type of time horizon operation, the valve operations could be divided into three operation terms.

5. Self-Organizing Maps Analysis

Input vectors to the SOM are all sets of electric motor valves for the studied three years of available hourly data. Considering that the size of SOM will affect directly the classification of input vectors to the different SOM competitive layer units, therefore a suitable size of SOM should be used. Different map size has been evaluated by calculating the above mentioned topographic and quantization errors. **Figure 5** shows contour map for both kinds of errors used in this study for all possible two-dimensional map sizes which varies from 2 to 30 neurons.

It is clear from both error contour maps that the size of the map has a strong effect on the distribution efficiency of input data vectors to the different neurons of the map. In general, increasing the map size will increase the topographic error which is calculated using Eq. 4 and represented in percentage (**Fig. 5A**) while in **Fig. 5B** brings more resolution into mapping when the quantization error decreases. It is not recommended regarding both figures to select a rectangular SOM shape, the topographic error increase rapidly near both horizontal and vertical axis and the quantization error contour lines has concave shape near the diagonal line which starts from the origin.

It is important to select an optimal map size therefore we decide to select a square shape and also a middle map size. The map size selected to present the different classification of

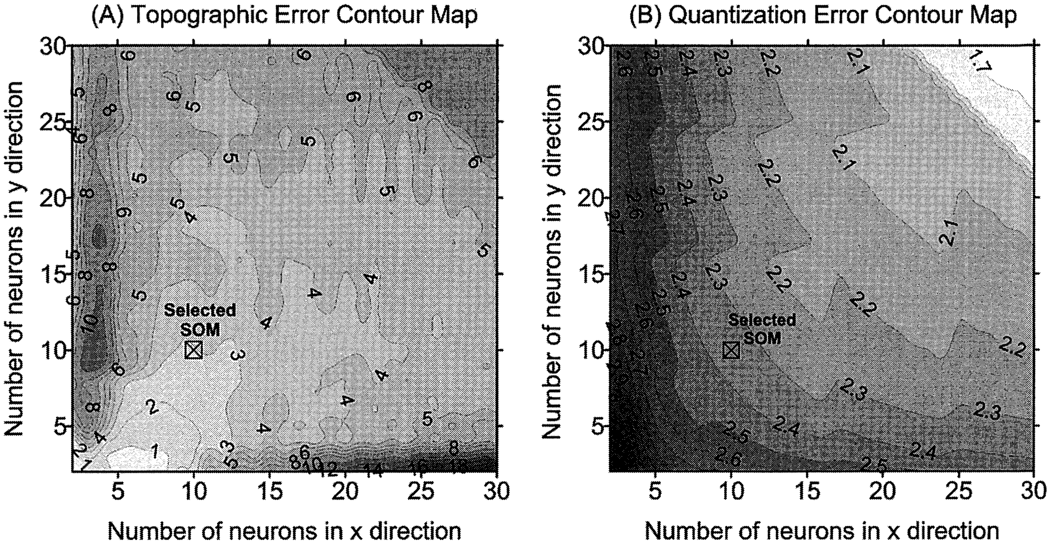

Fig. 5 Contour map of topographic and quantization errors, selected SOM size 10×10 (Topographic and quantization errors equal 2.9541 and 2.3456, respectively).

motor valve operations is . At that size the topographic and quantization errors equal 2.9541 and 2.3456, respectively. That's mean that out of the 24799 vector used in the training of SOM there is only 733 vector in which the first and second BMU aren't adjacent.

After selecting a map size of 10×10 the map is trained with the valve opening data subjected to Eq. 1 and 2. **Figure 6** shows a representation of all data components on the trained SOM. As shown in **Fig. 6** SOM could be considered as a good tool to visualize a high dimensional data. In **Fig. 6**, 24799 vectors are presented where each vector contains 20 motor valve opening. One of the good advantages upon classifying different input vectors by SOM that if any vector contains missing data the SOM could deal with this vector during the training process; each corresponding weight for the missing data in the vector will be neglected temporally from the calculation. Focusing on any unit of the map (for example the upper left one), we will see that V1 represents an opening of 10%, V2 correspond to an opening of 2% up to V20 which is completely closed. The same procedure could be carried on other units. The good distribution of colors in SOM for all components offers a suitable representation of any valve setting and also gives a good idea about the operation rule of this valve and the relation with other valves.

For all the three types of valve operations mentioned in the correlation analysis section, relatively high cross correlations exist between all valves located in the same type. For *Type 2* valves (V13, V15, V16 and V20) the upper area in the component analysis map (**Fig. 6**) indicates that those valves are completely closed while the lower units show that the four valves are partially opened at their maximum values during the three years of operation.

To compare the presentation of SOM components with the box-whisker plot of motor valves shown in **Fig. 3**. Both presentations give a good indication about different valves operation. When presenting an operation rule it is difficult for the box-whisker plot to efficiently represent the complicated electric motor valve operations like the presentation of the SOM shown in **Fig. 6** in which any unit represent an operational rule while each component represent the characteristics of the corresponding motor valve.

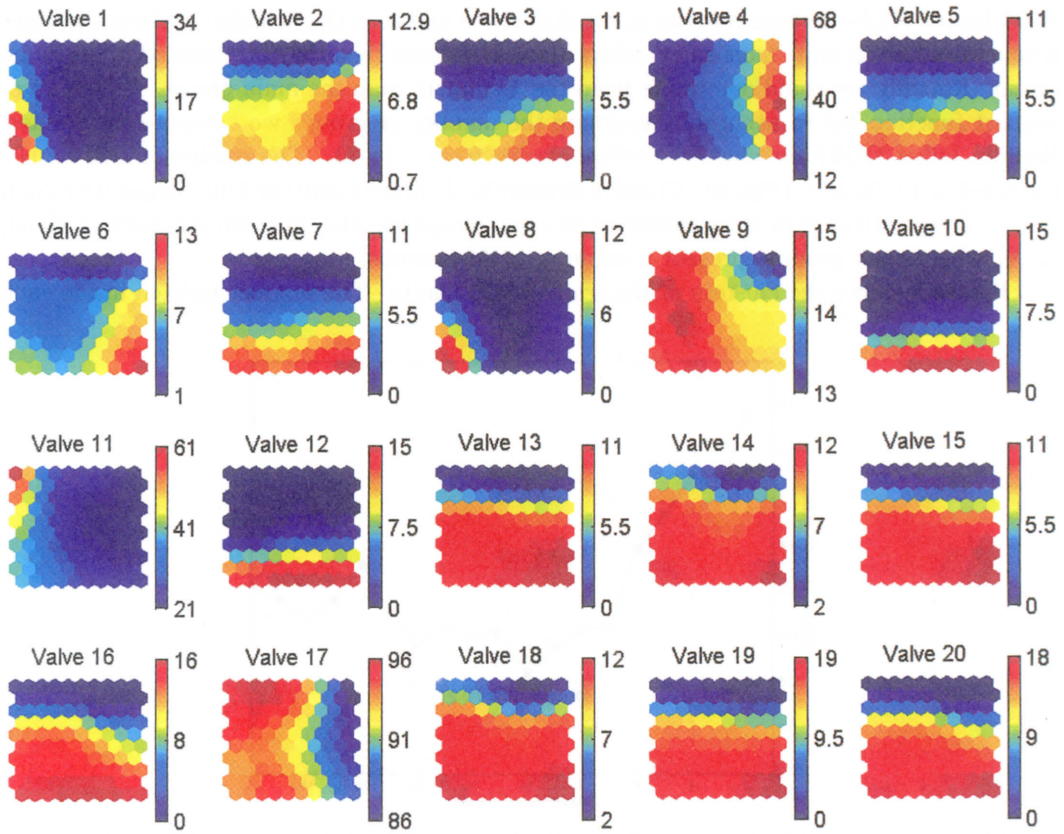

Fig. 6 Visualization of all electric motor valves openings of Block 12 calculated in the trained SOM.

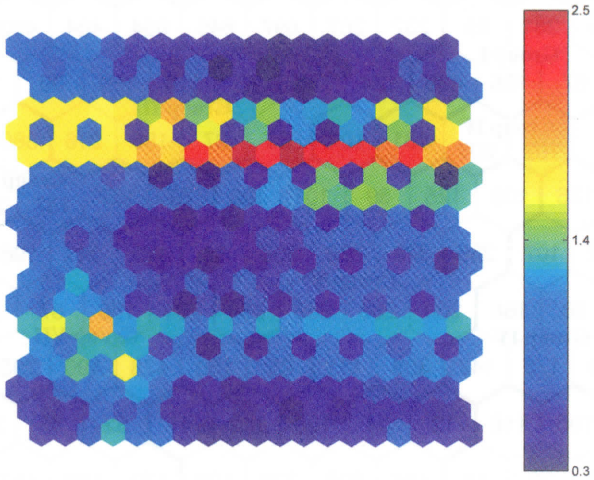

Fig. 7 Unified distance matrix of trained SOM of the electric motor valves (U-Matrix).

To cluster the different 100 units of the trained SOM to its main groups, the U-matrix technique has been applied. **Figure 7** shows the unified distance matrix of size 19×19 where scale color bar on the right represents the differences between SOM units; each unit in the U-matrix map represents weight difference between two adjacent neurons of the competitive

SOM layer. Highest value represents big difference and then the boundary between groups; if several adjacent units have same colors (lowest values) then they are located in the same group. Roughly we could determine from the U-matrix map the main groups of the valves support function but to accurately estimate the number of groups we compute the Davies-Bouldin Index (DBI) for clusters number varies from 2 to 20. The minimum DBI is 0.61 recorded at 10 clusters (**Fig.** 8). Clusters defined by U-matrix and the DBI agreed with each other. Thus, Valves data were classified into ten groups mention in Latin numbers (I, II, III, ..., X) where each group represent a union of SOM neurons.

Figure 9 shows the clusters of the trained SOM units. The number written inside each

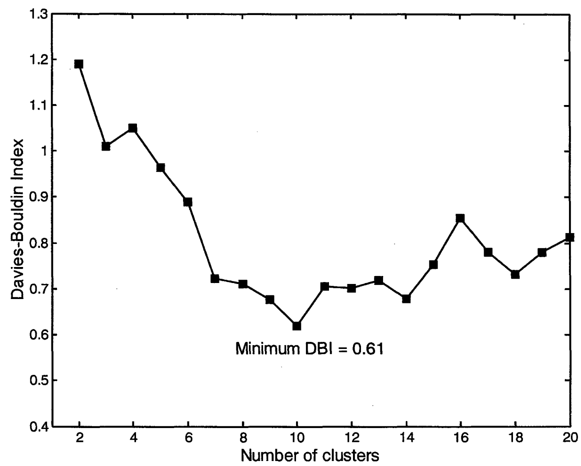

Fig. 8 Davies-Bouldin Index (DBI) at different number of clusters on the trained SOM.

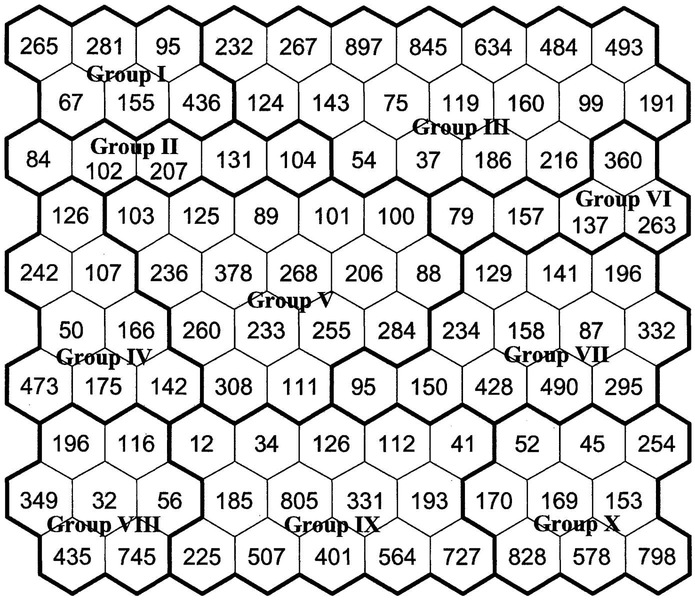

Fig. 9 Clusters of the trained SOM units. The boundaries of different groups mentioned in Latin numbers are set using the DBI and U-matrix methods. The number written inside each unit indicates the total number of hits associated with those units (Total number of hits is 24799)

unit indicates the total number of hits associated with those units or the location of BMU each vector of input data. Boundaries of different groups mentioned in Latin numbers are set using the DBI and U-matrix methods. Distribution of the 24799 hit varies between a minimum value of 628 hit recorded at group II to 5256 hit recorded at group III.

SOM could be considered as good tool for the presentation of highly dimensional data. It presents the characteristics of each data component and also presents the relation between different components. For time series analysis SOM could presents also the trajectory of data occurrence in which the movement of events from one unit to another on the map indicates important information about the studied problem. After the clustering of motor valve operations to its main groups, in **Fig. 10** we plot the three years hourly data distribution

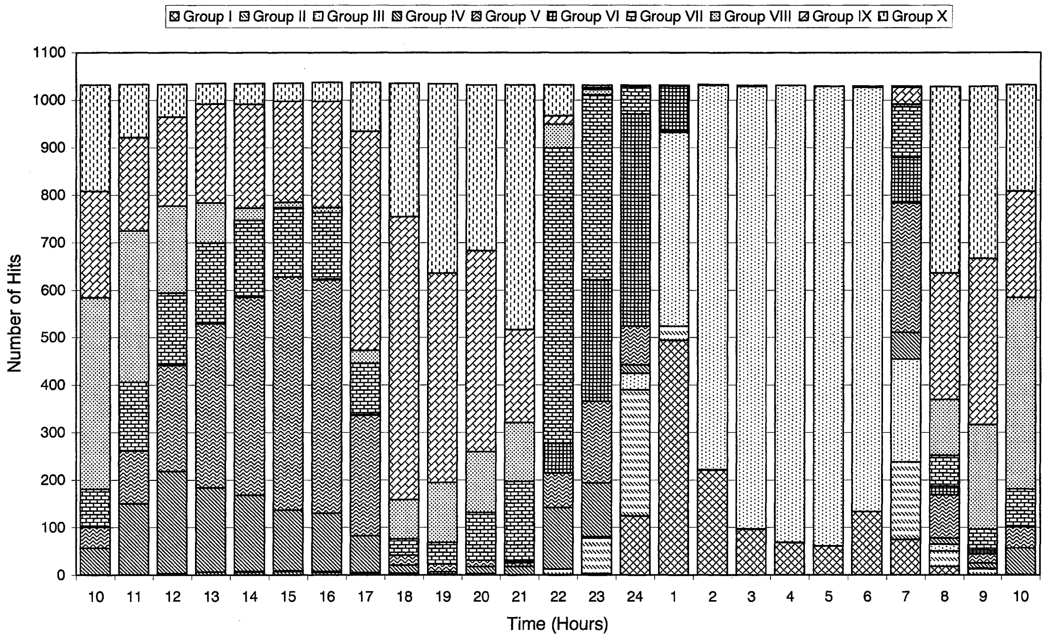

Fig. 10 Three years hourly data distribution of the trained SOM classified into ten categories according to the total number of hits recorded at each group.

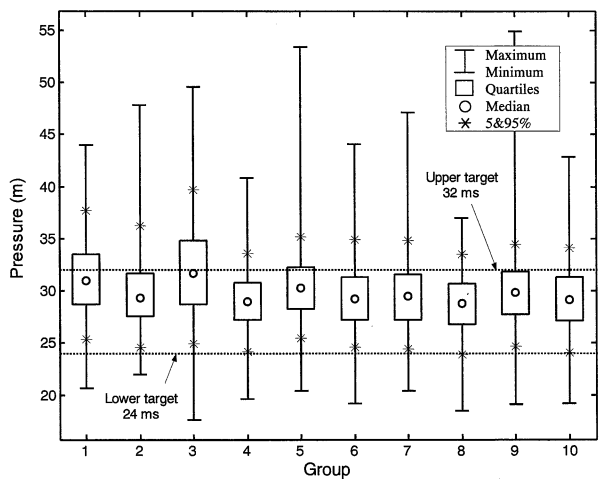

Fig. 11 Box-whisker plots for pressure gauge P3 classified to the different 10 groups of the trained SOM.

of the trained SOM into the ten classified categories according to the total number of hits recorded at each group. The occurrence of events for all ten groups are presented in this figure in which each group is located at a specified time interval. During the night time operation, both groups I and III are the dominate groups with 1299 hit and 5256 hit, respectively. Group IX which present a big number of hits (4263 hit) occurs during daily operation with its maximum number of hits at 6.00 p.m. Group V with 3145 hit occurs mainly in the afternoon period while Group X presented with 3047 event has its biggest effect after the night rush-hour at 9.00 p.m. and before the main change of valves operation in the night time. All detailed distribution of the different ten groups is plotted in **Fig. 10**.

In order to detect the water pressure variance in the different groups with respect to pressure gauges, **Fig. 11** outlines the pressure monitored in all ten groups with respect to a selected pressure gauge (P3). The box-whisker plot shows the median, upper and lower quartiles, upper and lower 5% of events and also the maximum and lower pressure recorded for each group of the trained SOM. From this chart it is seen that the median value of pressure at all groups varied from 24 m to 32 m, while for the upper 5% of all events, the pressure exceeds the value of 32 m and the maximum pressure value could reach the value of 55 m. On the other hand for less than 5% of all events, the pressure approximately equal to the minimum target value (24 m) and the minimum pressure value reached 17 m. When relatively comparing the groups, both groups 1 and 3 which the majority of their events occurred during night time show an increase in pressure compared to the remaining 8 groups. In Group I and III, 41% and 50% of events exceed the permissible upper target value, respectively. Therefore a future improvement of motor valve operations in both groups should be done in order to prevent the relatively high percentage of events that exceed the upper target value.

SOM could be used for improving the existing valve operation support functions by training a map with the flow meter readings which represent an embedded representation of the real water demand of the network. The training data for flow meters should be selected from well regulated pressure cases. In this map any unit in the SOM will present a case in which the pressure is well regulated and this unit contains also the corresponding valves opening set. After training the SOM, a simulation step is used to classify the unregulated pressure cases to the different SOM units according to their flow meters reading. Based on those classifications the appropriate electrical motor valves setting for the well pressure regulation events are used for the unregulated ones. This methodology offers good alternative solutions for improving future valve operational support functions.

6. Conclusions

This paper presents an analysis of motor valve operations in Block 12 of the Fukuoka City water distribution networks. The analysis has been performed on three years of telemetry data by using correlation analysis and an unsupervised class of artificial neural networks named Self-Organizing Maps (SOM). Correlation analysis has successfully classified the different motor valve operations of Block 12 into three categories in which each category is responsible of a term of operation. Those categories have been defined upon their effect on the studied block and the adjacent blocks. The SOM has been applied for understanding the motor valve operational rules. It has shown a high performance in visualization and abstraction of motor valve data comparing to traditional methods. The trained SOM efficiently classified the different operational rules and displayed all data components characteristics. With the assistance of the unified distance matrix (U-matrix) and the Davies-Bouldin Index (DBI) the trained SOM has been clustered into ten main groups. The characteristics of each group have been analyzed to determine its effect on pressure values recorded at observed nodes. An analysis of different operational rules has been performed and an application of SOM for improving future motor valve operation has been suggested.

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