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# Analysis of ambient $SO_2$ concentrations and winds in the complex surroundings of a thermal power plant

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**Summary.** — SO<sub>2</sub> pollution is still a significant problem in Slovenia, especially around large thermal power plants (TPPs), like the one at Šoštanj. The Šoštanj TPP is the exclusive source of  $SO_2$  in the area and is therefore a perfect example for air pollution studies. In order to understand air pollution around the Soštanj TPP in detail, some analyses of emissions and ambient concentrations of  $SO_2$  at six automated monitoring stations in the surroundings of the TPP were made. The data base from 1991 to 1993 was used when there were no desulfurisation plants in operation. Statistical analyses of the influence of the emissions from the three TPP stacks at different measuring points were made. The analyses prove that the smallest stack (100 m) mainly pollutes villages and towns near the TPP within a radius of a few kilometres. The medium stack's (150 m) influence is noticed at shorter as well as at longer distances up to more than ten kilometres. The highest stack (230 m) pollutes mainly at longer distances, where the plume reaches the higher hills. Detailed analyses of ambient  $SO_2$  concentrations were made. They show the temporal and spatial distribution of different classes of SO<sub>2</sub> concentrations from very low to alarming values. These analyses show that pollution patterns at a particular station remain the same if observed on a yearly basis, but can vary very much if observed on a monthly basis, mainly because of different weather patterns. Therefore the winds in the basin (as the most important feature influencing air pollution dispersion) were further analysed in detail to find clusters of similar patterns. For cluster analysis of ground-level winds patterns in the basin around the Soštanj Thermal Power Plant, the Kohonen neural network and Leaders' method were used. Furthermore, the dependence of ambient  $SO_2$  concentrations on the clusters obtained was analysed. The results proved that effective cluster analysis can be a useful tool for compressing a huge wind data base in order to find the correlation between winds and pollutant concentrations. The analyses made provide a better insight into air pollution over complex terrain.

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P. MLAKAR



Fig. 1. – Šoštanj Thermal Power Plant and its complex terrain surroundings.

# 1. – Introduction

Šoštanj is the largest Slovenian thermal power plant (TPP, fig. 1). Before installation of desulphurisation equipment it emitted about 100000 tons of SO<sub>2</sub> per year [1]. Local lignite of low calorific value and very high percentage of sulphur (up to 2%) is used. The TPP is the only important source of SO<sub>2</sub> pollution in the area. Emissions and several ambient automatic measurements of SO<sub>2</sub> and meteorological parameters can be treated as a large tracer experiment. That is the reason why it is very suitable for pollution analysis. The TPP has 5 blocks and three stacks of very different heights: 100 m for units 1, 2 and 3, 150 m for unit 4 and 230 m for unit 5.

The TPP is located in a basin in the north-east part of Slovenia. The basin is



Fig. 2. – Complex orography around Šoštanj TPP with locations of automatic measuring stations (20 km  $\times$  20 km).



Fig. 3. – Frequency distribution of  $SO_2$  emissions from the three stacks in the year 1992.

surrounded by the semi-mountainous continuation of the Karavanke Alps which are up to 400 m above the basin floor, and with many narrow valleys (fig. 2). Very low winds and frequent thermal inversion situations are typical of the winter months. Many air pollution episodes occurred there. In 1990 a modern Environmental Information System (EIS) for the Šoštanj TPP [2] was installed in the surroundings to monitor emissions, ambient pollutant concentrations and meteorological parameters at different sites in the surroundings of the TPP.

From the EIS of Šoštanj TPP a huge data base is available. It was used in the present work to study the relationship between emissions, ambient  $SO_2$  concentrations and local ground-level winds. The data collected in the period from 1991 to 1993 were used (before the installation of a desulfurization device).

Statistical analyses of the influence of the emissions from the three TPP stacks at different measuring sites were made. A detailed analysis of the duration of ambient  $SO_2$  concentrations was also made. Half-hourly increments of ambient  $SO_2$  concentrations were analyzed over a longer period.

The second aim of our work was to find clusters of similar wind field patterns measured on a short-scale domain. For regional-scale wind fields a similar study has been made by Kaufmann and Weber [3]. Typical patterns obtained by this analysis can be used as the input for air pollution forecasting models. Another possible application is preparation of scenarios of typical pollution situations for advance warning (alarm) purposes. As a tool for wind data cluster analysis, the Kohonen neural network [4] was used. A comparison was also made with a basic version of dynamic clustering methods—the leaders' method [5].

## 2. – Atmospheric pollution from TPP stacks of different height

Emissions from the three different TPP stacks vary very much from each other. The smallest stack is connected to the three oldest TPP blocks. It emits less than 5 tons of  $SO_2$  per hour, while the two highest stacks are connected to modern blocks of much higher power, and each of them can emit up to 8 tons per hour of  $SO_2$ . The distribution of annual emissions for 1992 is shown in fig. 3.

In order to analyse the effects of pollution from different stacks, intervals in which only one of the stacks was in operation were selected from the 1991-1993 data base. These are rare situations, but worth of analysis.

In the spring of 1991, 514 half-hour intervals were found when only the smallest



Fig. 4. – Ambient concentrations at different locations vs. emissions from the smallest stack (the two other units having 0 emission).

stack was in operation. Emission was from 1.5 to 2 tons of SO<sub>2</sub> per hour. The scatter plots (fig. 4) show the values of SO<sub>2</sub> ambient concentrations at three stations in the TPP surroundings. It can be observed that the smallest stack mainly pollutes in the vicinity of the TPP. The Šoštanj measuring station located close the power plant can have extremely high concentrations (19 cases over 0.25 mg/m<sup>3</sup>). Also, the Veliki vrh station that is located on the top of a hill near the TPP can have very high concentrations due to emissions from the lowest stack (26 cases over 0.25 mg/m<sup>3</sup>). But the Zavodnje station, which is located on the slope of a hill 7 km away from the TPP, did not record any concentrations over 0.25 mg/m<sup>3</sup> of SO<sub>2</sub>. It can be concluded that the worst influence of the smallest stack emissions is expected within a 3-4 km radius around the TPP.

For the analysis of the impact of the medium stack, 227 half-hour intervals in spring and autumn 1993 were examined when only this stack was operating. Concentrations up to  $0.4 \text{ mg/m}^3$  of SO<sub>2</sub> were recorded at Šoštanj, Zavodnje and Veliki vrh stations due to emissions of 3 to 7 tons of SO<sub>2</sub> per hour. Their distribution was approximately the same at all three stations. This proves that the medium stack causes pollution at short and medium distances around the TPP.

In 1993, 2274 half-hour intervals were found with emission only from the highest stack. The emission rates were from 3 to 7 tons of  $SO_2$  per hour. Concentrations up to 0.6 mg/m<sup>3</sup> of  $SO_2$  were recorded at Šoštanj, Zavodnje and Veliki vrh. But at the Zavodnje station there were 9 cases when concentrations were over 0.25 mg/m<sup>3</sup> and 5 such cases at Veliki vrh and 4 at Šoštanj stations. That proves that the highest stack pollutes more at longer distances, and only partially at short distances.

Due to the rarity of situations when only the medium stack was operating, 4015 half-

598



Fig. 5. – Frequency and duration of  $SO_2$  pollution episodes at the Sostanj station (1993).

an-hour intervals in 1993 were also examined when both higher stacks were operating. 16 intervals were found when  $SO_2$  concentrations at the closest Šoštanj station were extremely high—from 1 to 2 mg/m<sup>3</sup>. This fact demonstrates the stack tip downwash effect in complex terrain; very high stacks do not prevent extremely high concentrations being reached near the source.

## **3.** – Frequency and duration of episodes of high ambient $SO_2$ concentrations

One of the important characteristics of air pollution at a particular location is certainly the duration and frequency of pollution episodes. Such episodes depend mainly on the local microclimatology. In the case of the complex terrain around Šoštanj, a variety of pollution episodes is expected.

The duration and frequency of episodes of high ambient  $SO_2$  concentrations were analysed for the period from 1991 to 1993 for six stations. More than 90% of the halfhourly intervals have valid measurements. The results for different years show that the pollution patterns mostly remain the same at a given station. But if we analyse shorter time intervals—for instance every 2 months—the patterns differ very much from each other for the same station. The conclusion is that one year of data is enough to obtain reliable information about the frequency and duration of pollution episodes at a particular station.

Further, the analysis showed that the six stations of the EIS STPP can be classified into three groups according to the frequency and duration of  $SO_2$  pollution episodes. For every station, the number of episodes of high concentrations were counted for 4 different classes of  $SO_2$  concentrations. The duration unit for these episodes was a half-hour interval. It is important that a long period of medium concentration can also include a shorter period of high concentration. In such a case, both are counted.

The first type of pollution pattern is represented by the Šoštanj station, which is situated close to the stacks. The second type is at the Veliki vrh, Topolšica, Graška gora and Zavodnje stations, and the last type is represented by the Velenje station.

The Soštanj station (shown on fig. 5) has a very high percentage of high-concentration (upper two classes of concentrations, *i.e.* > 0.80 mg/m<sup>3</sup>) pollution episodes. This is not the case elsewhere, as we will see. High-pollution episodes can last up to two or three half-hour intervals, while the low ones (> 0.15 mg/m<sup>3</sup>) can last much longer, up to 20



Fig. 6. – Frequency and duration of SO<sub>2</sub> pollution episodes at the Veliki vrh station (1993).

half-hour intervals, but usually less than 5.

At the Veliki vrh station (see fig. 6), which is a representative of the second group, episodes of the upper two classes of high concentrations are very short and very rare. Usually they last only one interval and rarely two. The histogram of low-pollution episodes has a similar shape to the one for the Šoštanj station.

The last type of pollution is represented by the Velenje station. 5 to 10 times fewer pollution episodes are recorded there than at the other stations. Most of the episodes are long-lasting low concentrations.

# 4. – $SO_2$ concentration change dynamics

The goal of the second part of our research was to find out how rapidly changes of  $SO_2$  concentrations occur at different stations. The analysis was made for all the stations for three years. For every two consecutive half-hour intervals, the concentration change at a particular station was examined. The changes were divided into 30 classes (15 for increasing concentrations and 15 for decreasing), as shown on the histograms. It turned out again that one year of data is sufficient to describe the patterns at a particular station.

According to the observed dynamic patterns, the stations can be divided into three groups.

Soštanj and Veliki vrh stations are representatives of the first group, where very rapid concentration changes prevail. The histograms (fig. 7) are approximately symmetric. The concentrations increase at the same rate as they decrease.

Topolšica, Zavodnje (see fig. 8) and Graška gora stations are representatives of the second group, where slow concentration changes prevail. Half-hour changes greater than  $0.2 \text{ mg/m}^3$  are rare which is not the case at Šoštanj and Veliki vrh stations.

The third group again consists of only the Velenje station, where most of the concentration changes are very slow and rapid concentration changes do not occur at all.

For the Soštanj station, analysis was also made on a two-month basis for several consecutive monthly pairs from 1992 to 1993. The histograms are more asymmetric and there is no similarity as was found on a year-by-year basis. The pairs of histograms for 1992 and 1993 are much more similar than the histograms within one year. Figures 9



Fig. 7. – Histogram of SO<sub>2</sub> concentration changes for Šoštanj station (1992).

and 10 show examples of different histograms for two seasons, in which the presence of higher concentration changes in the spring pair can be seen. This can be explained by winter thermal inversion situations that are typical of this region. During thermal inversions high concentrations are formed slowly by pollution accumulation and they are not dispersed quickly (peak on decreasing side of fig. 9).

### 5. – Kohonen neural network

The Kohonen neural network [1], also called a "Feature map", is a neural network capable of performing unsupervised clustering and classification. No knowledge of the clusters is needed in advance. It takes the data and organises it into clusters —groups with similarity. Typical topology of a Kohonen neural network is shown in fig. 11. It consists of one layer of neurons organised in a rectangular shape.



Fig. 8. – Histogram of SO<sub>2</sub> concentration changes for Zavodnje station (1992).



Fig. 9. – Histogram of SO<sub>2</sub> concentration changes for Šoštanj station (January and February 1993).



Fig. 10. – Histogram of SO<sub>2</sub> concentration changes for Šoštanj station (May and June 1993).



Fig. 11. – Sketch of the Kohonen neural network.



Fig. 12. – Graphical representation of the leaders' method in three-dimensional space.

The data set that we want to classify consists of patterns also called vectors.

Each neuron represents one cluster. Each input vector component has a weighted connection to every neuron. When classifying a particular input vector, each neuron takes the input vector component values and passes their weighted sum to the output. The neuron with the extreme output score is called the "winning neuron". The input vector belongs to the cluster represented by the winning neuron. Neighbouring neurons represent clusters with high similarity.

In the iterative process of learning the network [4], the weights from input features to the neurons are adjusted to ensure that input patterns belonging to the same cluster activate the same neuron and that similar clusters are represented by neighbouring neurons.

The number of clusters should be selected in advance and is given by the number of neurons.

## 6. – Leaders' method

Another unsupervised clustering method is the leaders' method [5], a basic version of a dynamic clustering method.

The leaders' method searches for the cluster centres that are also called leading vectors or leaders (see fig. 12).

The number of leaders should also be set in advance as in the case of the Kohonen neural network. When starting the training algorithm, the leaders are initialised randomly.

The patterns in the training set of data are then divided into groups. Each pattern belongs to the group with the most similar leader. When the patterns are divided, new centres (leaders of the clusters) are recalculated. This algorithm is repeated until stabilisation of the leaders is reached.

P. MLAKAR



Fig. 13. – Wind roses for the analysed data set.

# 7. - Clustering of the Šoštanj region wind measurements

For cluster analysis of wind measurements, data from the first six months of the years 1991, 1992 and 1993 were taken. The data base consisted of approximately 26000 readings at half-hour intervals. Every interval forms one pattern. Each pattern consisted of the half-hourly average values of ground-level wind measurements (direction and speed) at five EIS ŠTPP stations: Šoštanj, Veliki vrh, Zavodnje, Velenje and Graška gora (see fig. 13). As a distance measure between the patterns, the Euclidean distance was used.

The number of clusters was not known in advance. In order to obtain a meaningful number of clusters, several runs were made with different numbers of clusters: 10, 20, 26, 32, 40, 50, 60, and 100.

To determine the clustering quality, a cost function was calculated. Its value becomes smaller the less the members within each cluster are scattered. Firstly mean vector wind speed and direction for each station and each cluster were calculated. Then the standard deviation of wind speed for every cluster and every station was calculated. This was followed by calculation of a weighted sum of the standard deviations over all clusters for each station. As a weighting factor, the probability of each cluster was used. Finally, the

TABLE I. – Values of cost functions for clustering quality determination in the Kohonen neural network.

Average weighted standard deviation for wind direction (°)	Average weighted standard deviation for wind speed (m/s)	Weighted index
57.7	0.66	1.24
51.9	0.61	1.13
50.7	0.58	1.09
48.2	0.57	1.05
46.8	0.56	1.02
47.2	0.55	1.03
46.1	0.55	1.01
43.7	0.51	0.95
	Average weighted standard deviation for wind direction (°) 57.7 51.9 50.7 48.2 46.8 47.2 46.1 43.7	Average weighted standard deviation for wind direction (°) Average weighted standard deviation for wind speed (m/s)   57.7 0.66   51.9 0.61   50.7 0.58   48.2 0.57   46.8 0.56   47.2 0.55   46.1 0.55   43.7 0.51

weighted sums were averaged over all the stations. A similar function was also calculated for the wind direction. The final weighted index W was calculated:

(1) 
$$W = \frac{\sigma_{\rm d}}{100} + \sigma_{\rm s} \,,$$

where  $\sigma_d$  is the weighted standard deviation of wind direction and  $\sigma_s$  is the weighted standard deviation of wind speed.

The formula was derived by noticing that the standard deviation of wind speed ranges around 1 m/s, while the standard deviation of wind direction is around  $100^{\circ}$ ; the factor "100" in eq. (1) eliminates the influence of different units. Table I shows the results for several numbers of clusters.



Fig. 14. – Searching for the meaningful number of clusters.  $\bullet$  AWSD<sub>D</sub>: average weighted standard deviation of wind direction;  $\times$  AWSD<sub>S</sub>: average weighted standard deviation of wind speed.

Number of clusters	Average weighted standard deviation of wind direction (°)	Average weighted standard deviation of wind speed (m/s)	Weighted index
10	56.9	0.67	1.24
32	49.54	0.56	1.05

TABLE II. - Values of cost functions for clustering quality determination in the leaders' method.

If the values of the functions are plotted, fig. 14 is obtained. If the number of clusters is greater, the values of the weighted average standard deviations decrease. From a certain number of clusters on, the decrease in the weighted average standard deviations becomes smaller than before. This effect is shown by the two pairs of lines in fig. 14. Each pair of lines have an intersection at the so-called meaningful number of clusters. This method is not very precise. In our case, we can estimate the meaningful number of clusters as 32.

A comparative study was also made with the leaders' method for 10 and 32 clusters. They are shown in table II. We can see that the quality of clustering with both methods is approximately the same, because the values of the cost functions do not differ significantly.

### 8. - Clustering results of wind measurements

As the best final result, the number of 32 clusters was taken. This does not mean that the other results are unuseful. If the winds are divided into less than 32 clusters, then the clusters differ very much from each other. But the elements within clusters are much more scattered and are not so similar to each other. On the other hand, if there are a lot of clusters, the clusters are much more similar, but the elements of clusters are less scattered—the division is more precise.

Figure 15 shows wind roses for one of the clusters from a division into 10 clusters and for one of the corresponding clusters from a division into 100 clusters, to show this aspect. The last one is certainly significantly less scattered.

Figure 16 shows some of the results for a division into 32 clusters using the Kohonen neural network. The division is very precise. Figure 17 shows its frequency distribution.



Fig. 15. – Wind roses for one cluster from a division into 10 clusters (left), and from a division into 100 clusters (right) (stations are positioned as on fig. 13).



Fig. 16. – Wind roses for 4 clusters of the division into 32 clusters with the Kohonen neural network (stations are positioned as on fig. 13).

Division using the leaders' method for the same number of clusters gave very similar results and can also be used. The only but useful difference between the two methods is that the Kohonen neural-network clusters are more similar if their numbers are close to each other, but the clusters obtained by the leaders' method are numbered randomly.

Furthermore, additional analyses were made of how the ambient  $SO_2$  concentrations



Fig. 17. – Frequency distribution of patterns: division into 32 clusters using the Kohonen neural network.



Fig. 18. – Dependence of ambient  $SO_2$  concentrations on wind field clusters for the Šoštanj and Veliki vrh stations (Kohonen neural network, 32 clusters). Continuous line represents the trend line using a 6th-order polynomial function.

measured at the stations around Šoštanj TPP depend on the wind clusters. Figure 18 shows an example. High  $SO_2$  concentrations depend on the wind field clusters. Therefore the probability of high concentrations for a particular cluster can be a useful feature in air pollution stochastic forecasting models or models based on neural networks [6,7].

#### 9. – Discussion and conclusions

An analysis of the influence of stack height on ambient  $SO_2$  concentrations in an area of complex terrain around the Šoštanj TPP located in Slovenia shows the need to use sophisticated numerical models for the modelling of air pollution.

High ambient  $SO_2$  concentrations and analyses of the dynamics of concentration changes explain why a Gaussian model does not perform well in the Šoštanj area [8,9], which is a typical example of complex terrain. Simple Gaussian model equations are valid for steady-state examples and homogeneous meteorological fields, but the very rapid concentration changes and peaks with a duration of one half-an-hour interval, together with the non-homogeneous wind field (due to complex terrain), are certainly not suitable for the application of Gaussian models.

The Kohonen neural network proved to be a very effective tool for unsupervised cluster analysis of wind data in complex terrain. The cluster analysis of ground-level wind measurements gave new information about wind fields in the Šoštanj region. The typical wind patterns obtained can be a good platform for further analyses and prediction of pollution situations in the region [10].

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