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Jämsä-Jounela, S.-L.; Laine, Sampsa; Ruokonen, Eeva
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Ore Type based Expert Systems in Mineral Processing Plants

Sirkka-Liisa Jämsä-Jounela*, Sampsa Laine**, Eeva Ruokonen***

Abstract

Artificial intelligence (AI) includes excellent tools for the control and supervision of industrial processes. Several thousand industrial applications have been reported worldwide. Recently, the designers of the AI systems have begun to hybridize the intelligent techniques, expert systems, fuzzy logic and neural networks, to enhance the capability of the AI systems. Expert systems have proved to be ideal candidates especially for the control of mineral processes. An expert system based on on-line classification of the ore type has been developed.

Self-organizing maps (SOM) are used for pattern recognition of the type of feed. The system has been tested in two concentrators, the Outokumpu Finnmines Oy, Hitura Mine and Outokumpu Chrome Oy, Kemi Mine. The methodology for the development of the ore type based expert system is presented and the preliminary results obtained in the above plants are described.

1 Introduction

Ten years ago, expert systems were introduced, and this was followed by an explosion in the use of fuzzy logic and neural networks. Since then, these three technologies have received several thousand industrial applications worldwide: monitoring and analysis of process operations, fault diagnosis, supervisory control, feedback control and scheduling and planning of operations. Recently, the designers of these systems have begun to hybridize these intelligent techniques to enhance the current capability of expert system.

Expert systems have proved to be excellent tools especially for the control of mineral and metallurgical processes. Successful industrial applications have been reported in the area of diagnosis of process operations and intelligent control.

Ore deposits are almost always heterogeneous in composition and structure. Heterogeneity impairs profitable production because dissimilar parts of an ore deposit require different treatments in beneficiation. The primary reason for concentrator instability is variations in the type of feed. This problem can be approached in two ways. The first approach is to determine explicitly the type of feed and to develop respective strategies. Determination can be based on the location of the source of the ore (geostatistical approach) or on measurements carried out inside the concentrator (on-line determination). The second approach is to treat the problems caused by varying feed types without explicit knowledge of the feed type.

An expert system based on the geostatistical approach for concentrator control has been realized at the Kemira Siilinjärvi mine. The concentrator uses homogenization piles into which the ore is hauled from the excavations. The plant geologist determines the type of ore in the excavation, and the composition of the piles can be deduced from the excavation data. A database storing the process behavior of each type is maintained. As the feed type is known, the operator can find, using the system, the best method of treating the type of feed in question [1, 2].

In the second approach, mathematical models are required in the determining the ore type. Cluster analysis [3] has been used for the off-line determination of the ore type [4]. Significant work related to the determination of the feed type has been carried out by *Ginsberg* and *Whiten* [5]. They demonstrated that the cluster algorithm is a good mathematical method for classifying data of high dimensionality. The

corresponding on-line algorithm has been developed by *Ylinen et al.* [6]. *Laine et al.* [7, 8] have studied self-organizing maps for ore-type determination.

As successful case projects, expert system based on on-line classification of the ore type is described in this paper. The essential feature of this expert system is the classification of different ore types and their distinct control strategies at the plant. In addition to the classification, the expert system has a database containing information about how to handle the determined ore type. This self-learning database scans historical process data to suggest the best treatment for the ore type under processing. The system has been tested in two concentrators, the Outokumpu Finmines Oy, Hitura mine and Outokumpu Chrome Oy, Kemi mine.

2 Generic Methodology for the Development of the Ore Type based Expert System

The major tasks of the development of the expert system are presented in [Figure 1](#). The first task is the off-line determination of the feed types of the concentrator. The results are used in the development of the on-line classification and also in the feed type based process study that results in the authoring of the knowledge base.

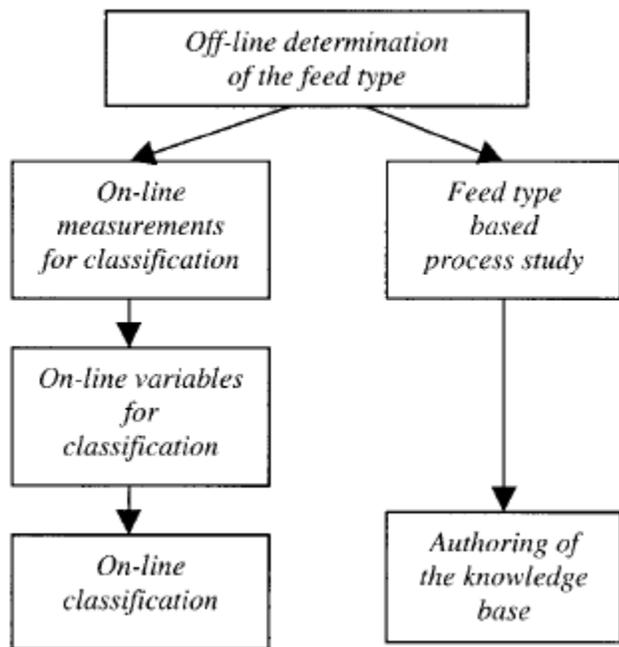


Fig. 1. Utilization of off-line classification

The different types of information can be used in the off-line determination of the feed type. A spatial model of the mineralogy of the ore body can be created and the type of concentrator feed can be determined using the location of the excavation. Another possibility is to sample the concentrator feed and to study the feed type on the basis of the laboratory analysis. If possible, independent sources of off-line information should be used as the results derived from one source can be verified using another source.

The data are classified using a classification algorithm and the results are verified. In this research the self-organizing map (SOM) has been selected for the classification. The development phases of the on-line SOM are presented in [Figure 2](#). The on-line measurements available in the process automation system are studied and the measurements reflecting the feed type are collected. The on-line classification variables are created on the basis of these measurements; the primary objective of the phase is to remove the influence of the operator present in the measurements. An on-line SOM is calculated and verified using these measurements.

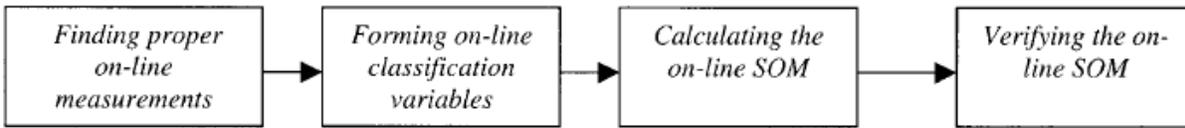


Fig. 2. Formulation of the on-line SOM

The structure of the expert system proposed for the Hitura and Kemi concentrators is presented in Figure 3. The main function of the system is the on-line determination of the feed type performed by the classification block. It is based on the SOM which classifies the on-line information received from the automation system. This block is supported by the update classification block. It contains the functions for the calculation and modification of the SOM.

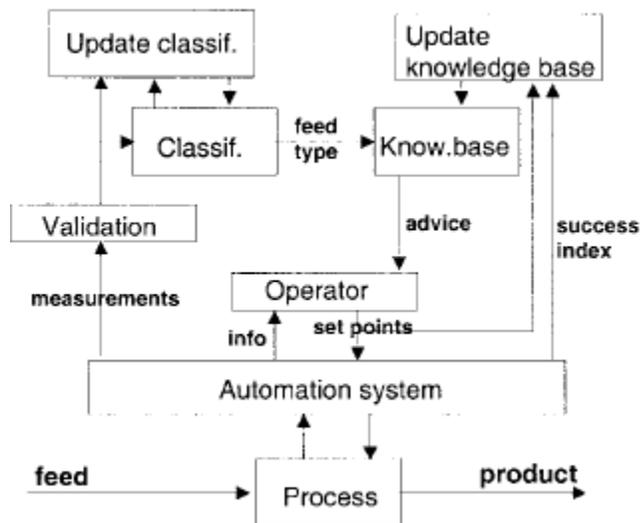


Fig. 3. Structure of the expert system

Prior to the classification, the data must be validated to remove invalid data produced by process or measurement disturbances. The second major set of functions in the system is related to the knowledge base block. The block itself stores the data about the proper treatments for various feed types. The block is supported by the update knowledge base block that updates the knowledge if new proper methods of treatment appear. The method is based on a success index indicating the profitability of the relevant treatment. The success index is an on-line measurable parameter.

3 Self-Organizing Map

Of the architectures and algorithms suggested for artificial neural networks, the SOM has the special property of effectively creating spatially organized internal representations of various features of input signals and their abstractions. Self-organization is based on competitive training that is able to find clusters from the learning data.

3.1 Training Algorithm

In training, the elements of the SOM compete for the input vector; the element that is closest to the input vector is the winner. The selected element (winner) and its neighborhood are moved closer to the presented

input vector. The elements of the network gradually learn to represent the training data. Because the neighborhood is taken into account, the properties of adjacent elements become similar. The map becomes ordered in such a way that clusters with similar properties are located near to each other [9].

If the input vector is denoted by $x = [x_0 \ x_1 \ \dots \ x_{N-1}]^T$ and the location vector of a mapping element by $m_i = [m_{i0} \ m_{i1} \ \dots \ m_{iN-1}]^T$, it is possible to write the algorithm that describes the self-organizing operation:

- (I) Initiate the locations of the elements with random values
- (II) For each vector of the training data compute C1 and C2

(C1) Find the SOM element m_c (winner) best matching the data vector $x(t)$ by searching all elements m_i

$$|x(t) - m_c(t)| = \min_i \{|x(t) - m_i(t)|\} \quad (1)$$

(C2) and adjust the locations of the elements

$$m_i(t+1) = \begin{cases} m_i(t) + \alpha(t)\{x(t) - m_i(t)\} & \text{for } i \in N_c \text{ (} N_c = \text{neighborhood)} \\ m_i(t) & \text{for all other indices} \end{cases} \quad (2)$$

In Eqs. (1) and (2) the Euclidean metric can be used as the distance measure.

The parameter $\alpha(t)$ in Eq. (2) is a coefficient that determines the movement of the winning element and the neighborhood in the direction of the data vector $x(t)$. The parameter $\alpha(t)$ is equivalent to the learning rate used in the back propagation algorithm for feedforward neural networks. $\alpha(t)$ is recommended to decrease slowly with time. Initially $\alpha(t)$ may be chosen as unity. In the final stages, the values are recommended to be less than 0.01. One method for calculating $\alpha(t)$ is presented in the following equation, in which T , the total number of iterations, and α_0 , the initial value of $\alpha(t)$, are provided by the user of the algorithm.

$$\alpha(t) = \frac{\alpha_0 T}{T+100t} \quad (3)$$

The neighborhood of the winning element c is defined by $N_c = \{i | d(i, c) < r(t)\}$, where $d(i, c)$ is the distance between map elements i and c , and $r(t)$ is the radius of the neighborhood. To ensure good global ordering, the radius $r(t)$ should initially be more than half the diameter of the network. The radius should slowly decrease with time. In the final stage a small radius gives the map a good local spatial resolution. In addition to arranging the map topologically, the use of the neighborhood equalizes the number of input vectors classified in each cell.

The third parameter of the training is the number of iteration steps. To achieve a good statistical accuracy, the number of training steps must be at least 500 times the elements in the SOM.

3.2 Visualization of the SOM

The topology of the trained SOM in the training data space RT can be inspected graphically. Each SOM element carries a vector specifying its location in the RT . In one-dimensional SOM the value corresponding to the dimension is collected from the location vector of each element. The values are set into a matrix that can be presented graphically. The elements with high values are colored black and elements with low values are colored white. This is illustrated in [Figure 4](#). In the two-dimensional SOM, the top left corner corresponds to the section of training data closest to the origin of the XY presentation: the values of both variables are close to zero. Similarly, the top right corner of the SOM corresponds to the bottom right corner of the XY presentation: the value of $Var1$ is at its maximum and the value of $Var2$ is approximately one.

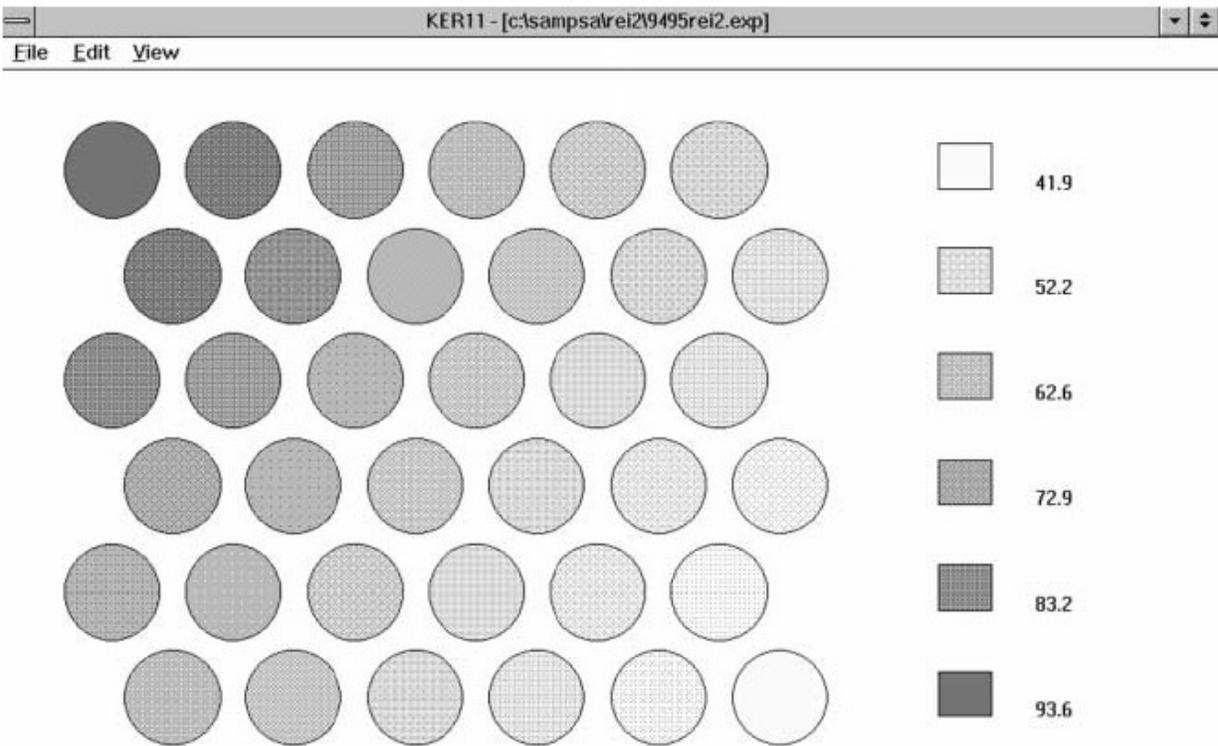


Fig. 4. Graphical illustration of the values of a variable in the elements of the SOM

4 Hitura and Kemi Mines

The Hitura mine is a nickel mine located in central Finland. The mine capacity is 530 000 t/a ore and production currently is 38 000 t/a of NiCu concentrates with a grade of 6.5% Ni, 1.7% Cu and 10–12% MgO.

The Hitura ore (0.65% Ni, 0.2% Cu) occurs in amphibole-bearing rocks at contact of a pipe-shaped serpentine against mica-gneiss. The main sulfide minerals are pyrrhotite, pentlandite and chalcopyrite. The inner part of the ore body is strongly serpentinized ultramafite and parts of the sulphides have been converted to mackinavite and vallerite. At the same time the grain size of the sulfides decreases. There are many problems in beneficiating the deposit: natural flocculation, grindability variations, slime formation and natural floatability of MgO-rich sheet silicates. This results in low recovery and grade of the concentrate and a high consumption of chemicals and energy.

At the Hitura mine the underground ore is truck-hoisted to the three-staged crushing plant at the surface. The fine ore is heap-stored and its fineness is 100% – 0.022 mm. The conventional rod mill-ball mill grinding circuit consumes 20–30 kWh/t-new-200 mesh. The throughput varies from 60 to 75 t/h. Slurry densities in grinding are exceptionally low owing to the tendency for flocculation.

Rougher flotation consists of four rougher banks, each including four OK-16 cells. The residence time of roughers is approximately 50 min. The concentrate from the first rougher bank is cleaned once. The concentrates from the other rougher banks are reground and cleaned three times. The cleaner tails are fed into the third rougher bank. Sulfuric acid has been used for pH adjustment (pH5–6), and it also has a dispersing effect on the slurry. The Kemi chromium mine is part of Outokumpu Oy's stainless steel business

segment, which is engaged in the fully integrated production of stainless steel. At present over 106 tons of ore are mined annually at the Kemi open pit mine. The chromite concentrates, upgraded lumpy ore (36% Cr₂O₃) and metallurgical grade concentrate (44% Cr₂O₃) are used as raw materials in ferrochrome production at Tornio. The output from the Kemi mine is currently 500 000–600 000 tonnes of concentrates per year. Production is based on a chromite deposit with an average content of 26% Cr₂O₃ and a Cr/Fe ratio of 1.55. Proven and provable ore reserves are about 70 Mt. Roughly 10 Mt of the deposit can be excavated by open-pit methods. The ore deposit is part of an ultrabasic layered formation located in the area around Kemi in Northern Finland. The almost vertical ore horizon can be used for a distance of 4.5 km and has an average thickness of 40 m. The mineable ore consists of 11 orebodies. There are differences between the orebodies as regards mineralogy, mineral chemistry, physical properties and structure. The average content of the major minerals in the Kemi ore are chromite 73,0%, chlorite 10,7%, tal 5,1%, serpentine 3,7%, flogopite 1,03%, tremolite 2,4% and dolomite 2,2%. The ratios of the gangue mineral composition varies in the individual ore bodies.

The processing of chromite at the Kemi concentrator is mainly based on gravity concentration. A high magnetic separation is used to recover the chromite from slimes. After crushing, concentration of the ore takes place in two steps: heavy medium separation and concentration. The flowsheet of the Kemi concentrator is presented in Figure 5.

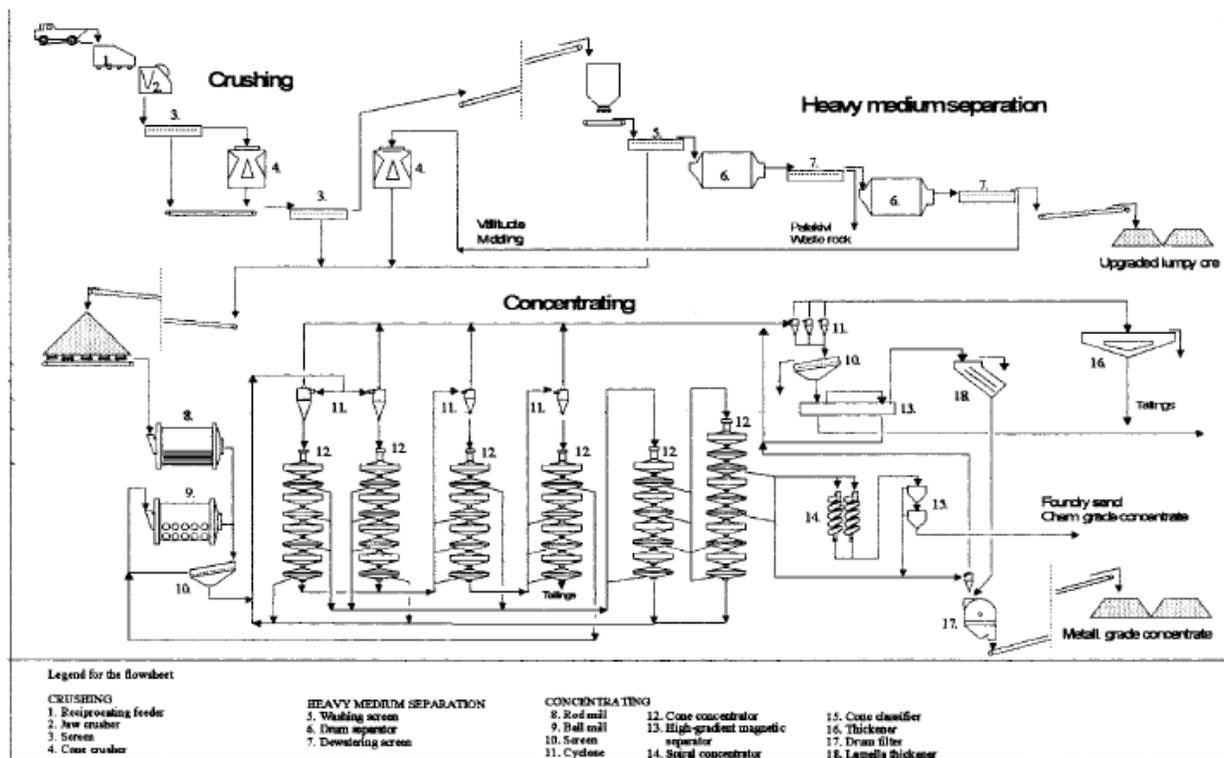


Fig. 5. Flowsheet of the Kemi concentrator

The ore is separated into upgraded lumpy ore, middling and waste rock in the two stages of heavy media separation. The process consists of feed preparation in a washing screen, heavy media separation in drum separators and medium recovery by means of low intensity magnetic separators.

The concentrating plant is divided into four main unit processes: grinding, cone concentrating, slime circuit and dewatering. The grinding circuit consists of a rod mill and a ball mill operating in a closed circuit with vibrating screens.

The mill product after processing by the vibrating screens is classified in hydrocyclones prior to the Reichert cones. The cyclones are for dewatering and desliming. Cyclone underflow, which represents most of the material, is concentrated in the Reichert cone concentrators. The overflow is fed to the slime circuit for further dewatering, classification and enrichment.

The concentrates from the Reichert cones and the slime circuit are combined to form the metallurgical grade concentrate (~44% Cr₂O₃). Foundry sand (~47% Cr₂O₃) is produced from the cone concentrators in the spirals and classified in the cone classifiers. It is produced only when needed and when the ore quality is suitable for making foundry sand.

5 Case 1: Hitura Concentrator

At the Hitura mine, changes in the mineralogy of the concentrator feed cause problems in process control. After a change in the feed type a new process control method has to be found. This is done by experiment because the new type is often unknown. These experiments take time and the resulting treatment method may not be optimal.

An expert system has been developed for solving the problem. The system receives variables from the automation system of the concentrator process containing information about the type of feed. The SOMs are used to classify the variables to determine the type of feed. The proper treatments are called from a knowledge base and presented to the operator.

The structure of the expert system tested at the Hitura concentrator is outlined in [Figure 3](#).

The classification program with the interfaces has been implemented with C++ in MS-Windows 3.1. The system is connected to the Procon 210 automation system by means of the ×10 comm communication program. The system supports the calculation and study of a SOM and a preliminary version of the knowledge base as follows:

- on-line measurable classification variables from the concentrator are validated and classified using the Kohonen SOM;
- feed type is forwarded to the knowledge base (KB);
- KB will give advice on the proper treatment of this feed to the operator.

The two modules form the main segment of the system: classification (CLA) and updating of classification (UCLA) together. The CLA provides with the mapping of the n-dimensional ore type data to the two-dimensional ore type SOM, thus performing classification. The on-line SOM is provided by the UCLA module and is updated automatically to new ore types.

The two modules form the second segment of the system: knowledge base (KB) and updating of knowledge base (UKB). The KB contains the set points of controllers and written information for various types of feed. This data are provided with the UKB module. The UKB can be updated adaptively or manually. Adaptive operation is based on an on-line measurable success index that indicates how well the ore is treated. The KB is updated if the success index indicates a new good method of treating an ore type. Manual operation is based on knowledge of the process engineer. The knowledge follows from experience, process study or experiments.

5.1 On-line Determination of the Type of Feed

5.1.1 On-line Measurements for Classification

The on-line information available at the plant was studied and a search was made for useful on-line measurements. The domain experts of the Hitura concentrator recommended the use of measurements related to grinding, the consumption of sulfuric acid and the channel intensities of the on-line XRF analyzer. The grinding measurements reflect the specific energies required to grind the ore, which in turn reflect the host rock mineralogy; the relevant measurements were the power draw of the mills, the feed rate of ore to the rod mill, the particle size distribution at the hydrocyclone overflow and the pulp density at the hydrocyclone feed. The set related to the consumption of sulfuric acid reflects the content of serpentine in the feed; the relevant measurements were the channel intensities of the Courier 30 analyzer relevant to the analysis of the concentrator feed.

5.1.2 On-line Variables for Classification

The three formulation methods were used to create five classification variables. Of the original 24 feed types defined by the off-line SOM, only four were used in the task. Representatives of group 1 were selected to represent serpentine feed types with a low nickel content. The representatives of group 19 are serpentine feed types with a high nickel content. Group 22 represents talc-amphibole-serpentine feed types and group 24 talc-amphibole types. These types were chosen to represent the feed types of the Hitura concentrator. The reduction in the number of groups was necessary in order to control the amount of information presented in the plots. The variable NIMO estimates the nickel content of the feed. It indicates the amount of pentlandite in the feed and is a good indicator of the feed type. The nickel content is estimated by two Courier 30 channel intensities: nickel and molybdenum.

The variable NISU estimates the nickel content in the sulfide phase of the ore and reflects both the sulfide phase and the host rock mineralogy.

The CUFE variable is the ratio between the copper and iron channels of the Courier 30 analyzer analyzing the concentrator feed. The variable GRIN reflects the grindability of the ore.

The classification variable ACID represents the consumption of sulfuric acid. The mineralogical justification is the presumed dissolution and/or adsorption of sulfuric acid by serpentine. As talc, amphibole and chlorite are rather insoluble in sulfuric acid, and the consumption can be used to estimate the proportion of serpentine.

5.2 Formulation of the On-line SOM

The on-line SOM was trained using the five variables presented above. The product is a mapping of the ore types of Hitura by on-line data. The on-line SOM is used in on-line determination of the feed and in presenting the classification result to the user.

The on-line measurement values were collected from the automation system historical database. Daily-average values in the period between 19.3.1994 and 30.10.1995 were used. The data were screened for process shutdown time; days with more than 3 hs of downtime were removed. After this, 526 cases were available for classification. The data were validated with high-low boundaries to remove faulty values due to disturbances in the unit processes or measurement devices. The boundaries were determined from the histograms of the variables. Weighting for variables was not used. The data were scaled into a standard deviation of 1.0 and mean of 0.5.

The pre-processed data were classified using the Kohonen SOM. The bubble algorithm was used to train a hexagonal SOM with 8 rows and 12 columns.

The locations of the ore types in the on-line SOM were studied. The high values of variable NISU were on the right side and the low values on the left side of the map. Thus the serpentized ore types are on the right side and the talc-amphibole types on the left. The average and high values of variable NIMO were found at two locations: in the top-left corner and in the middle right area of the map. They represent the variations in the nickel content within the major feed types. The result of the study on the on-line SOM is presented in Figure 6.

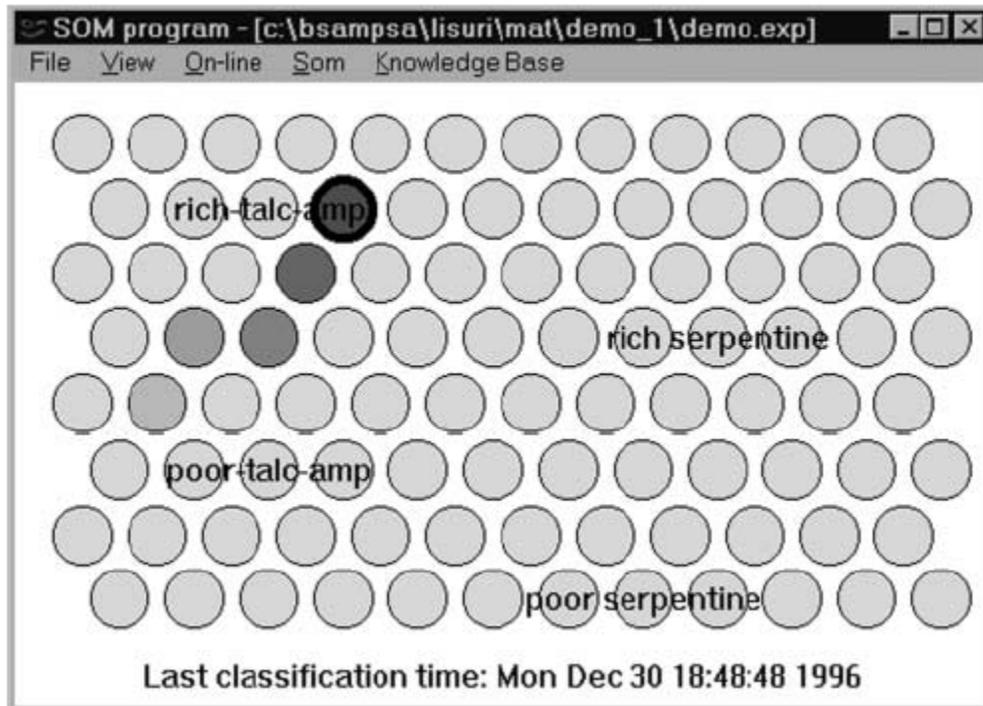


Fig. 6. On-line SOM presenting the current feed type and the feed type history to the user

Table 1

Estimated savings in the Hitura mine

	75% limit	50% limit	25% limit
Savings (kFIM/a)	933	2088	3962

5.3 Formulating of the Knowledge Base

The knowledge base contains the treatments for various types of feed. Methods to formulate the treatment are used. The first method is based on the calculated average values of the controlled and manipulated variables. The calculation was made based on the long term historical values of the variables. The average values are connected to the SOM.

The second method is based on the adaptive self-learning database. The optimal processing conditions for each feed type are found based on on-line success indexes. The best treatments are updated to the top-ten list after every successful treatment.

5.4 Estimation of the Economical Results of the Expert System

The economic benefits of the expert system are mostly due to the faster and more accurate adaptation for the ore type changes. The calculated estimation is based on the penalties inflicted by excess MgO in the concentrate and on the nickel lost in the concentrator tailings. Each ore type group in the off-line SOM was studied. The system has been in use at the Hitura concentrator since December 1996. During this period, the Hitura personnel have maintained the system. According to the users, the system is capable of approximately indicating the feed type. The operators have accepted the system for daily use. The operators of the concentrator suggest the authoring of the knowledge base as the next step in the development of the system.

6 Case 2: Kemi Concentrator

6.1 Main modules of the Expert System

Chromite has to be separated from the constantly varying mineralogical environment. Rapid changes in ore grade, hardness and chromite grain size make it difficult to control the separation. The process control strategies in the different unit processes are based on dissimilar behaviors of the ore types.

The modules of the expert system under development at the Kemi concentrator are as follows:

- Choice of the best calibration model for the on-line assay analyzers.
- Optimization of the grinding circuit.
- Optimization of the Reichert cone circuit.
- Optimization of the HGMS circuit.

The main modules of the expert system at the Kemi concentrator are presented in [Figure 7](#).

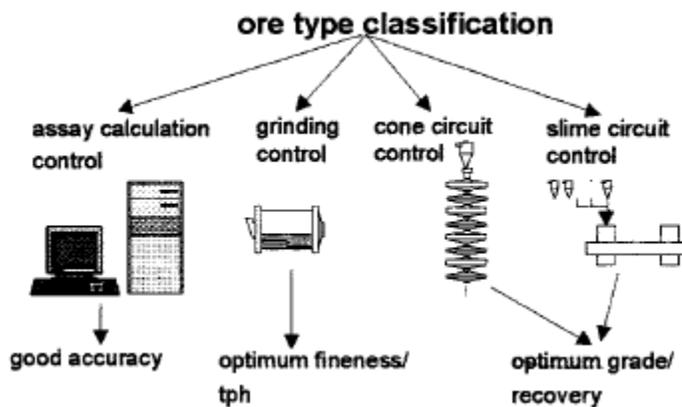


Fig. 7. Structure of expert system at the Kemi concentrator

For the development of the expert system, the classification system developed at the Hitura concentrator was implemented at the Kemi concentrator. The system was used for the study of the present control strategies in the cone classification circuit. After the training of the SOM, the system was implemented to run on-line. At the grinding circuit, the system was trained to give information on the ore hardness and the correct treatment to the operators.

6.2 Testing of Classification

The process history data from the grinding process and the Reichert cone circuit were classified using the neural networks. The aim of the cone circuit data classification was to study the control strategies the operators use to control. The choice of the optimum cone settings is critical for the grade and recovery obtained in the concentrates. There are 94 manipulated variables controlling the concentration: 38 variable slot settings, 36 double cone settings, 9 feed density measurements and 10 dilution water additions. At present the cones are controlled manually from the control room based on the grade of the concentrate. The operators select the set point values for the controllers on the basis of experimentation. Determination of the correct set point values takes time and subsequently reduces profits. The control method currently in use does not optimize the recovery/grade and results in reduced economic profit of the plant [10].

The present control strategy was studied in order to develop the instructions for controlling the cones. The initial aim was to study the control methods used by the operators to control the cones by investigating the set point values of the controllers. A secondary aim was to study the correlation between an ore type and the control methods used.

The methods used by the operators to control the cones was studied using an expert system developed at the Hitura mine. The off-line training data contained 17 variables from 1232 shifts. The classification variables were shift averages of the cone setting combinations typically (40–100%) used by the operators.

The on-line SOM of the system produces a map with a classification result. Each element in the SOM represents a specific type of treatment method and group of cone settings. The on-line values of each variable in the element are shown in the separate variable window in [Figure 8](#).

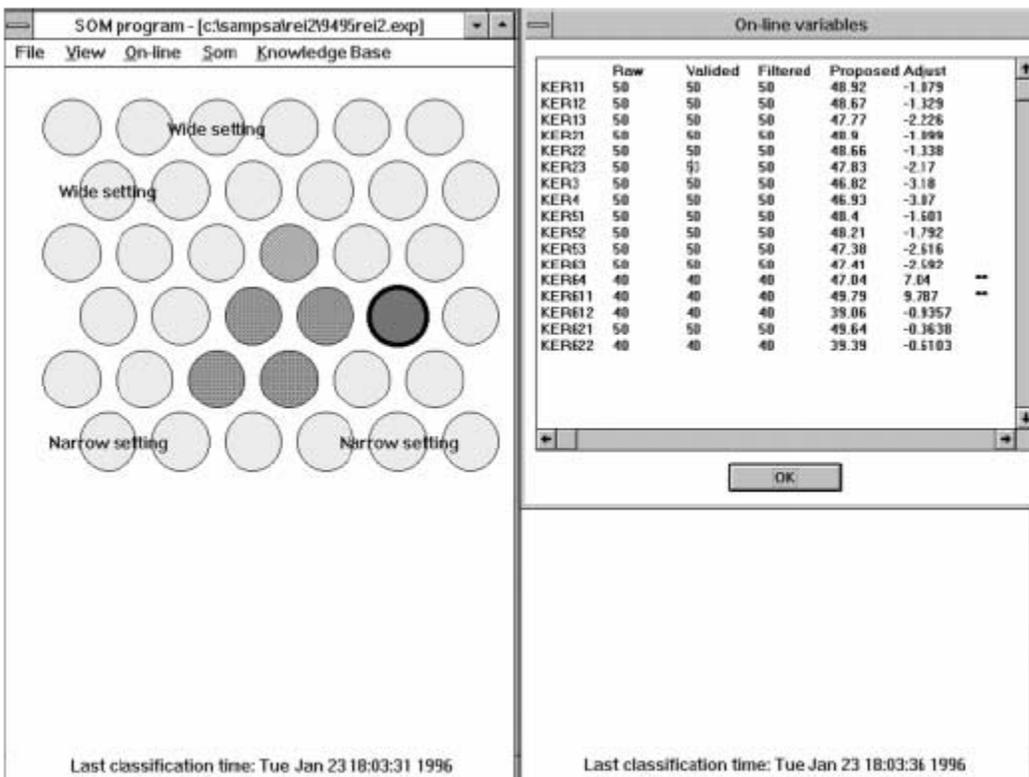


Fig. 8. On-line SOM of the cone circuit and the data for the latest element in the variable window

The position of the on-line classification element in the SOM visualizes the classification presentation. In this case the wide cone settings are located in upper corners in the SOM and the narrow cone settings are located in bottom corners.

The pattern followed in changing the slot settings was found to be very simple. According to the classification study, the operators keep the cone settings constant (from wide to narrow settings) for roughing and scavenging. The cleaning stage slot settings are changed more frequently in order to achieve the desired grade of concentrate. When these settings are unsuitable, they change the position of the slots for roughing and scavenging on all the individual cones.

The study also revealed that a specific ore type was occasionally treated with group of set point values that resulted in reduced economic results.

The grinding circuit SOM was trained to give information on the ore hardness and to give suggestions for ore type treatment. The classification variables were 800 shift averages from the feed t/h, mill powerdraw and mill rotation speed. Figure 9 shows the on-line SOM of the grinding circuit. The black circle around the element presents the current type of feed under processing; the window of the top right corner was been used to study the values of a variable in the elements of the SOM.

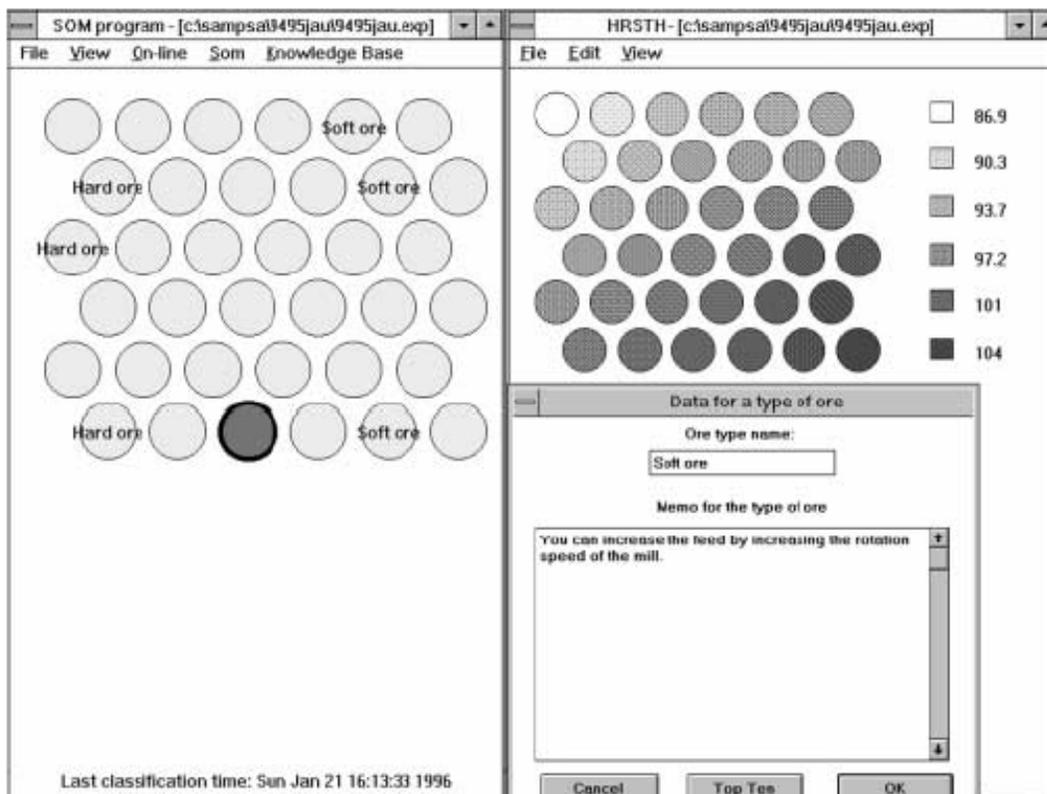


Fig. 9. On-line SOM of the grinding circuit and the suggestion for the ore type treatment

The results and experiences during the test period have been promising. In the near future, studies will be focused on developing operating instructions for the operators and adding them to the system.

7 Conclusions

Expert systems have proved to be ideal candidates especially for the control of mineral processes [11].

An expert system based on on-line classification of the ore type has been developed and tested in two concentrators. The advantage of the SOM for process control was found to be its capability for visualization and its computational lightness, and also a large amount of data and/or high dimensionality can be used.

In addition to the classification, the expert system included a database concerning information about how to handle a determined ore type. This self-learning database scans historical process data to suggest the best treatment for the ore type under processing. The preliminary results of applications have been promising. The economic benefits are based on faster and more correct adaptation for ore changes.

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