

COLD-CATHODE IONIZATION GAUGE - PREPROCESSING AND MODELLING OF THE GAUGE PARAMETERS USING NEURAL NETWORKS

IONIZACIJSKI MERILNIK S HLADNO KATODO - PREDOBDELAVA IN MODELIRANJE PARAMETROV MERILNIKA Z NEVRONSKIMI SISTEMI

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This article describes the modelling of the operating characteristics of a cold-cathode ionisation gauge (CCG) using neural networks. The gauge characteristics were measured on a gauge-comparison UHV calibration system with a test chamber, an extractor gauge, a spinning rotor gauge, and a gas manifold with a variable leak valve. The discharge intensity was measured vs. the anode voltage at different pressures, selected in the range from $1 \cdot 10^{-9}$ mbar to $1 \cdot 10^{-5}$ mbar, and vs. pressure at different operating voltages ranging from 1.2 kV to 9 kV. In all cases the magnetic field density was the same and amounted to about 0.13 T.

The CCG discharge current versus pressure characteristic is non-linear and in some cases even discontinuous. In our previous studies we found that neural networks are a very suitable tool for modelling the CCG input-output characteristics. Since CCGs are considered to be coarse vacuum gauges, modelling results with the maximum relative error within a 25 % limit are quite acceptable.

Our further research of modelling introduces the pre-processing of the measured data, where the originally measured data set is replaced with a filtered data set. The filtered CCG characteristics were used as an input for the artificial neural network, which was used to generate the non-linear CCG input-output function used for the linearisation purposes.

The neural networks were trained to perform the transfer function between the filtered input gauge parameters and the pressure. The modelling results were tested a separate, independent set of measured points.

Keywords: cold-cathode ionisation gauge, neural networks, linearisation, approximation, modelling.

V članku opisujemo modeliranje karakteristik ionizacijskega vakuumskega merilnika s hladno katodo (CCG) z nevronskimi sistemi. Karakteristike merilnika so bile izmerjene na primerjalnem ultra visoko-vakuumskem sistemu, ki ga sestavljajo: preskusna komora, ekstraktorski merilnik, viskoznostni merilnik z lebdečo kroglico in plinski razdelilni sistem z dozirnim ventilom. Razelektrivni tok ionizacijskega merilnika v odvisnosti od anodne napetosti smo merili pri različnem tlaku, ki smo ga spreminjali od $1 \cdot 10^{-9}$ mbar do $1 \cdot 10^{-5}$ mbar, in v odvisnosti od tlaka pri različni delovni napetosti, ki smo jo spreminjali od 1,2 kV do 9 kV. Gostota magnetnega polja je bila pri vseh meritvah enaka, in sicer 0,13 T.

Odvisnost med razelektrivnim tokom v CCG in tlakom v notranjosti merilnika je nelinearna, ponekod je celo nezvezna. V naših predhodnih študijah smo ugotovili, da so nevronski sistemi zelo primerno orodje za modeliranje karakteristik CCG merilnika. Ionizacijski merilniki s hladno katodo spadajo v skupino manj natančnih merilnikov tlaka, zato so rezultati, ki smo jih dobili z modeliranjem karakteristik in ki omogočajo modeliranje z največjo relativno napako pod 25 %, praktično uporabni in sprejemljivi.

Relativno napako modeliranja smo želeli zmanjšati, zato smo pred modeliranjem uvedli še postopek filtriranja merjenih podatkov. Filtrirane podatke meritev smo nato uporabili kot vhodne podatke za nevronski sistem, ki se je tako naučil ustvariti vhodno - izhodne karakteristike CCG-merilnika. Kvaliteto dobljenega modeliranja smo ovrednotili na množici neodvisno merjenih podatkov ionizacijskega merilnika.

Ključne besede: ionizacijski merilnik s hladno katodo, nevronski sistemi, linearizacija, modeliranje

1 INTRODUCTION

In our previous work we focused our attention on modelling the CCG characteristics using neural networks^{1,2}. The results showed that neural networks can be used to produce the non-linear transformation between the CCG discharge current and the pressure inside the vacuum chamber. We found that such a simulation of CCG characteristics allows a simulation relative error of up to 25 %². Although such errors are practically acceptable we wanted to minimize it as much as possible. During our previous experiments, the learning of the neural network was carried out on the original measured data points. Since these data points contain

measurement errors, we decided to filter the data. The filtered data were then used as the learning data set for the neural network. In such a way we tried to minimize the simulation error.

Real measurements of the inverted magnetron were the starting point for this study. Measured characteristics (**Figure 1**) were used to train the multilayer neural network¹. The model based on the trained neural network should be capable of producing the CCG input (pressure, operating voltage)-output (discharge current) function.

Finally, we wanted to use the neural network to correct the nonlinearity of the CCG and to enable the

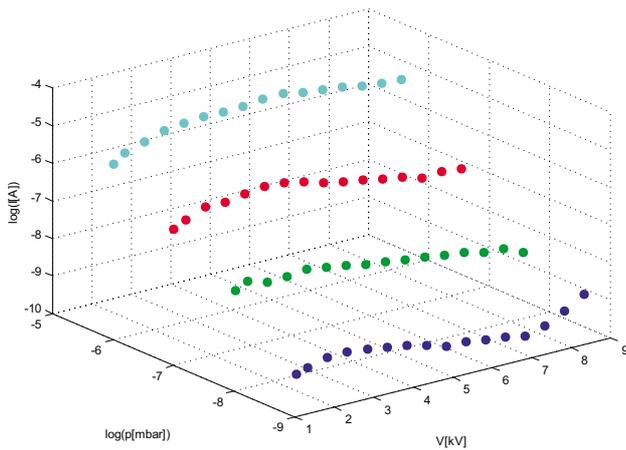


Figure 1: The measurements of a CCG characteristics are presented in 68 points at four different pressure values. The measured data set is used as the training set for the neural network.

Slika 1: Meritve karakteristik CCG so narejene v 68 točkah pri štirih različnih vrednostih tlaka. Izmerjene podatke smo uporabili kot učno množico za učenje nevronskega sistema.

conversion of the value of the discharge current reading to the actual vacuum-chamber pressure.

1.1 Cold-cathode ionisation gauge

The inverted magnetron is, together with the Penning and normal magnetron, a member of the cold-cathode ionization-gauges group. CCGs are intended for measurements of pressure in the range from 10^{-12} mbar to 10^{-2} mbar³.

Cold-cathode ionisation gauges are very robust devices with low electrical power consumption, high sensitivity, and they operate without a hot filament. They are relatively cheap devices⁴, commonly used as more-or-less relative pressure gauges in vacuum systems. CCGs exhibit an extremely low thermal outgassing rate, they are free from x-ray and electron-stimulated desorption errors. The disadvantages of CCGs are: stray magnetic fields, relatively high pumping speed and non-linear characteristics. The major CCG drawback is the nonlinear relationship between the discharge current and the pressure. The relationship between discharge current and pressure is, in some cases, even discontinuous. In the absence of any starting device this delay may be considerable.

The nonlinear but continuous portion of a CCG discharge current vs. pressure characteristic may be piecewise fitted to a power-law equation⁵:

$$I = kp^n \quad (1)$$

The corresponding discharge intensity vs. pressure characteristic can be presented as:

$$I/p = kp^{(n-1)} \quad (2)$$

where I is the gauge discharge current, and n and k are constants. The departure from linearity is not great. Values of n found in the literature usually fall between 1,05 and 1,2⁵. The constant k is dependent on the magnetic and electric field, the length of the discharge cell and the type of gas in the vacuum chamber, while the constant n is dependent on the magnetic field density, the operating voltage and the diameter of the discharge cell.

1.2 Neural networks as a general modelling tool

We wanted to find out whether it is possible to model the characteristics of a CCG using a neural network. Our goal was to produce a numerical model of the cold-cathode ionisation gauge, based on a relatively small set of measured points. We intended to use the formed model of the CCG to optimise the fabrication process as well as an aid for using the CCG in measurements. It is important that the numerical model covers the complete usable pressure range of the CCG.

The simulation process started with measurements of the CCG characteristics. The measured data points were not measured equidistantly. The number of the measured points is a necessary trade-off between the density of measured points and the time used to execute the measurements. The neural networks consist of artificial neural cells organised in layers.

Two of the layers are always obvious and are named by their function as the input and output layer, respectively. The number of neurons in the input (in our case, discharge current and operating voltage) and the output layer (pressure, sensitivity) depends on the dimensionality of the problem¹. Additionally, there is a number of hidden-layer neurons. They are very important and they contribute significantly to the building of the input-output transformation. The most important feature of the neural networks is their ability to learn the input-output relationship from the set of data called the training set. Once the neural network is properly trained, it generates the input-output characteristic for any given input-data pattern^{6,7}.

It is known from the literature⁸, that neural networks are capable of learning, and finally reproducing, almost any kind of mathematical function that is in the form of a countable set of representing points.

It was proven that any non-polynomial type of input-output function can be achieved using a neural network with only one hidden layer of neurons⁹. Although it is theoretically possible, it is a matter of the practical application that limits the use of this principle. Practically, it means that there always exists a neural

¹ To avoid confusion it is necessary to clear the relative nature of the terms input and output. When speaking of a CCG, the input parameters are the vacuum-chamber pressure, the operating voltage between the cathode and the anode and the magnetic field density. Since the magnetic field remains constant, it can be omitted in our study. The CCG output is the discharge current. When speaking of the neural network, the input parameters become the CCG discharge current, and the operating voltage, while the output parameter becomes the pressure in the vacuum chamber. For clarification, please refer to **Figure 3**.

network with one hidden layer to produce the required input-output transfer function, but the problem is how this theoretically existing function can be found and realised. In our experience it is a far better solution to take neural networks with more than one hidden layer.

We have also found in the literature¹⁰ that the input-output characteristics of neural networks can, in some cases, become discontinuous. Therefore, we tested a generated network for discontinuities.

During the training process, the input samples are presented to the neural network. Each sample must have the desired output value. Each pair of discharge current and input voltage is followed by the measured pressure detected inside the calibration vacuum chamber. The cycles, when all the input samples together with the appropriate output values are presented to the neural network, are called epochs. The learning is done over many epochs, and the overall error of the learned input-output relationship compared to the desired output should decrease. The training process is convergent when the output error decreases with an increasing number of epochs^{6,7}.

When the neural network is properly trained, the CCG characteristic is modelled for any point within the limits of the input data space. The neural networks are trained to simultaneously produce the pressure and sensitivity planes.

The training process of the neural network consists of the following steps:

- The measured values of the discharge current and the applied voltage are presented to the neural network input.
- For each input pattern the desired output values for the pressure and the sensitivity are applied on a special "training" input.
- The neural network calculates the error between the values of pressure and sensitivity obtained by the network and those applied on the "training" input.
- According to the calculated output error, the artificial neural cells parameters (weights, thresholds) are changed in order to lower the output error. This process is called learning.
- The complete set of the measured input patterns together with the desired output values are presented to the network in a cycle called an epoch.
- The network learns the input-output relationship in a series of epochs. The number of epochs is limited by the error produced by the neural network (present at the start of the training process).

Basically, there are two different ways of using the measured data - uncorrected or filtered. In our first experiments the original data set was used. The results of the modelling showed quite substantial relative errors. The other choice is to filter the measured data prior to the learning process. The filtering was obtained by classical non-linear curve-fitting (data-fitting) in the least-square sense. That is, giving the data (1) P (measured pressures), the observed output I , we wanted

to find coefficients k and n that "best fit" equation 1. The least-square problem can be described by finding the minimum of the expression

$$\min_{k,n} \sum_i (kP_i^n - I_i)^2. \quad (3)$$

All the measured data was filtered (curve-fitted) and as such used for the learning process of the neural network.

2 EXPERIMENTAL

In the inverted-magnetron geometry the anode is represented by the metallic rod in the axis of a metallic cylinder, which is the cathode. To achieve the gauge operating conditions, the CCG was placed in a homogeneous magnetic field (a SmCo permanent magnet with a magnetic field density of about 0.13T), while the cathode and the anode were connected to a high voltage of several kV. The magnetic and electric fields are orthogonal.

The gauge was constructed on a basis of the small ion-getter pump with a nominal pumping speed of 2 l/s. The gauge was electrically isolated from the connecting ConFlat® (CF) flanges by a glass-to-metal seal. The high-voltage feedthrough was designed to have a very high electrical breakdown voltage.

Measurements of the CCG characteristics were obtained using a UHV calibration system, specially designed for the comparison measurements. The vacuum system consists of a stainless-steel vacuum chamber with a volume of about 6 l, a stainless-steel pumping system and a gas manifold with a precise leak valve. For comparison measurements, an extractor gauge IE514 (HCG with an x-ray limit below 10^{-12} mbar), and a spinning rotor gauge VISCOVAC VM 212 were used for calibrations in the range from 10^{-10} mbar to 10^{-5} mbar^{11,12}.

All the measurements were obtained in a nitrogen atmosphere. The measurements were made at different pressures of about 10^{-9} mbar, 10^{-8} mbar, 10^{-7} mbar, 10^{-6} mbar and 10^{-5} mbar. At a constant pressure, the high voltage between the cathode and the anode was varied in the range from 1.2 kV to 9 kV, in 500 V steps.

The evaluation measurements were taken at 4.5 kV.

3 RESULTS AND DISCUSSION

In the first part the measured data set was used as the training set for the neural network. When the neural network was adequately trained, it was ready to reproduce the input-output characteristics of the processed CCG¹.

The used neural network had four layers (two hidden layers). The training method was the error back-propagation algorithm. Tests began with one hidden layer. It is theoretically proven⁸ that a neural network with one hidden layer can perform almost any kind of input-output mapping. In our case it exhibited very poor training capabilities. Several different neural networks

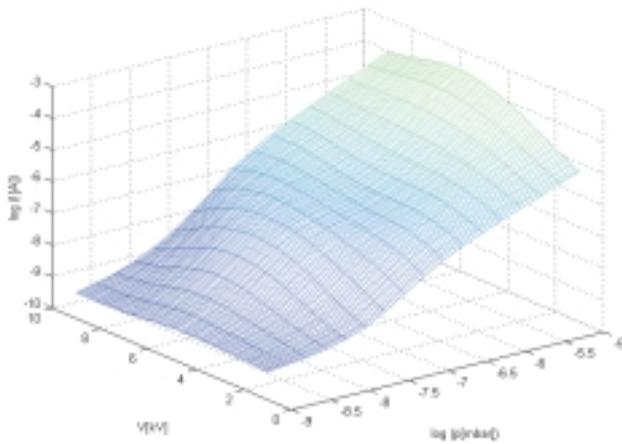


Figure 2: The relationship I-V-P, simulated by the neural network for the inverted magnetron CCG

Slika 2: Karakteristika I-V-P, ki jo je generiral nevronski sistem na osnovi merjenih podatkov

with one hidden layer were tried, but we did not succeed in finding the right number of neurons in the hidden layer that would exhibit the convergent (linear decrease in output error) training process. Tests started with 20 neurons in a hidden layer and were continued until we reached 100 neurons; unfortunately, without satisfactory results. We decided to continue testing with two hidden-layer neural networks. We found experimentally, that the neural network with 20 neurons in each hidden layer achieved the modelling process satisfactory. Taking more neurons in the hidden layer did not improve the functionality of the network.

Once the training is finished, the neural network is fixed - its input-output characteristic does not change any more, it can only reproduce the trained function. In our case this means that once the CCG properties are learned, they can be used for any point of the input space. Practically, for any pair of a measured CCG discharge current and operating voltage, the neural

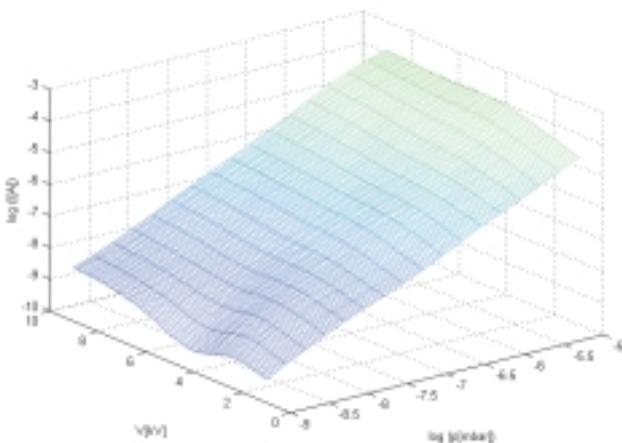


Figure 3: The relationship I-V-P on the filtered data set, simulated by the neural network for the inverted magnetron CCG

Slika 3: Karakteristika I-V-P. Nevronski sistem je generiral karakteristiko na filtriranih podatkih meritev.

network produces a unique value for the pressure and the sensitivity. This is one of the advantages of using a neural network rather than prepared lookup tables, where an additional interpolation is required.

To learn the CCG characteristic, typically from 10000 to 20000 epochs were usually needed.

The results of the modelling show that it is possible to model the CCG characteristics with the multilayer neural networks. The neural network is capable of reproducing the measured input-output function of a CCG within 0,5 % at each point (on a logarithmic scale). The input-output function outside the measured points is smooth, without detected discontinuities, **Figure 2**.

The simulated input-output characteristics are presented in 3D mesh plots. For this purpose an equidistant mesh grid was generated and prepared for the graphical post-processing. **Figure 2** shows the simulation of the I-V-P characteristics, while **Figure 3** shows the I-V-P characteristics learned on filtered data.

The quality of the simulated CCG characteristic was evaluated by additional measurements not included in the learning data set. The CCG characteristic was measured at a constant operating voltage of 4.5 kV, and a pressure that varied from $1 \cdot 10^{-9}$ mbar to $1 \cdot 10^{-5}$ mbar. The relative error between the measured and simulated pressure was calculated, and the obtained results are presented in **Figure 4**. The relative error was calculated with the equation:

$$E = (P_s - P_m) / P_m \cdot 100 (\%) \quad (4)$$

Where E is the relative error in the simulation of pressure, P_m is the measured pressure, and P_s is the simulated pressure. Although it seems from **Figure 4** that the relative error of simulated pressure is quite high, and reaches 25 % (the maximum simulation error occurs

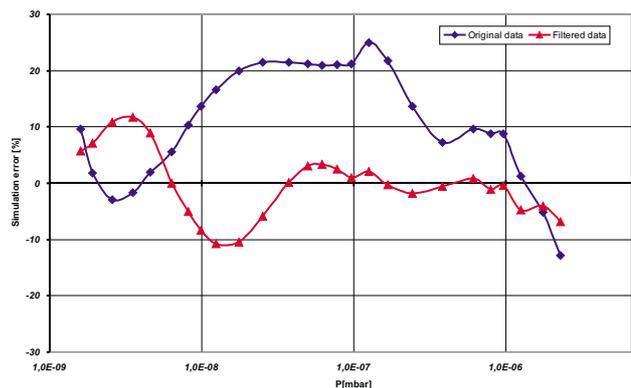


Figure 4: The neural network simulation relative error calculated on the evaluation set of separately measured points. One curve represents the relative simulation error obtained on the intact data while the other shows the error on the filtered learning data set. In both cases the evaluation CCG characteristic was measured at a constant operating voltage of 4.5 kV.

Slika 4: Relativna napaka simulacije karakteristike. Napaka je bila izračunana za množico izmerjenih vrednosti, ki niso bile vključene v proces učenje nevronskega sistema. Prikazani sta dve krivulji relativne napake - ena za simulacijo, narejeno na originalnih podatkih, ter druga, ki je za učenje nevronskega sistema uporabljala filtrirane podatke.

at the measured pressure: $1.26 \cdot 10^{-7}$ mbar; simulated pressure: $1.57 \cdot 10^{-7}$ mbar; simulation relative error 24.95 %) the simulation of the CCG characteristic is practically a very useful solution since CCGs are coarse vacuum gauges with poor repeatability and a significant hysteresis effects. Vacuum measurements with CCGs are typically in the 20 % tolerance range.

The second part includes the data filtering prior to the learning process. As already mentioned, we wanted to reduce the relative simulation error. As a result of the data-fitting process the parameters k and n (1) were obtained for the different CCG operating voltages. **Table 1** shows the calculated parameters.

Table 1: The parameters k and n from the equation 1 for the different CCG operating voltages

Tabela 1: konstanti k in n , ki nastopata v enačbi (1) pri različnih napetostih

Operating voltage (kV)	k	n
2,5	0,9130	1,0026
3	1,3866	0,9973
3,5	1,8302	1,0371
4	2,2576	1,0657
4,5	2,7023	1,1448
5	3,0021	1,1127
5,5	3,2945	1,0753
6	3,5140	1,0412
6,5	3,9903	1,0319
7	4,3364	1,0218
7,5	4,9055	1,0398

From the fitted data in **Table 1** we can see that the parameter k varies from 0.9 to 4.9. It is also evident from **Table 1** that the parameter k increases with the operating voltage. The parameter n also increases, and from 5,5 kV up it starts to decrease.

The process of the neural network training was the same as for the case where unfiltered data was used. The evaluation of the simulation relative error was also the same. The results show (see **Figure 4**) that the filtering process can substantially lower the simulation relative error. In our experiments the maximum relative simulation error fell from 25 % to 11 %.

4 CONCLUSIONS

The main goal of our work was to find a way to model the behaviour of a CCG using neural networks. It is useful because CCG operation is stable and repeatable. Special emphasis was given to the selection of the neural network topology that was used for the modelling purposes.

The trained neural network can model the relationship between the CCG discharge current, the operating voltage and the pressure. It reads the CCG

discharge current and the operating voltage and estimates the values for the pressure and the sensitivity. Practically, this means that for any point of the input data - discharge current and operating voltage the neural network generated the corresponding pressure.

Tests proved that the neural network is capable of learning the CCG characteristics with the preset accuracy. The modelled three-dimensional function is smooth, without detected discontinuities produced by the neural network.

The neural networks were trained to simultaneously produce the pressure and sensitivity planes.

The results of this study introduce the use of neural networks for the post-processing of measured data. They proved to be a very promising tool, especially in the cases where the exact mathematical model is not known or is not good enough to adequately describe the behaviour of the observed problem. The neural networks build the model function in a process called learning.

Another important aspect of the simulation process with neural networks is the data preparation. In our case we made two separate tests, one with unchanged, measured data, and the other with the data fitted to the given function in the least-square sense. Results proved that the maximum relative simulation error can decrease (in our case from 25 % to 11 %) if the measured data is filtered prior to the neural network learning process.

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