

Efficient dead time correction of G-M counters using feed forward artificial neural network

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Abstract. Dead time parameter of Geiger-Müller (G-M) counters causes a great uncertainty in their response to the incident radiation intensity at high counting rates. As their applications in experimental nuclear science are widespread, many attempts have been done on improvements of their nonlinear response. In this work, response of a G-M counter system is optimized and corrected efficiently using feed forward artificial neural network (ANN). This method is simple, fast, and provides the answer to the problem explicitly with no need for iteration. The method is applied to a set of decaying source experimental data measured by a fairly large G-M tube. The results are compared with those predicted by a given analytical model which is called hybrid model. The maximum deviation of the corrected results from the true counting rates is less than 4% which is a significant improvement in comparison with the results obtained by the analytical method. Results of this study show that by using a proper artificial neural network structure, the dead time effects of G-M counters can be tolerated significantly.

Key words: dead time • artificial neural network (ANN) • Geiger-Müller (G-M) detector • hybrid model • source decaying experiment

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Introduction

Build-up of the positive ion space charges after each discharge process turns the G-M tube off for the next incident radiation measurement. A considerable amount of time should elapse before next avalanche can take place in the tube. Depending on the physical characteristics of the detector, this time is of the order of 20 to 300 μ s. This dead period makes the G-M tube response as a nonlinear and complicated function of the incident radiation intensity. Several analytical models are proposed for the correction. They are based on consideration of two types of behaviour of G-M tubes to model the dead period of the detector, paralyzable and non-paralyzable models [8]. These idealized models are based on the two types of behaviour for one or two degrees of freedom published elsewhere [4, 7, 9, 12–14]. Lee and Gardner [10] have suggested a hybrid model, which is the top accurate explanation of the dead time in G-M tubes. The proposed correction formula is:

$$(1) \quad m = \frac{n \exp(-\tau_p n)}{1 + \tau_n n}$$

where: m – observed counting rate, n – true counting rate, τ_p – paralyzable dead time, τ_n – non-paralyzable dead time, τ_p and τ_n are determined by fitting Eq. (1) to a set of G-M tube experimental data. Equation (1) is nonlinear and the true counting rate, n is determined by numerical root finding methods such as fixed-point

iteration method [3] choosing an appropriate initial guess. Equation (1) can be rearranged as:

$$(2) \quad n_i = F(n_{i-1}) = m_i(1 + \tau_n n_{i-1}) \exp(\tau_n n_{i-1})$$

As an example of numerical solution of the implicit equation, substituting the generic values for $\tau_n = 100 \mu\text{s}$, $\tau_p = 100 \mu\text{s}$, $m_i = 1000$, and the initial value of the true counting rate, n_{i-1} , equal to m_i , then 22 iterations are needed to calculate the true counting rate equal to 1283. One of the difficulties of the analytical models is that, they do not estimate the true counting rate explicitly. Therefore, software based instrumentation is needed for on-line correction of the observed counting rates. The only convergence criterion for fix-point iteration method is $|dF(n)/dn| < 1$, if the first approximation of n is chosen truly [3]. In the next section, it is shown that at high counting rates, the convergence of fixed-point iteration method for the arrangement of Eq. (2) encounters a problem; however the convergence condition is softly satisfied. Another source of error in using the analytical methods is the postulation of a simplified model for the dead time process whereas in practice it is more complicated. Therefore, any correction based on these models is considered as an estimation of the true count.

It is desirable to use the G-M tubes over a wide range of counting rates. At low count rates, increasing

the measurement time is the only possible solution to achieve the required statistical accuracy. In the opposite extreme, at high counting rates, two strategies are useful:

- Decreasing the dead time of the counting system. Using a proper electronic instrumentation can reduce the dead time losses [8].
- Correction of the dead time losses using theoretical dead time models. These models need experiments to measure the G-M tube parameters using curve fitting methods. Two popular experiments are two-source method and decaying source method. The latter one is more accurate because it covers the entire range of the counting rates but it needs a suitable activated foil as well as being time consuming. Although two-source method is simple, it examines the G-M tube in two counting rates only. Therefore, the correction may contain a systematic error. For accurate measurements, decaying source experiment and efficient correction of the observed counting rates using theoretical methods are inevitable.

In this paper, the main concern is about the theoretical correction of the dead effects of the observed counting rates using artificial neural network (ANN). A detailed description of the method is explained in the next sections.

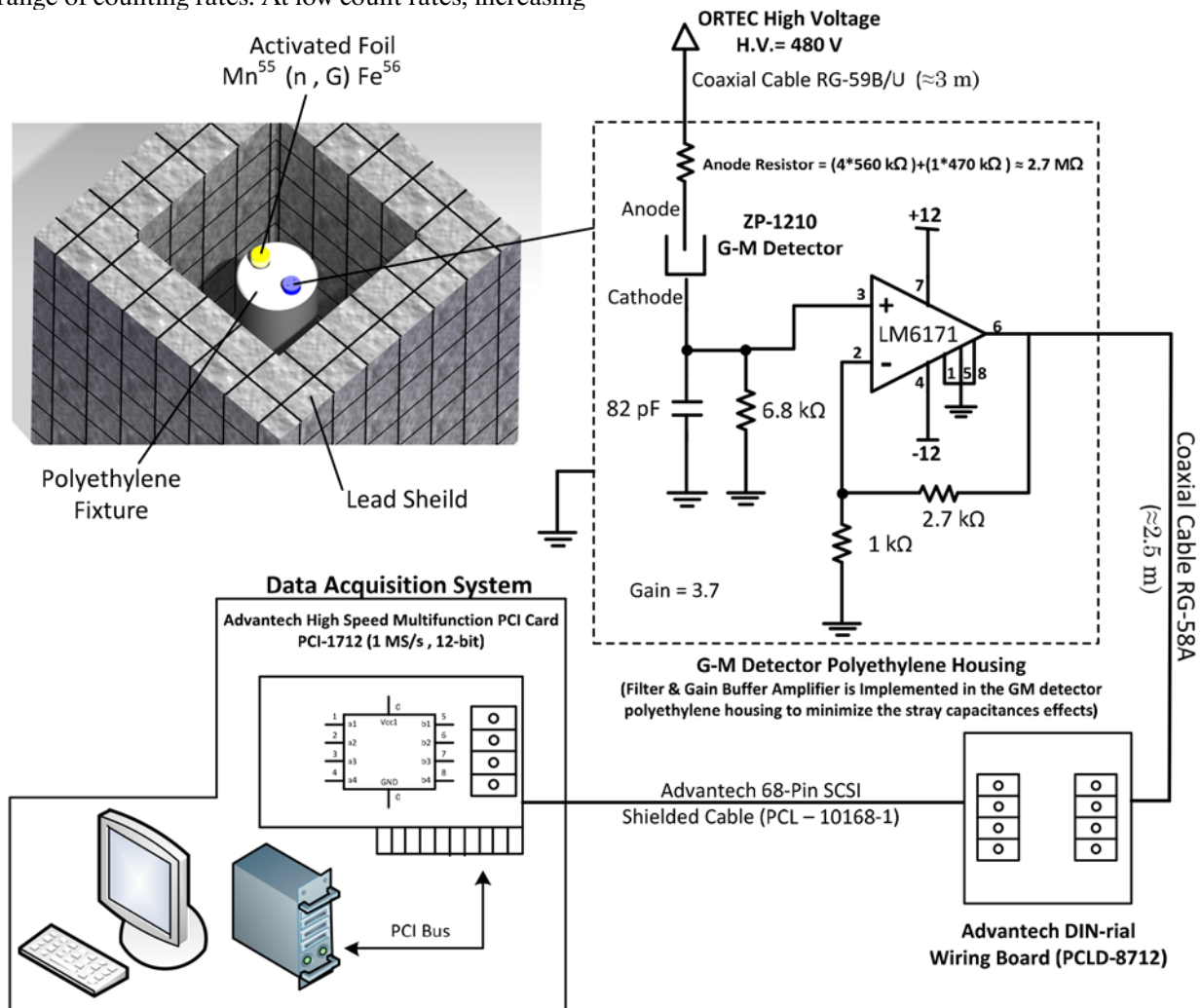


Fig. 1. Experimental setup of the G-M detector counting rates measuring system.

Experimental setup

Decaying source experiment is performed to produce the experimental data for examination of the correction methods. Several practical considerations are important for decaying source method. First of all, the half-life of the radioactive source should not be too long or too short. Therefore, full counting rate range of interest can be measured in a reasonable time. Secondly, the half-life should be known accurately. Finally, the radioisotope should be pure with a single decaying mode. ^{55}Mn with half-life of 2.578 h is a perfect activation foil for the experiment.

Tehran Research Reactor (TRR) is facilitated with a remote irradiation system [15]. A ^{55}Mn activation foil with purity of 99.99% is activated by the irradiation facility. The activated source is placed in front of ZP-1210 G-M tube detector [6] surrounded with suitable lead shields. Figure 1 shows the setup of the experiment. To have a fixed geometry of the detection system during three days of the measurement, both activated foil and the detector package are placed in a polyethylene fixture.

To minimize the interference of the noise and stray capacitances, a filter gain buffer amplifier is implemented in the detector polyethylene housing. The LM6171 is a high speed low power low distortion voltage feedback operational amplifier which is perfect for amplification of the output pulses of the detector. The 2.7 and 1 k Ω resistors set the gain of the amplifier equal to 3.7. By this method, loading effects of the coaxial cable and the data acquisition system onto the detector pulse shape are avoided. The noise of the output signal of the amplification circuit is less than ± 12 mV. This feature allows a very good signal to noise ratio more than 53 dB for accurate post analyses. A detailed description of nuclear instrumentation is published elsewhere [8].

During the three days of the measurement, the output signal of the detector is recorded by the Advantech high speed multifunction PCI card [1]. The sample rate of 1 MS/s is sufficient. Data acquisition and off-line data reduction is performed using MATLAB software [11]. Other details of the experimental setup are illustrated

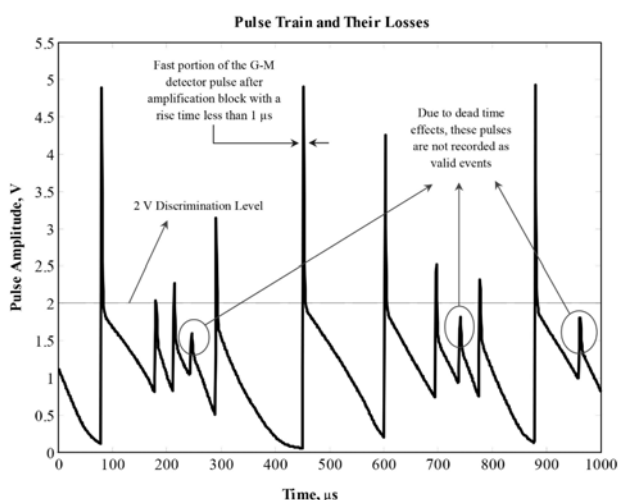


Fig. 2. Schematic of pulse train at high counting rates. The discrimination level is set to 2 V. Due to dead time effects, some pulses do not cross the discrimination level, i.e. they are not recorded as valid events.

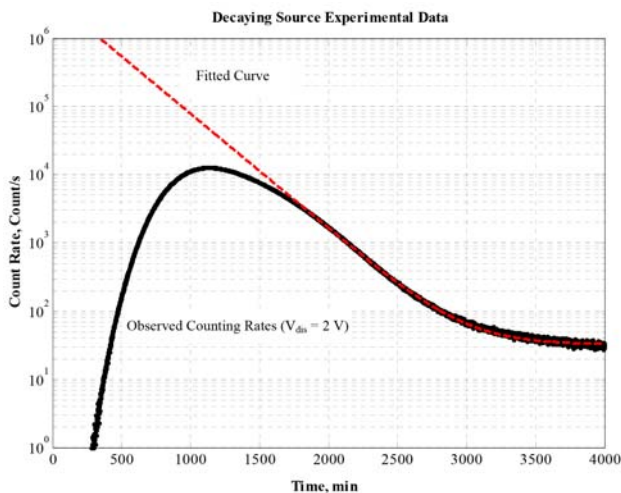


Fig. 3. Experimental data by the decaying source method. Dashed line shows the true counting curve and points show the observed counting rates.

in Fig. 1. This instrumentation allows proper off-line investigation on the recorded readout of the detector.

Two profound changes in output signals of G-M detectors occur at high counting rates. Firstly, due to pulse pile up, the base-line or direct current (DC) level of the signal is shifted. For the circuitry shown in Fig. 1, the shift in base-line is upward. Secondly, the amplitude of the short time interval pulses is weak. These vicissitudes directly act on the operating point of the detector, therefore causes significant losses at high counting rates [8]. A typical recorded pulse train of the detector output is illustrated in Fig. 2. Three pulses do not cross the discrimination level, so they are lost. This figure shows that the number of valid pulses is a function of the set point for discrimination level. The 2 V discrimination level is chosen. Dashed line in Fig. 3 shows the fitted curve of the true counting rate to the experimental data.

Feed forward artificial neural network

For the observing counting rates of a G-M, feed forward neural network structure is the appropriate configuration. The chosen structure of the neural network is shown in Fig. 4 which is optimized by iteration on different structures. This is a three-layer single-input single-output configuration. The number of neurons in the output layer is equal to the number of outputs of the network. Input layer consists of five neurons equal to the hidden layer. Because the input data are normalized between zero and unity, sigmoid transfer function is chosen. Each layer is connected to the next layer through a tree of weights. In addition to weighted inputs, a constant bias is also connected to each neuron of the network. Weights and biases are the variables which are adjusted during learning process. Input is m , target value is n (true counting rate), and the output of the network is the predicted true counting rates. Figure 4 shows more on the chosen structure. The relation between input and output of the network is shown by Eq. (3):

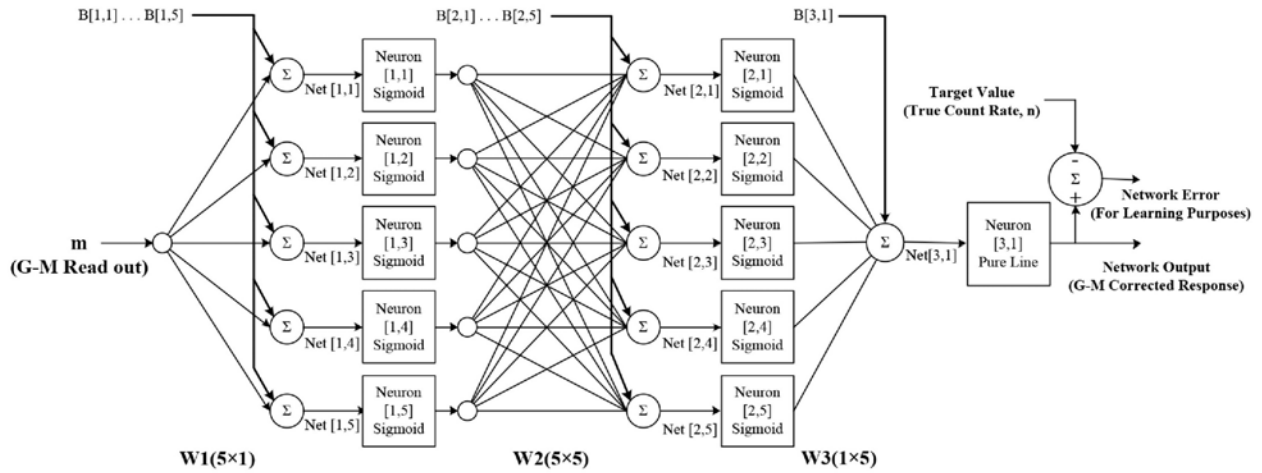


Fig. 4. Structure of the feed forward neural network for G-M dead time correction.

(3) Network Output = Pure Line (Sigmoid (Sigmoid ($mW1 + B1$)) $W2 + W2$) $W3 + B3$)

$W1 \rightarrow W3$ and $B1 \rightarrow B3$ are the weight and bias vectors of the network respectively. Sigmoid and Pure Line transfer functions are expressed by Eqs. (4) and (5) [5].

$$(4) \quad \text{Sigmoid (Net)} = \frac{1}{1 + \exp(-\text{Net})}$$

$$(5) \quad \text{Pure Line(Net)} = \text{Net}$$

Pure Line neurons are used in the final layer of multilayer networks to make a summation on all outputs of the previous layers. This structure is trained by the experimental data shown in Fig. 3 using the Levenberg-Marquardt learning algorithm. The programming is developed using MATLAB software.

Results and discussion

The neural network explained in the previous section is used to correct the nonlinearity response of ZP-1210

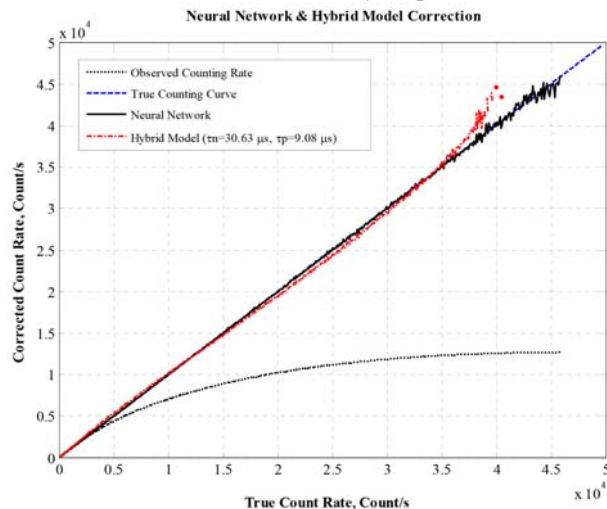


Fig. 5. Comparison of results for neural network and hybrid model correction.

G-M detector. To see the effectiveness of the method, the correction is also applied using the hybrid model. Equation (1) is fitted to the experimental data via Gauss-Newton algorithm. The calculated paralyzable and non-paralyzable dead times of the model are 9.08 and 30.63 μs , respectively. The neural network and the hybrid model correction results are shown in Fig. 5. The observed counting rates and the true counting curve are also included in this figure. It is noticeable that the dead time of the G-M tube reported by the manufacturer [6] is 200 μs , while results of this study show smaller values.

Figure 5 clearly shows that the neural network gives a very good response, which is nearly close to the true counting curve. Up to 35 000 cps, the slope of the observed counting rates is gentle for correction purposes. Therefore, a favourable response is met. Actually, any correction method maps the observed counting rates onto the true counting rates. More than 35 000 cps, the slope of the observed counting rates is very slight. Therefore, any little statistical fluctuation in the counts causes around 4% deviations in the neural network response. This is a systematic error of G-M counters. The hybrid model is more sensitive to the fluctuations; because its response shows a considerable deviation from true counting curve between 35 000 and 40 000 cps. For higher counting rates, this model does not converge into the answer considering n_1 equal to m as the initial guess for n . These important features of the results are carefully reflected in the next two figures.

Figure 6 compares the relative errors of the methods. It is evident that the neural network relative error is small within a reasonable range less than 4%. The neural network error has a uniform plus or minus relative error distribution which is mostly related to the statistical fluctuations of the observed count rates and the systematic. At very low and high counting rates, the relative error of the hybrid model increases up to 12%. At high counting rates, the hybrid model overestimate the answer as well as low counting rates. More than 40 000 cps no convergence for implicit iteration of Eq. (2) is seen. The convergence rule as described earlier is $|dF(n)/dn| < 1$ if the initial guess, n_1 , is chosen truly. Note that the recursive formula (Eq. (2), $n = F(n)$) can be formed in an ultimate number of ways. There-

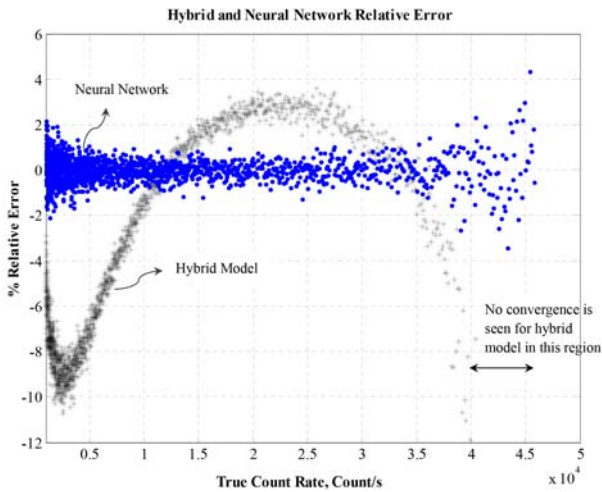


Fig. 6. Comparison of relative errors of neural network and hybrid model $\left(\% \text{ Relative error} = \frac{\text{true value} - \text{corrected value}}{\text{true value}} \times 100 \right)$.

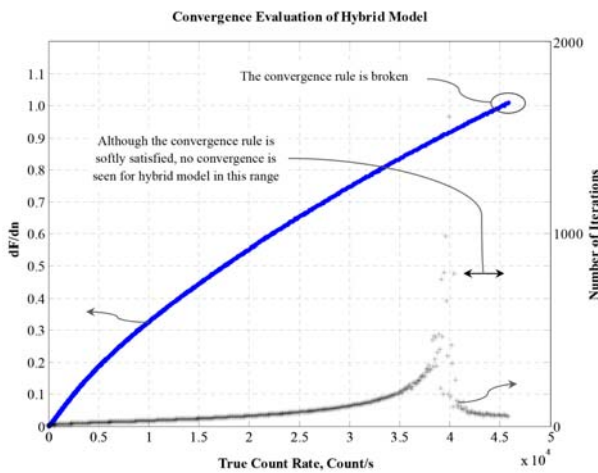


Fig. 7. Comparison of hybrid model convergence criterion with the number of needed iterations (the condition to stop the iteration loop is $|n_{i-1} - n_i| < 10^{-10}$).

fore, a more suitable arrangement might be derived to achieve an enhanced numerical solution of the hybrid model [2]. For the choice of $F(n)$ shown in the form of Eq. (2), $dF(n)/dn$ is:

$$(6) \quad \frac{dF(n)}{dn} = m \exp(-\tau_p n) [\tau_n + (1 + \tau_n n) \tau_p]$$

Equation (6) and the number of needed iterations are depicted in Fig. 7. More than 45 000 cps of the true counting rates, no convergence exists because the condition of $|dF(n)/dn| < 1$ is not satisfied. Around 40 000 cps, the number of needed iterations rises dramatically. Although the condition of $|dF(n)/dn| < 1$ is softly satisfied, but no convergence exists for true counting rates higher than 40 000 cps. The hybrid model can be forced to be converged by better approximation of n_1 or using other ultimate arrangements of $F(n)$.

Conclusion

G-M detectors are widely used in different radiation measuring devices. The paralyzable and non-paralyzable

dead time parameters of the present G-M counter system are 9.08 and 30.63 μs , respectively. A three-layer feed forward neural network structure is used for correction of the observed counting rates. Both neural network method and hybrid model are applied to the experimental data set measured by decaying source method. The correction results obtained by the neural network were compared with those from hybrid model, commonly used for correction. The maximum relative error at high counting rates for the neural network and hybrid model are 4 and 12%, respectively. Also, a major benefit of the neural network, as compared to the implicit iteration of the hybrid model, is its explicit prediction of the true counting rate. In addition, the neural network can be trained to respond to the physical behaviour of any specific G-M counter system while the hybrid model is a simplified description of the dead time process. The problem of dead time is not limited only to the G-M detectors or radiation detectors. Therefore, this paper is also useful in other fields of detections.

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