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# Estimation of postmortem period by means of artificial neural networks

Ahmed Chibat, Dalel Zerdazi*, and Fouad Lazhar Rahmani

*Laboratory of Applied Mathematics and Modeling, Department of Mathematics, University of Constantine 1, 25000 Constantine, Algeria*

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The issue of estimating the postmortem period has always been a serious problem. Current methods do not provide satisfactory solutions. The problem is highly nonlinear and the variables involved are many and various. In this work we aim to propose a new method for estimating the postmortem period. This method is based on artificial neural networks. We use Multilayer Feedforward Networks. Learning takes place in supervised mode. We give a comparative study on a sample of 257 individuals to prove the advantage brought by this new technique, improving in this way the precision of the estimates given by the traditional methods.

**keywords:** Period postmortem, thermometry, artificial neural network, estimation.

## 1 Introduction

An important problem in forensic science is the estimation of the postmortem period. Research has been developed over long decades and has produced very different methods, elaborated in order to achieve acceptable estimates (Naumenko, 1983; Kaliszan et al., 2009). Different approaches have been explored, as diverse as forensic entomology or organic liquids analysis (Amendt et al., 2011; Lin et al., 2011). Thermometric method, which is one of the main tools for the estimation of postmortem interval in the first few hours after death, has been the subject of sustained interest; see for instance (Berent, 2004; Verica et al., 2007). Its advantage lies in the fact that it is built on the basis of quantitative measures. Successive assumptions such as:

*Corresponding author: dalel.zerdazi@hotmail.com.


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- Cooling of the body is proportional to the time;
- Heat flow is proportional to the temperature difference between body and ambient air

have led to the evolution of the thermometric method. The Henssge method (Nokes et al., 2002), although better than its predecessors, does not solve completely the problem; the estimation interval (over three hours) is too broad to properly respond to the requirement of practical considerations. The point relies on the fact that the law underlying the phenomenon might be far too complex to be captured by this formula. The model is manifestly highly non-linear, and there is not yet sufficient knowledge to determine its structure. It seems that there is not yet decisive progress, although several attempts at mathematical modeling of the phenomenon of body cooling were undertaken (Henssge and Brinkmann, 1984; Biermann and Potente, 2011). Unfortunately, actual observations show that the resulting models, which are linear for the first assumption and exponential for the second, remain too imprecise. The newest model and the currently the most used one, is built on the formula (1), in 4.2, proposed by Henssge C (Nokes et al., 2002). This formula takes into account three factors, ambient temperature, body temperature and body weight. In this work we aim to propose a new method for estimating the postmortem period. This method is based on artificial neural networks. It will be compared to that of Henssge, adopting the same predictor variables.

## 2 Selected Method

The estimation of postmortem period arises naturally in a modeling problem. It comes to design a formula which establishes quantitatively the precise relation linking the different predictor variables to the variable to predict. The predictor variables are the different characteristics measured on the body and on the surrounding environment. The variable to predict is the period of time between the moment of death and the moment of taking measurements.

Thereby, this amounts to find a mathematical function that is, first susceptible to explain the observations in our possession and mainly continues to be verified outside the data set that was used in its preparation. This mathematical function may result from a well developed knowledge model. It seems however, that this is not yet the case in the field of estimation of postmortem period.

Different successive models have brought more and more improvement in the accuracy of estimates, but nonetheless without reaching satisfactory answers. The margin of errors in the estimates, even with the latest methods, remains too large. It is not clear whether the models proposed so far fit the data distribution in an optimal way for prediction. If such is the situation, imposing to the relationship a pre-established form is a restriction that cannot be conceived, as there is no theoretical basis that could justify it.

If, conversely, we admit that the real purpose is ultimately the quest of quality of prediction rather than the explicit formulation of the law, then it might be more advantageous to turn to newer technologies, more effective to meet this objective. These are the artificial neural networks, which have the ability to learn from data directly and automatically, without the need for an a priori formulation. They have the ability to approximate as closely as possible the law in question and have a reliable generalization power, see for instance (Dunne, 2007; Dreyfus et al., 2002). If we admit that the true law that governs the phenomenon necessarily leaves its trace in the observations, outcomes of our measurements, the challenge is to find ways to extract useful information from them. This, in spite of the fact that the data are probably noisy and affected by errors.

Fortunately, in the framework of the approximation of functions, it is proved in the theory of artificial neural networks that this could be achieved in a highly satisfactory manner; we may refer the reader to (Hornik et al., 1989; Hornik, 1991). It suffices to gather a number of conditions to ensure a good approximation of the function embedded in the data. This approximation, once obtained, would provide results in the estimation of postmortem period more satisfactory than those given by current methods. The first condition is primarily the existence of a deterministic relationship between the predictor variables and the variable to predict.

The second condition is the availability of a sufficient number of cases, for each of which we know the values of the predictor variables and also the true value of the variable to predict. The third condition is the implementation of a network built correctly and adequately trained.

This proposed work is not an attempt to achieve an ideal solution, its primary purpose is to prove that neural methods are likely to lead to much more satisfactory solutions than those produced by existing methods. This, therefore, would open a very promising field of research. To this end, we have chosen to conduct a comparative study between the neuronal method and the Henssge method (Nokes et al., 2002).

We have fixed our choice on the recent thermometric method of Henssge because it is recognized as the most accurate among all the existing methods, thermometric or not. Since it is a comparison, the conditions must be rigorously identical for the two methods, for variables as well as for cases. The neuronal technique will adopt the same predictor variables which are used in the Henssge one. The postmortem period is the variable to predict by the two methods.

The data used 257 cases were harvested with great care by a forensic doctor. This data collection was done over years, well before our comparative study. It has not been conducted to advantage a method over the other.

The comparison between the two approaches is based on the extent of errors in the estimates, produced by each one, on the set of 257 cases.

The criterion we adopt is the mean square error, and for a more immediate illustration we also give the mean absolute error.

## 3 Technical aspects

One of the fundamental differences between the two methods is that the formula of Henssge is definitively established and is no longer subject to changes. The values of

its coefficients were set by the sample used in its elaboration. It remains fixed and its performances remain constant.
On the other hand, the model built on neural networks could still be improved if there would be new data to add to the training set. The new data can be added to what has been used in order to form a new training set. This always leads to a gain in performance. The network architecture is not necessarily final, it can move in the direction that takes full advantage of any new training set.
From this perspective, the neural method can be seen as a process rather than as a formula. Several researchers can share their data to build a more powerful network than they would have separately built, each using its own data.
Two major issues must be taken into consideration when comparing the two methods, the level of the performance and the quality of generalization.
A method will be considered better than the other if it has, on the comparative sample, a mean square error smaller than that of the other. But this criterion alone is not sufficient. It is necessary to ensure that the generalization ability is good, that is to say that the same quality of results should be observed in any other prospective sample.
For the Henssge method, the quality of generalization does not depend on the set used for comparison; it is an intrinsic property which derives from the formulation of this method. But, for neuronal method, the quality of generalization depends on the training set, and we must ensure that it has a satisfactory level. Indeed, when the network is properly constructed and when the training method is adequate, we may reach an overall fitting. This would be a perfect solution, but which is valid only if the data is not altered by errors, and all predictor variables have been taken into account. This is undoubtedly not the case in the problem we consider. Thus, the strength of neuronal method may become a disadvantage because the network may include errors in the model. The results would be too good on the sample, but in return, the generalization to other data would be weak.
To avoid this situation, the data set is divided into three parts, a training set, a validation set and a testing set. In this way, the network training is achieved, which will improve the performance as much as possible without affecting the ability of generalization.
The construction and training of an artificial neural network are quite easy. There are a lot of softwares designed for this purpose. It is therefore possible for each one, having sufficient data, to create and train its own network.
For those who have not enough data, please contact the authors to get the trained network at their disposal, or get a simple program designed in Excel which emulates the trained network ready for use. It should be stressed that we did our comparison, and draw our conclusions on the basis of the data at our disposal. We are convinced that with more data the results will be better, mainly with respect to all possibilities for ambient temperature for which we only had values between $4.5^{o}$C and $18^{o}$C. It remains to extend this interval beyond the two extremities. It may be that there are researchers or practitioners who already have this kind of data and can therefore train networks with what they have. We can also propose for them our data in order that they can have a more substantial set.

# 4 Comparative study

## 4.1 Description of the data

The location of the data collection extended over several years is the university hospital center of Constantine. All measurements were performed by a qualified forensic pathologist who first recorded the moment of death. Then the values of the three variables (body weight, body temperature and ambient temperature) were recorded in times more or less distant according to each case.
The listed cases are patients who died within the same hospital. For each of these cases, the forensic pathologist was immediately called to note the actual death of the patient. The time of death is noted with the greatest possible accuracy.
Our initial sample consists of all cases of death recorded by the same forensic pathologist. From this set we excluded cases where death was accompanied by a high fever and cases when the time of death is not very sure. The remaining set, consisting of 257 cases, constitutes our study sample. The corpses were moved to the morgue as soon as the ascertainment of the death was recorded by the forensic pathologist.
For each of these corpses, a specific time has been chosen for the measurement of body weight and rectal temperature. At this very moment the ambient temperature is noted, which is the temperature inside the morgue during the stay of the corpse. It is always measured with the same device.
We have thus, on the one hand three predictor variables, the body weight (P), the rectal temperature (Tr) and the ambient temperature (Ta), and on the other hand a variable to be predicted, which is the post mortem period (PMP), which is the time elapsed between the moment of death and the moment of taking measurements. For each of these 257 bodies we know the exact values of the three variables (P), (Tr) and (Ta) as well as the true value of the variable (PMP).
Measurements on all individuals were made in the same conditions:

- Dry air without movement.
- Body totally nude from the time of death.

The taking of rectal temperature was done in all cases with a device having the same sensitivity, as well as the weighting of bodies.
All measurements on the three variables were made with the greatest care, and possibly if there would be some bad measures, this would affect both estimation methods, and would not favor one over the other.

## 4.2 PMP estimation using Henssge method

Henssge model (Nokes et al., 2002) is built on the formula:

$$\frac{T_{corps} - T_{ambient}}{37.2 - T_{ambient}} = 1.25.e^{-kt} - 0.25.e^{-5kt} \tag{1}$$

where $k$ is a parameter depending on the weight $P(kg)$ of the individual :

$$k = \frac{1.2815}{p^{0.625}} - 0.0284$$

This formula takes into account three factors, body weight $P$ (in kilograms), ambient temperature ($Ta$) and body temperature ($Tr$) (in Celsius degrees). The time (t), marking the period between the occurrence of death and the time measurements of temperatures and weight, is deduced from this formula.
This time ($t$) is the estimation of postmortem period. We calculated this time for the 257 observations.
For each observation, the difference between this time ($t$) and the true value of PMP is the estimation error. The average of the squares of these differences is the mean squared error (MSE).

## 4.3 PPM estimation using neuronal method

### 4.3.1 Network building

We use MATLAB 2012 furnished by The MathWorks, Inc, to build our network.
The network used is a feedforward network. It features:
- A hidden layer of 10 neurons, each one with the hyperbolic tangent as activation function.
- An output neuron with a linear activation function.
The choice of this architecture is motivated by the followings:

- The outstanding work of Hornik et al. (1989), Hornik et al. (1990) and Hornik (1991) guarantees that if there is a deterministic relationship between the input variables and the output variable, we may be able to build a network capable of providing the best approximation of this relationship. This network comprises a hidden layer of neurons having the same transfer function and an output layer having a single neuron whose transfer function is linear.

- Thus, the only concern is the determination of the appropriate number of neurons in the hidden layer. This number is related to the amount of data at our disposal. Whenever this number of neurons is large the network is flexible and therefore the approximation is much better, (Fine, 2006). However, this optimization cannot be carried to its limits, because the predictor variables are altered by errors and we need to ensure the quality of the generalization. The bias-variance equilibrium must be ensured. A too small number of hidden neurons causes a large model bias, while too many leads to a large variance. In both cases a poor generalization is obtained.
  There are no systematic methods to obtain the optimal number of hidden neurons. This number remains dependent on the sample used for training the network. In our present study, we found that ten hidden neurons provide the best equilibrium between bias and variance. However, this number is not strictly the only optimal

number, we can add or subtract up to two neurons without degrading substantially the quality.

- We chose to use the hyperbolic tangent as the activation function for the hidden neurons because it is antisymmetric. This property allows the feedforward network, when trained with the back-propagation algorithm (or its variants), to learn faster, in terms of required number of training iterations. The other sigmoid functions, which lack this property, lead to a slower learning.

### 4.3.2 Training method

The Levenberg-Marquardt algorithm is the most appropriate method for training our network. Indeed, this network is not really big, it is not wise to use simple gradient method or its variants whose convergence times are greater by several orders of magnitude than those of second order methods, in this direction we refer to (Hagan and Menhaj, 1994). Moreover, among second order techniques the Levenberg-Marquardt algorithm is distinguished by the fact that it is specifically designed to minimize the mean square error, which is the cost function that we have adopted in our study.
The set of observations at our disposal composed of 257 observations was subdivided by a random procedure into three subsets:

- A training set consisting of 60% of observations. These are 155 cases that are presented to the network during training. The network is adjusted according to the errors registered on those cases.
- A validation set consisting of 20% of observations. These are 51 cases that are used to measure the generalization ability of the network. The training automatically stops when the performance ceases to improve on this set.
- A testing set consisting of 20% of observations. These are 51 cases that did not have an effect on the training and provide thereby an independent measure of network performance during and after training.

The quality of the training of the network depends on the subdivision of the data set into these three subsets. Each of the possible subdivisions leads to a trained network with its own parameters values and its own performance.
Therefore, it may be necessary to train the network on the same data several times till we reach satisfactory results. The training automatically stops whenever the mean squared error ceases to decrease on the validation set.
The mean squared error calculated on the validation set is nearly always higher than that calculated on the training set. Nevertheless, it must be the first to be taken into consideration because the quality of generalization is assessed on the basis of its value. The best training is the one that produces the smallest value for this quantity. Additionally, we must ensure as much as possible that the value of the mean squared error calculated on the testing set will be of the same order of magnitude.

#### 4.3.3 Estimation

The network resulting from the best training is the one which will be adopted for subsequent estimates. Its parameters are fixed and the estimation procedure is to provide the network with the values of the predictor variables for each case and observe the response. This response is the estimate of the value of the post mortem period for the considered case.

## 5 Results and Discussion

### 5.1 Results

Our data set consists of 257 observations. For each of these observations, we know the true value of postmortem period ($PMP$). Henssge formula is used to estimate the postmortem period using the values of body weight ($P$), rectal temperature ($Tr$) and ambient temperature ($Ta$). We used the trained neural network to perform the same task of estimation by using the same values.
Our goal is to compare the performance of the Henssge method with that of the neuronal method, in terms of the difference between the estimate of the postmortem period and its true value.
The criterion of comparison between the two methods is built on these differences, in the form of mean squared error (MSE):

$$MSE = \frac{1}{257}\sum_{i=1}^{257}(PMP_i - ev_i)^2 \tag{2}$$

Where $i = 1, 2, ..., 257$ is the number of observations.
$PMP_i$ and $ev_i$ are respectively the true value and the estimate of postmortem period for the case number $i$. The results are in Table 1 :

Table 1: MSE values Henssge method vs Neural method

| MSE | Value | Confidence interval (level 95%) |
|---|---|---|
| Henssge method | $MSE_H = 20.83$ | $(17.34 - 24.32)$ |
| Neural method | $MSE_{NN} = 5.69$ | $(4.54 - 6.84)$ |

Note that, in this formula, the unit of time is squared. For this reason, we also calculated the mean absolute error ($MAE$) for each method, which is:

$$MAE = \frac{1}{257}\sum_{i=1}^{257}|PMP_i - ev_i| \tag{3}$$

Then we obtain the following results, in Table 2 :

Table 2: MAE values Henssge method vs Neural method

| MAE | Value | Confidence interval (level 95%) |
|---|---|---|
| Henssge method | $MAE_H = 3.52$ (about 3 hours and a half) | $(3.17 - 3.88)$ |
| Neural method | $MAE_{NN} = 1.85$ (about one hour and 50 minutes) | $(1.66 - 2.03)$ |

## 5.2 Discussion

### 5.2.1 First issue: Postmortem period less than 7 hours.

Neuronal method provides a substantial improvement in the accuracy of estimation of period postmortem. The result is significant, even with a fairly small training set. The advantage of this method is that it suffices to bring some more data to make the results even better.
In the set of 257 observations used in our study, the values of true postmortem period are spread out from 20 minutes to 18 hours and 20 minutes. So we have an average of about 15 cases per unit of time.
We have resumed our comparative study in exactly the same way, but by restricting it to the observations whose postmortem period does not exceed seven hours. This set consists of 184 observations. The average is about 32 observations per unit of time.
The results are in Table 3 and Table 4:

Table 3: MSE values Henssge method vs Neural method

| MSE | Value | Confidence interval (level 95%) |
|---|---|---|
| Henssge method | $MSE_H = 21.14$ | $(16.84 - 25.45)$ |
| Neural method | $MSE_{NN} = 1.21$ | $(0.95 - 1.46)$ |

Table 4: MAE values Henssge method vs Neural method

| MAE | Value | Confidence interval (level 95%) |
|---|---|---|
| Henssge method | $MAE_H = 3.51$ (about 3 hours and a half) | $(3.08 - 3.94)$ |
| Neural method | $MAE_{NN} = 0.86$ (about 52 minutes) | $(0.76 - 0.96)$ |

This quality of estimation is accompanied by a quality of generalization of the same order.
In the light of both studies, over the entire data set and on the subset limited to the first seven hours of death, we may suspect that there are several reasons for which the performance of the neuronal technique is bad when the range of the variable to predict is wider. This deserves some further investigation.
However, as we have maintained the same conditions for both cases, it seems that the most likely reason is the density of data per unit of time.
The precise choice of seven hours is not obligatory, neither entirely arbitrary. In fact, all the values that are adjacent can be taken as separating boundaries. In addition, this choice was not dictated solely by the question of the density of observations per unit of time, but there are other reasons that have led us to focus on the first few hours after death.
The first is the fact, generally admitted, that body cooling goes first through a plateau in which the lowering of the body temperature is slow and makes it difficult to estimate the postmortem period, (Smart and Kaliszan, 2012).
The second reason is that we observed, in our data, that the method of Henssge tends to overestimate the postmortem period in the early hours. The average error on the first seven hours is 2.86 hours, and it tends to underestimate thereafter with an average error of $-1.42$ hours.
There is as a model break, and we think it would be interesting to train a network exclusively on this first time interval after death.
Our first network, which is trained on all the data, tends to underestimate the postmortem period in the early hours with an average error of $-0.64$ hours. But this second network, which is specialized on this interval, does not produce any systematic bias, and the average error is less than 0.07 hours.

### 5.2.2 Second issue: Correction coefficients

Henssge formula applies without change when the body is in a location where the air is dry and without movements, and when the body is totally naked from the time of death. But when these conditions are not satisfied, a correction coefficient is applied in order to take into account the different variants.
The value of the estimate is multiplied according to the following cases:

- by a number ranging from 0.35 to 0.95 in the presence of factors that accelerate the cooling of the body, such as mobility of air or presence of water.
- by a number ranging from 1.1 to 2.4 in the presence of factors that slow cooling, such as blankets or warm clothing.

As for Henssge method, the neuronal method also needs correction coefficients in order to take into account the various situations encountered in practice.
The coefficients adopted for the Henssge method can equally be used, in the same manner we may apply this to the neuronal method. The reason for this is that, if one of the

methods produces a greater estimation error than the other, the correction coefficient which only amplifies or attenuates these errors does not cause a change in the sense of the inequality.

### 5.2.3 Third issue: Avoid overfitting

Multilayer feedforward networks can produce perfect solutions because they are universal approximators. They are capable of approximating any measurable function from one finite dimensional space to another to any desired degree of accuracy, provided sufficiently many hidden units are available, (Hornik et al., 1989; Hornik, 1991). However, this is only valid if, on the one hand, the predictor variables are appropriately identified and secondly that the function values are accurate and not affected by errors. This is undoubtedly not the case in the problem we consider. Thus, we must be careful when treating this problem because looking for too good performance may lead to an overfit. It is therefore necessary to ensure the quality of generalization while seeking a good performance. For this reason, the validation set and the test set should not be too small (less than 20% of observations).

## 6 Conclusion

This study shows that the estimates obtained by the neural networks method are far more satisfactory than those obtained by the Henssge formula. They are particularly important for the first level of cooling (the first 7 hours after death). It is precisely this level which posed problems for traditional methods because of the slowness of the thermal variation.

Furthermore, an extension of the study is quite conceivable. Indeed, when the number of observations increases, the neural networks improve the accuracy of estimates and the generalization ability. Compared to traditional methods that produce fixed formulas and whose performance remains constant, the neural networks have the ability to be continuously improved.

Because of the practical and quite easy implementation, the training can be resumed whenever we have additional data.

These new techniques, such as artificial neural networks or neuro-fuzzy systems, based on learning by example rather than on determining the parameters of a pre-established model could allow us to make a very large prospection. The data necessarily contains information inherent to the phenomenon; the challenge is to extract it from the data. Thus, all measurable variables are candidates for study. The method we have proposed is valid for thermometry and still remains valid whenever predictor variables are quantitative.

This approach which does not require an a priori knowledge model broadens the scope of investigations in several directions and does not confine uniquely to the field of thermometry. We may envisage to:

- Strengthen the results on the same areas of learning.

- Extend these areas of learning, especially that of the ambient temperature.
- Include the variables involving, directly or indirectly, the body surface and its volume.
- Include quantifiable variables other than temperature (such as the concentrations of certain chemical elements in different parts of the body).
- Check the influence of age and sex.
- Quantify and integrate environmental features.
- Check the influence of medico-legal form of death (violent and non-violent).

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## References

Açikgöz, H. N. (2009). [forensic entomology]. *Turkiye parazitolojii dergisi/Turkiye Parazitoloji Dernegi= Acta parasitologica Turcica/Turkish Society for Parasitology*, 34(3):216–221.

Al-Alousi, L. M. (2002). A study of the shape of the post-mortem cooling curve in 117 forensic cases. *Forensic science international*, 125(2):237–244.

Al-Alousi, L. M., Anderson, R. A., Worster, D. M., and Land, D. V. (2002). Factors influencing the precision of estimating the postmortem interval using the triple-exponential formulae (tef): Part ii. a study of the effect of body temperature at the moment of death on the postmortem brain, liver and rectal cooling in 117 forensic cases. *Forensic science international*, 125(2):231–236.

Amendt, J., Krettek, R., and Zehner, R. (2004). Forensic entomology. *Naturwissenschaften*, 91(2):51–65.

Amendt, J., Richards, C., Campobasso, C. P., Zehner, R., and Hall, M. J. (2011). Forensic entomology: applications and limitations. *Forensic science, medicine, and pathology*, 7(4):379–392.

Berent, J. (2004). [determining the post mortem interval based on temperature measurements. part i: From the first 19th century studies to marshall & hoare's double exponential model]. *Archiwum medycyny sadowej i kryminologii*, 55(3):209–214.

Berent, J. (2006). Determining post mortem interval by temperature data. part ii: research results from the 1970s to the end of the 20th century. *Archiwum medycyny sadowej i kryminologii*, 56(2):103.

Biermann, F. M. and Potente, S. (2011). The deployment of conditional probability distributions for death time estimation. *Forensic science international*, 210(1):82–86.

Bishop, C. M. (1995). *Neural networks for pattern recognition.* Oxford university press.

Bishop, C. M. (2006). Pattern recognition. *Machine Learning*, 128.

Den Hartog, E. A. and Lotens, W. A. (2004). Postmortem time estimation using body temperature and a finite-element computer model. *European journal of applied physiology*, 92(6):734–737.

Dreyfus, G., Martinez, J.-M., Samuelides, M., Gordon, M. B., Badran, F., Thiria, S., and Hérault, L. (2002). Réseaux de neurones-méthodologie et applications. *Réseaux de neurones-Méthodologie et applications.*

Dunne, R. A. (2007). *A statistical approach to neural networks for pattern recognition*, volume 702. John Wiley & Sons.

Fine, T. L. (2006). *Feedforward neural network methodology.* Springer Science & Business Media.

Green, M. and Wright, J. (1985). The theoretical aspects of the time dependent z equation as a means of postmortem interval estimation using body temperature data only. *Forensic science international*, 28(1):53–62.

Hagan, M. T. and Menhaj, M. B. (1994). Training feedforward networks with the marquardt algorithm. *IEEE transactions on Neural Networks*, 5(6):989–993.

Haykin, S. S. (2001). *Neural networks: a comprehensive foundation.* Tsinghua University Press.

Henssge, C. and Brinkmann, B. (1984). Determination of time of death by rectal temperature. mathematical analysis of empirical material versus thermodynamic modeling. a critical case presentation. *Archiv für Kriminologie*, 174(3-4):96.

Hornik, K. (1991). Approximation capabilities of multilayer feedforward networks. *Neural networks*, 4(2):251–257.

Hornik, K., Stinchcombe, M., and White, H. (1989). Multilayer feedforward networks are universal approximators. *Neural networks*, 2(5):359–366.

Hornik, K., Stinchcombe, M., and White, H. (1990). Universal approximation of an unknown mapping and its derivatives using multilayer feedforward networks. *Neural networks*, 3(5):551–560.

Jashnani, K. D., Kale, S. A., and Rupani, A. B. (2010). Vitreous humor: biochemical constituents in estimation of postmortem interval. *Journal of forensic sciences*, 55(6):1523–1527.

Kaliszan, M., Hauser, R., and Kernbach-Wighton, G. (2009). Estimation of the time of death based on the assessment of post mortem processes with emphasis on body cooling. *Legal Medicine*, 11(3):111–117.

Kil'diushov, E. and Kil'diushov, M. (2001). [determination of the time of death according to rectal thermometry data using computer calculations]. *Sudebno-meditsinskaia ekspertiza*, 45(5):3–5.

Knight, B. (1988). The evolution of methods for estimating the time of death from body temperature. *Forensic Science International*, 36(1):47–55.

Lin, X., Yin, Y., and Ji, Q. (2011). [progress on dna quantification in estimation of postmortem interval]. *Fa yi xue za zhi*, 27(1):47–9.

Muñoz Barús, J. I., Febrero-Bande, M., and Cadarso-Suárez, C. (2008). Flexible regression models for estimating postmortem interval (pmi) in forensic medicine. *Statistics in medicine*, 27(24):5026–5038.

Naumenko, V. (1983). [current state and perspectives of the solution of the problem of determining the time of death]. *Sudebno-meditsinskaia ekspertiza*, 27(2):9–12.

Nelson, E. L. (2000). Estimation of short-term postmortem interval utilizing core body temperature: a new algorithm. *Forensic science international*, 109(1):31–38.

Nokes, L. D. M., Henssge, C., Knight, B., Madea, B., and Krompecher, T. (2002). *The estimation of the time since death in the early postmortem period.* Hodder Arnold.

Pigolkin, I., Bogomolov, D., and Korovin, A. (1998). [the current methods for determining the time of death]. *Sudebno-meditsinskaia ekspertiza*, 42(3):31–33.

Smart, J. L. and Kaliszan, M. (2012). The post mortem temperature plateau and its role in the estimation of time of death. a review. *Legal Medicine*, 14(2):55–62.

Vavilov, A. and Viter, V. (2007). Using some modern mathematical models of postmortem cooling of the human body for the time of death determination. *Sudebno-meditsinskaia ekspertiza*, 50(5):9.

Verica, P., Janeska, B., Gutevska, A., and Duma, A. (2007). Post mortem cooling of the body and estimation of time since death. *Soudni lekarstvi/casopis Sekce soudniho lekarstvi Cs. lekarske spolecnosti J. Ev. Purkyne*, 52(4):50–56.

Viter, V. and Vavilov, A. (2007). [state-of-the-art of mathematical modeling of postmortal thermodynamics for the time of death determination]. *Sudebno-meditsinskaia ekspertiza*, 51(1):15–18.