University of Pécs

PhD thesis

Determining postmortem interval in dynamically changing environment

Author:
Lívia Mária Dani

Supervisors:
Dr. Zsolt Kozma PhD
Dr. András B. Frigyik

Leader of the doctoral school: Prof. Dr. Ferenc Gallyas
Leader of the program: Prof. Dr. Miklós Nyitrai

Interdisciplinary Medical Sciences Doctoral School (D93)
Pécs

2023

Interdisciplinary Medical Sciences Doctoral School (D93)

Leader of the doctoral school: Prof. Dr. Ferenc Gallyas

Program: Investigating functional protein dynamics using biophysical methods (B-130/1993)
Leader of the program: Prof. Dr. Miklós Nyitrai

Supervisors:
Dr. Zsolt Kozma PhD

University of Pécs, Medical School,
Department of Forensic Medicine

Dr. András B. Frigyik

Óbuda University, Bánki Donát Faculty of Mechanical and Safety Engineering,
Insitute of Mechatronics and Vehicle Engineering

Introduction

Since the 19th century, advanced nations have mandated that the occurrence of death be determined by a physician. During the autopsy, it is the doctor's responsibility to establish the fact, manner, and time of death based on a detailed examination of cadaveric phenomena and circumstances. Determining the time interval of death is one of the oldest investigated areas in forensic medicine, posing challenges to professionals from the beginning and remaining a subject of significant research to this day.

Estimating the postmortem interval

Following death, various postmortem processes are initiated and take place in the body, leading to the cooling and subsequent decomposition of the body: cessation of metabolism, livor mortis (postmortem lividity), rigor mortis (stiffening of the muscles), algor mortis (cooling), and decomposition. The cooling process continues until the body temperature reaches the ambient temperature. Over the centuries, numerous methods have been developed to determine postmortem body temperature, relying on the measurement of temperatures in various body parts, such as the external auditory canal, under the armpit, in the brain, eyes, liver, or rectum.

Measuring and observing the speed of algor mortis can play a crucial role in estimating the postmortem interval (PMI)[1]. However, this process provides only estimated time intervals, so in certain cases, a more accurate result for the time of death can be obtained by combining it with other methods such as rigor mortis and decomposition.

Newtonian cooling law

The first written results date back to the 1830s. The majority of measurements conducted in the 19th century focused on cloak temperature, using thermometers with different scales. The problem was first addressed by Rainy [1] using mathematical tools, describing it with the help of Newton's cooling law, and formulating the existence of a temperature plateau, which had been observed by several others before.

[1] The time elapsed since an individual's death.

The basic equation of heat conduction, the Newtonian cooling law: A body with heat capacity C_1 and temperature T_1, with surface area A, releases heat $dQ = C_1 dT$ during the time interval dt to its surroundings at a practically constant temperature T_2, with heat capacity C_2, where $C_2 \gg C_1$. Consequently, the body can be considered in a constant temperature environment (T_2).

The Newtonian cooling law is not suitable for providing a complete mathematical description of the cooling process of a cadaver, as it does not account for the plateau phase.

Marshall-Hoare formula

From a mathematical perspective, a new result is attributed to Marshall and Hoare, who in 1962 developed an empirical formula. This formula consists of a linear combination of two exponential functions, making it suitable for the mathematical characterization of the expected sigmoid cooling curve. The Marshall-Hoare formula [2]–[4] is as follows:

$$\frac{T_r - T_a}{T_0 - T_a} = A \cdot \exp\left(Bt\right) + (1 - A) \cdot \exp\left(\frac{AB}{A-1} t\right) \tag{1}$$

where T_r and T_a represent the rectal and ambient temperatures measured at time t, and $T_0 = 37.2°C$ is a constant, representing the would be rectal temperature measured at the time of death. In the formula, A and B are empirical parameters obtained through experimentation. The values depend on whether the formula is applied to measure temperature in brain and rectum. Technically, the formula is suitable for both cases, with different values for A and B (see Table 1).

(a)

T_a	≤ 23.2°C	≥ 23.3°C
A	1.25	1.11
B	depends on body weight	

(b)

T_a	10–20.5°C
A	1.135
B	-0.127

Table 1: A and B parameters for rectal and brain temperature measurements

In the case of rectal temperature measurements, B includes the body mass (m), i.e.:

$$B = -1.2815 \cdot m^{-0.625} + 0.0284 \tag{2}$$

The Marshall-Hoare formula for rectal temperature measurements in the two temperature ranges is as follows:

$T_a \leq 23.2°C$:

$$\frac{T_r - T_a}{37.2 - T_a} = 1.25 \cdot \exp\left(Bt\right) - 0.25 \cdot \exp\left(5Bt\right) \tag{3}$$

$T_a \geq 23.3°C$:

$$\frac{T_r - T_a}{37.2 - T_a} = 1.11 \cdot \exp\left(Bt\right) - 0.11 \cdot \exp\left(10Bt\right) \tag{4}$$

Determining the time of death, exploring its influencing factors, has prompted further investigations, methods, and the need for the continued development of the Marshall-Hoare formula.

Henssge formula

The practical introduction of the Marshall-Hoare formula is credited to Henssge [6], who presented a simplified method for determining the cooling constant and introduced empirical correction factors based on body mass [7]–[10]. Henssge determined correction factors for different numbers and thicknesses of clothing layers and environmental conditions, allowing these influencing parameters to be considered in the estimation of PMI since they can modify the resulting value. It's important to note that the correction factors range from 0.75 and can go up to 10.9. Additional correction is needed for body mass beyond a value of 1.4 [10].

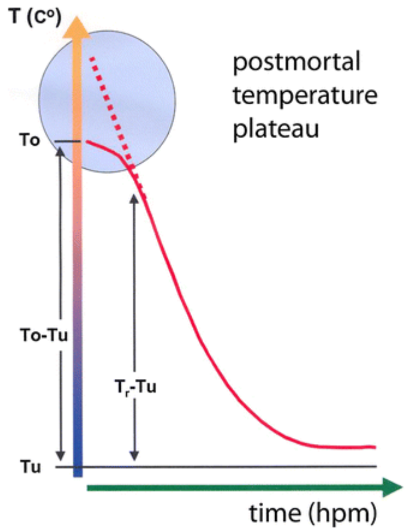


Figure 1: Henssge formula[5]

In the case of the Marshall-Hoare formula extended with correction factors, the correction applies to the estimated body mass. Thus, the B parameter described in equation (2) is modified as follows:

$$B = -1.2815 \cdot (k \cdot m)^{-0.625} + 0.0284, \tag{5}$$

where k is the correction factor introduced by Henssge. The relationships described in formulas (3) and (4) remain unchanged with Henssge's modification, with the only difference being the calculation of the B parameter value.

Since the Henssge formula is solved for t to estimate the time interval since death, it becomes a transcendental equation, meaning it cannot be solved in closed form. To find a solution, either a numerical method or a graphical solution method, known as a nomogram or calculation chart, is required.

Henssge nomogram

Henssge [6] developed the graphical solution method for the Marshall-Hoare/Henssge formula. He created various nomograms (see Figure 2) for rectal temperature measurements in cases where the environmental temperature is below/above $23°C$, and a separate nomogram was also designed for calculations involving the measurement of brain temperature [11]. For both nomograms, we need to account for a certain degree of uncertainty in the estimated time interval. In the case of $T_a > 23°C$, the correction factor can introduce uncertainties of up to $\pm 2.8, \pm 4.5, \pm 7$ hours. For a naked body, it can exceed $\pm 2.8, \pm 3.2, \pm 4.5$ hours, with a confidence interval of 95.45%.

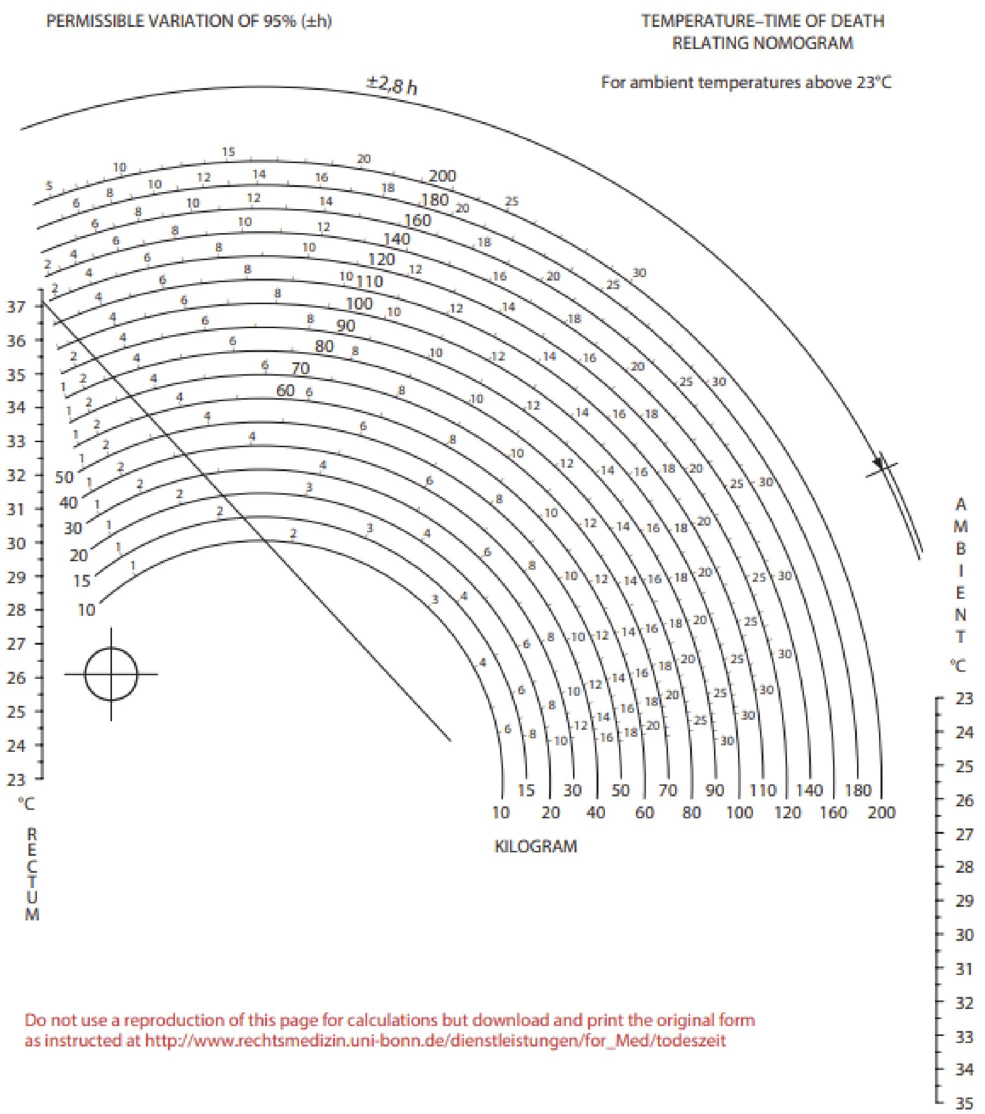


Figure 2.37 Henssge's nomogram method for estimating the time since death from a single rectal temperature, where the environmental temperature is above 23°C.

Figure 2: Henssge nomogram above 23 °C [2]

[2] Image source: Pekka Saukko, Bernard Knight: "Knight's Forensic Pathology" (2015, 4th edition), page 88.

Goals

The purpose of the study is to explore the influencing factors in estimating the PMI and consider the possibilities of taking them into account.

The goal was to create a flexible mathematical model that can be easily adapted to different ethnic groups with varying anthropometric characteristics. It should be suitable for application in various geographical regions and can be specifically retrained with a small number of training data.

During the research, I also examined the margin of error in estimating the post-mortem interval using the previously applied mathematical methods—the Henssge method and its numerical solutions. The aim was to compare the results of my own synthetic model with the results of other approaches.

During the research, the questions aimed to be addressed include:

1. Which regression method provides the best estimation?
2. What is the minimum amount of training data required for the synthetic model to be applicable for PMI estimation?
3. What is the expected error of the estimation?
4. In which cases is the model not applicable?
5. How can the synthetic model be further improved?

Experiments and results with synthetic model

A parameter estimation can be mathematically treated as solving a linear regression problem, where we obtain a model suitable for estimating the postmortem interval. There are various mathematical tools to choose from for this purpose, including different regression methods, decision trees, or solving it with neural networks. The goal is to find a real function that best fits a given training set. An example of a specific neural network is the Support Vector Machine (SVM), which belongs to the set of supervised learning methods. SVMs can be fundamentally used for linear classification, regression, and outlier detection. Different kernel functions can be applied to the decision functions. The purpose of kernel methods is to transform a linearly solvable problem, meaning that during their use, the data describing the task to be solved is transformed into a transformed space using nonlinear transformations. An example of such a kernel is the radial basis function (RBF).

The accuracy of estimating the invented mathematical model depends on the correctness of the relatively numerous parameters that can be provided. Based on these parameters, the system learns to fit a pattern to cases and subsequently makes decisions or estimates the time of death in cases it has not encountered before or similar scenarios.

I used several different regression tools with various settings as the basis for the synthetic model. I sought the best parameterization for each tool individually and then further improved the results by combining these mathematical tools. The examined methods included:

- Regression tree,
- Random forests,
- Extremely randomized trees,
- Bagging-modified tree,
- SVR with RBF kernel,
- SVR improved with adaptive boosting.

Results of training

Based on the results provided by the regression tools used with different parameterizations and tested with various settings, it can be observed for all methods that with a larger amount of training data, they are increasingly capable of estimating the time of death with smaller errors (3 figure). Considering both MAE, MSE, and R^2 values (approaching 1), the combined application of SVR and adaptive regression tree proves to be the most effective. This method further improves upon the results obtained by SVR alone.

(a) SVR

	MAE	MSE	R^2
C=10	0.2578	0.2746	0.9886
C=20	0.2255	0.2252	0.9906
C=50	0.1979	0.1828	0.9924
C=100	0.1683	0.1290	0.9947

(b) AdaBoost + SVR

	MAE	MSE	R^2
C=10	0.2177	0.1340	0.9944
C=20	0.1875	0.0987	0.9959
C=50	0.1820	0.1109	0.9954
C=100	0.1606	0.0762	0.9969

Table 2: Results obtained with SVR and AdaBoost + SVR with $C = 50$ and $C = 100$ parameters, using approximately 11,000 cases.

Here, the C parameter represents the compromise between minimizing misclassification errors and maximizing decision boundary. Based on Table 2, it can be concluded that increasing the value of C can further improve the achieved results.

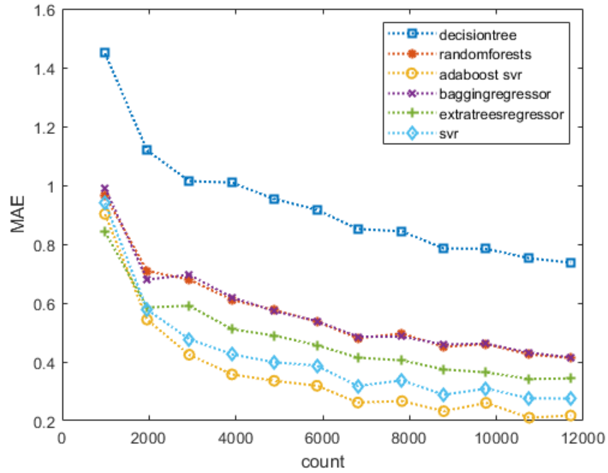
Comparing the results of various selected methods, it can be stated that the two best results are provided by SVR and AdaBoost+SVR, as seen in Figure 4 and Table 3. These two methods yield the most test results within 1σ.

Table 3: Results of various methods for 1σ and 2σ cases.

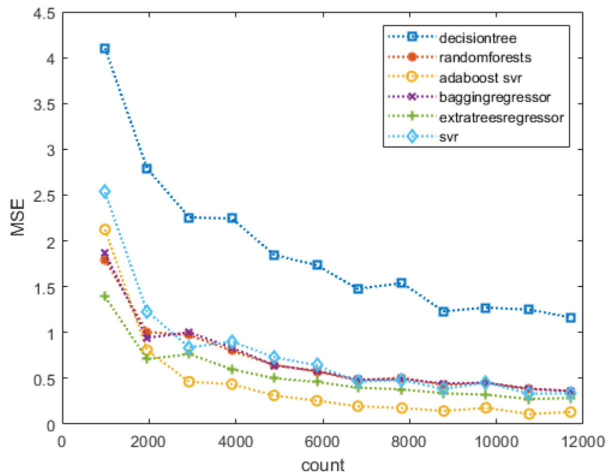
Name	**1σ value**	**2σ value**	**1σ**	**2σ**
Decision tree	−1.1751–1.0571	−2.2912–2.1732	2161 (80.36%)	2546 (94.68%)
Bagging	−0.64297–0.60864	−1.2688–1.2344	2004 (74.53%)	2506 (93.19%)
Random forests	−0.64995–0.59144	−1.2706–1.2121	2034 (75.64%)	2504 (93.12%)
Extra trees	−0.5316–0.51464	−1.0601–1.0395	2064 (76.76%)	2514 (93.49%)
SVR	−0.60545–0.54442	−1.1804–1.1194	2292 (85.24%)	2569 (95.54%)
AdaBoost + SVR	−0.3423–0.32924	−0.67807–0.66501	2076 (77.2%)	2552 (94.91%)

Comparing with the Henssge nomogram, where applying correction factors for both temperature ranges results in an accuracy of ±2.8 hours, it can be stated that the created model is capable of estimating the time of death with sufficient accuracy based on the learned dataset, taking into account the limitations.

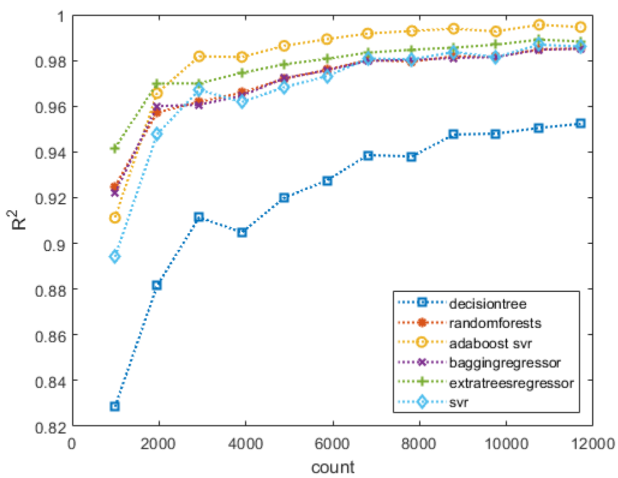
The current limitations of the synthetic model include the number of correction factors, training data provided with half-hour accuracy, and the body weight ranging from 50 to 100 kg.



(a)



(b)



(c)

Figure 3: Errors of the Synthetic Model

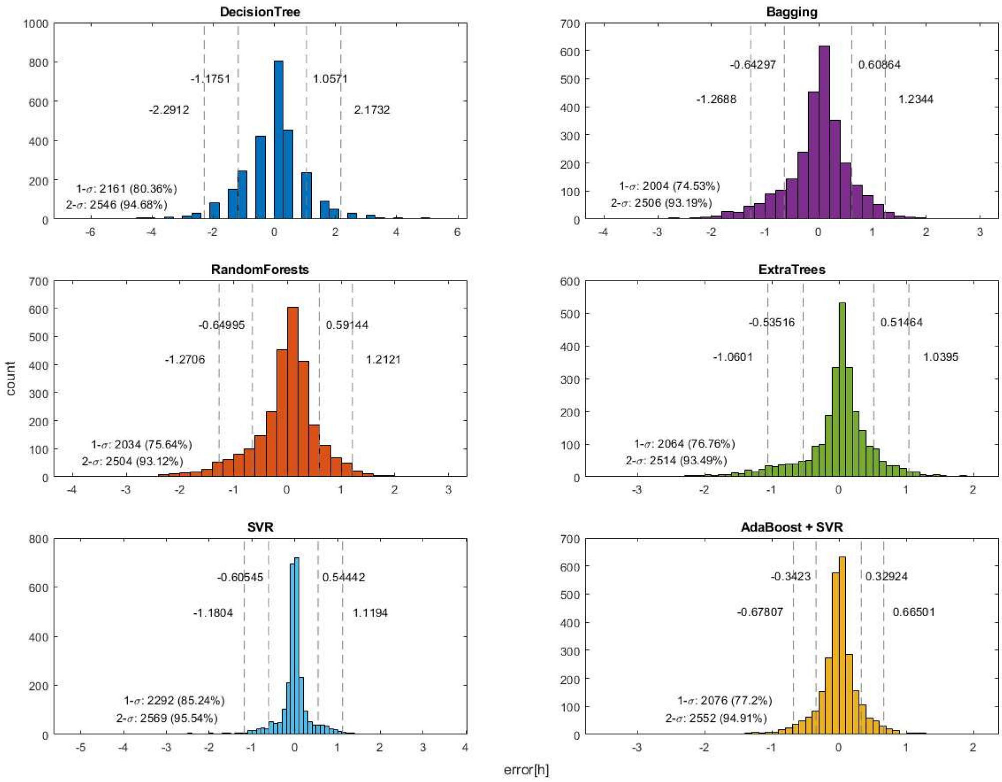


Figure 4: Results of various methods for 1σ and 2σ cases.

From Figure 3, it can be observed that most selected mathematical tools can estimate the time of death with low errors even with a minimum of 3000 training cases under the current settings. Since only a small amount of data is required for training, the model can be applied in various geographical regions (considering smaller geographical units). It is easily adaptable to specific populations with different anthropometric characteristics or residing in different climatic zones.

Comparison with other results

Neural Network

Zerdazi and colleagues [12] developed a neural network-based method for estimating PMI, using multi-layer feedforward networks and supervised learning. They used a learning sample of 257 individuals collected by a forensic pathologist to demonstrate the advantages of their new technique. They characterized the accuracy of their approach using mean squared error and mean absolute error and compared it with the results obtained by the Henssge formula. Measurements were consistently taken under the same conditions: dry, motionless air, and a completely naked body.

They compared the obtained results with the Henssge method and used mean squared error to characterize it. Based on this, it can be concluded that the neural network provides much more accurate PMI estimates (4). I compared these results with the ones obtained by the synthetic model.

Method Name	**MSE**	**MAE**
Henssge Formula	20.83	3.52
Zerdazi Neural Network	5.69	1.85
SVR	0.14	0.17
AdaBoost + SVR	0.12	0.17

Table 4: Comparison of MSE and MAE values for the Henssge formula, Zerdazi neural network, and the synthetic model

The next version of the comparative study was limited to cases where the post-mortem period did not exceed 7 hours. The results obtained in this way are summarized in Table 5. For the purpose of comparing the results of the Zerdazi neural network and the synthetic model, I retrained and tested the model with the parameters used by Zerdazi and colleagues to obtain their results. The errors of the synthetic model's SVR and AdaBoost + SVR estimated results are presented in Tables 4 and 5.

Method Name	**MSE**	**MAE**
Henssge Formula	21.14	3.51
Zerdazi Neural Network	1.21	0.86
SVR	0.08	0.18
AdaBoost + SVR	0.05	0.14

Table 5: Comparison of MSE and MAE values for the Henssge formula, Zerdazi neural network, and the synthetic model for cases with a post-mortem period under 7 hours

Overall, based on the MAE and MSE values in Tables 4 and 5, it can be concluded that the synthetic model estimated with an order of magnitude lower error compared to the Zerdazi neural network.

Results based on real test data

I tested the synthetic model on real data as well. For the test data, I randomly selected cases from the database published by Muggenthaler and colleagues, paying attention to verifying the limitations of the currently trained model [13].

Based on the evaluation of the results, it can be concluded that in 5 out of the 20 selected cases, the deviation is greater than 150 minutes compared to the values read from the graph. According to the published table, it can be determined that there could be several reasons for the deviation:

- In each case, there was a delay between the onset of death and the start of measurement (on average 130 minutes).
- The initial body temperatures also show deviations from the defined initial temperature in the Henssge method, which is 37.2°C,
- The synthetic model was trained on masses between 50 and 110 kg, and adjustments may be needed for values below and above this range, especially in cases involving multiple layers of clothing.
- Certain diseases, such as septic cases, can lead to body temperatures lower or higher than normal.
- No correction factors were specified in the published data, so I selected them based on the clothing.
- The corpses were lying on a metal table in the refrigeration chamber.
- In the published cooling curves, the delayed start of measurements resulted in the absence of the plateau phase in almost every case, and some do not exhibit the expected sigmoid but rather a linear cooling process.

I verified the real cases using the two methods that provided the smallest errors, namely AdaBoost + SVR and SVR. I evaluated the results more thoroughly for these methods, but it can be stated that the other regression methods did not yield significantly worse results.

Based on the results obtained from real cases, it can be concluded that the model is suitable for estimating PMI within the constraints of the training data. In non-standard cases, however, the results should be treated with caution, and other postmortem phenomena may need to be considered for a more accurate determination of PMI.

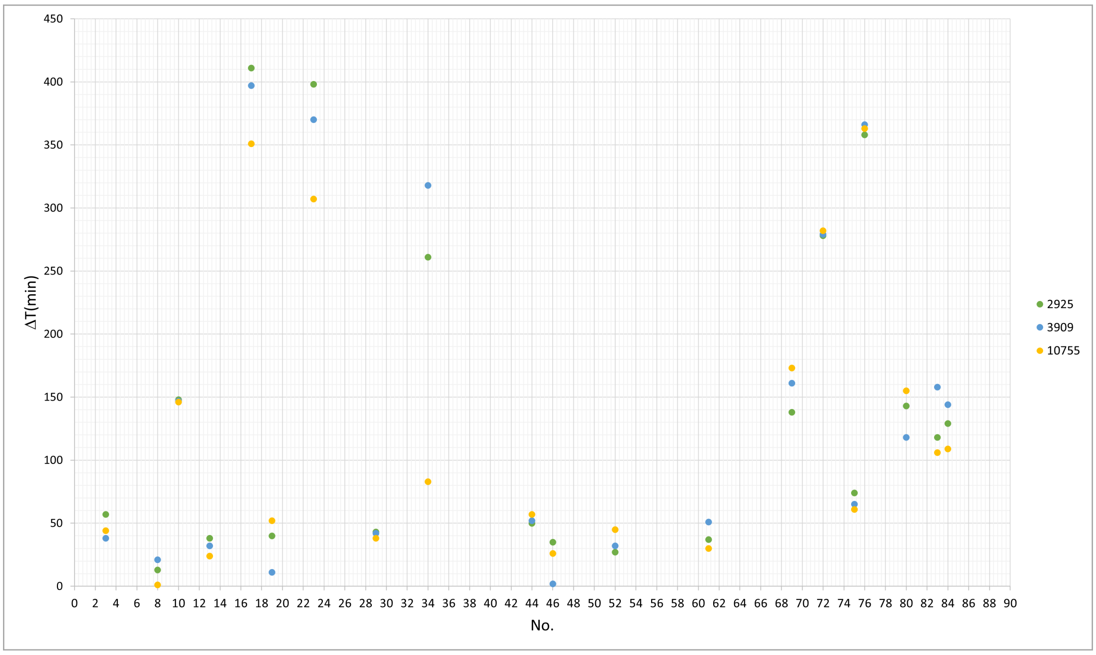


Figure 5: Divergence from readings on the cooling curve for AdaBoost + SVR

No.	$\|SM_{2925} - T_g\|$[min]	$\|SM_{3909} - T_g\|$[min]	$\|SM_{10755} - T_g\|$[min]
3	57	38	44
8	13	21	1
10	148	147	146
13	38	32	24
17	411	397	351
19	40	11	52
23	398	370	307
29	43	42	38
34	261	318	83
44	50	52	57
46	35	2	26
52	27	32	45
61	37	51	30
69	138	161	173
72	278	279	282
75	74	65	61
76	358	366	363
80	143	118	155
83	118	158	106
84	129	144	109

Table 6: Divergence from readings on the cooling curve for AdaBoost + SVR

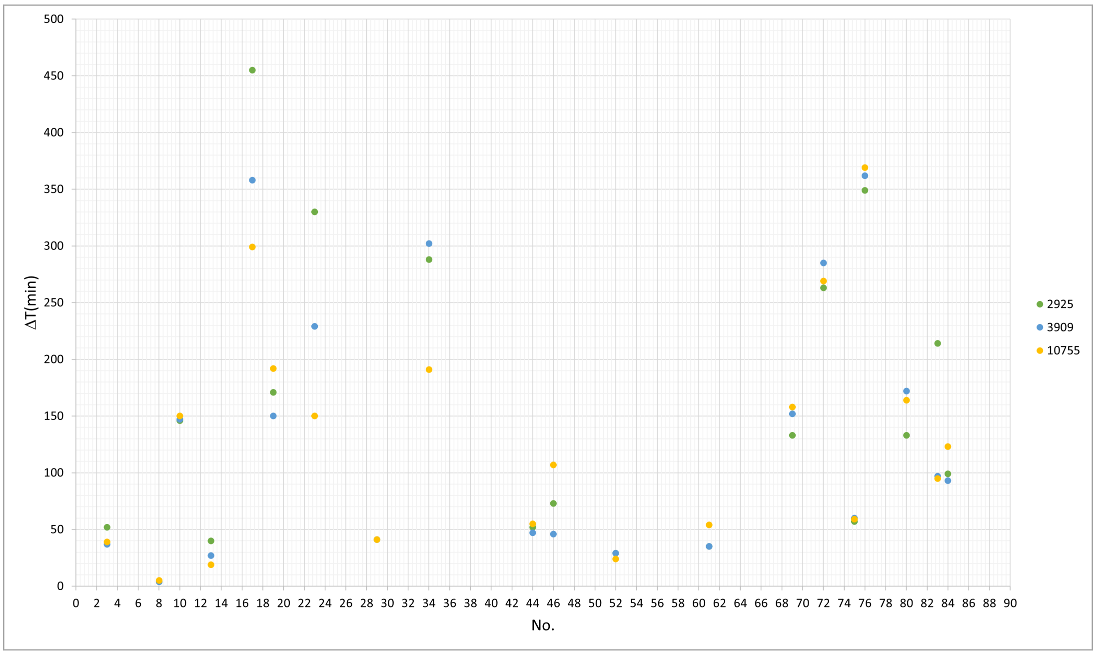


Figure 6: Divergence from readings on the cooling curve for SVR

No.	$\|SM_{2925} - T_g\|$[min]	$\|SM_{3909} - T_g\|$[min]	$\|SM_{10755} - T_g\|$[min]
3	52	37	39
8	4	4	5
10	146	147	150
13	40	27	19
17	455	358	299
19	171	150	192
23	330	229	150
29	41	41	41
34	288	302	191
44	52	47	55
46	73	46	107
52	29	29	24
61	35	35	54
69	133	152	158
72	263	285	269
75	57	60	59
76	349	362	369
80	133	172	164
83	214	97	95
84	99	93	123

Table 7: Divergence from readings on the cooling curve for SVR

Conclusion

In the course of my PhD work, the aim was to explore the factors influencing PMI estimation and to identify suitable tools for creating a flexible mathematical model capable of estimating with smaller errors than the Henssge nomogram.

During my research, I used machine learning tools to create a synthetic model capable of incorporating factors influencing PMI with training data, meaning it does not require knowledge and use of the Henssge formula with correction factors, and it does not contain empirical variables. The model was based on generated data resembling reality, and a more detailed discussion of this will follow later. The goal was to create a flexible, easily adaptable mathematical method. Since the estimation of the postmortem interval can be conceived mathematically as solving a linear regression problem, I chose machine learning tools based on this. My choice fell on a supervised learning method, Support Vector Machine (SVM), which can be considered as a special type of neural network suitable for solving both linear and classification problems. Various kernel functions can be chosen for the decision function, and the synthetic model uses the Radial Basis Function (RBF) to transform the data describing the task into kernel space through nonlinear transformations.

Throughout my work, the goal was to demonstrate that there is a regression method that provides better results than the Henssge formula. The examined tools include SVR with RBF kernel, regression tree, random forests, extremely randomized trees, bagging modified tree, and adaptive boosting improved SVR. The question is *which method provides the best estimation, and what is the expected error of the estimation*? Based on the results of the study, it can be stated that machine learning tools, such as decision trees or SVM, provided better results in estimating PMI than the Henssge formula. The created synthetic model was trained with various numbers of training data, ranging from 968 to 11708 cases, increasing by approximately a thousand in each step. For each different number of training cases, I estimated the PMI results with every selected regression method using a consistent set of 500 test cases. The errors (MAE, MSE, R^2) and parameterization of the methods were recorded.

To compare the errors, I used the results of Zerdazi's neural network [12], evaluating the errors in two ways: MAE and MSE. The results of Zerdazi's neural network were $MSE = 5.69$ and $MAE = 1.85$. Comparing these errors with the errors of the synthetic model, it can be concluded that the synthetic model provides a more accurate estimation of PMI. During the investigations, it was found that the best results for PMI estimation were achieved with the use of SVM with RBF kernel and

AdaBoost together. The errors of the model for the SVM method were $MSE = 0.14$ and $MAE = 1.17$, while for the AdaBoost+SVR method, they were $MSE = 0.12$ and $MAE = 1.17$. The average error of the model within the confidence interval is 0.17 ± 0.34 hours, considering the current limitations of the model.

An important question regarding the applicability of the synthetic model was how much test data is needed for training the model to estimate PMI accurately. The created synthetic model is easily adaptable to populations with different characteristics or living in different climatic zones. This adaptability arises from the fact that the model is not based on a fixed, empirical mathematical relationship but can estimate based on learned data, taking into account specificities typical for the given area or population, which are included in the training data. Another advantage of the synthetic model is that it requires a small number of training data for PMI estimation. Currently, the model can achieve low errors with as few as 3000 training data, considering the current structure and the number of features.

The question posed previously was: *In which cases can the model not be applied?* The model learns from data generated using the Henssge formula, which imposes limitations on its applicability. However, these limitations arise only due to the nature of the data; the method itself is universal. The aim of the study was to demonstrate the model's actual applicability under specific conditions. The nature of the method is such that if trained on real data, it can be used in more general cases. I base this claim on the fact that the current model, based on limited data, provided accurate estimates when compared with empirical data. In terms of environmental temperature, the applicability ranges between -10°C and 35°C; it cannot provide results below or above this range. Incorrect results may also be obtained if the rectal temperature is lower than the environmental temperature. In practice, this situation may occur if the body has been cooled and then moved to a warmer place or if the environmental temperature has been consistently low and starts to rise, but the body has not yet reached the ambient temperature. According to the Henssge nomograms, it can be observed that there is a temporal limitation to applicability (currently 18 hours), depending on the environmental temperature. Above 23°C, it is a maximum of 30 hours, and below 23°C, it can be up to 70 hours, but with a very high error. With the use of correction factors, this uncertainty can be as much as ± 7 hours, while for a naked body, it is ± 4.5 hours.

During the testing of the synthetic model, I encountered cases that, while not meeting the previously listed exceptions, still estimated with higher error both for the synthetic model and the Henssge formula. One notable example is when the body has a diaper, which leads to incorrect results for both the synthetic model and the Henssge formula. Since rectal temperature is taken into account by both the Henssge formula and the synthetic model, the correction factor for the entire body clothing is not suitable to characterize the insulating effect of the diaper. Therefore, mathematical models will provide much shorter times in such cases. These are typically situations that do not conform to a template suitable for applying an empirical formula. Thus, even if the mathematical model estimates with a small error, the obtained result must always be treated with caution and, if necessary, reconsidered, or interpreted in conjunction with early postmortem phenomena.

Current limitations of the synthetic model

1. It does not handle modified correction factors.
2. Since I used the Henssge formula to generate data, the model learned its possible errors and limitations.
3. The intervals for time, environmental temperature, and body weight cannot be changed without modifying the code:
   (a) time: 1–18 hours, with a step size of 0.5 hours,
   (b) environmental temperature: -10–35°C, with a step size of 0.5°C,
   (c) body weight: 50–100kg, with a precision of 0.5kg.
4. Reading training and test data from a file with a specific structure.
5. The code for training and estimation is usable from the command line with the appropriate switches.

Possible enhancements for the synthetic model

1. Automatic handling of modified correction factors.
2. Adapting the code to read training and test data from a file with a specific structure.
3. Allowing the generation of data for arbitrarily specified time, environmental temperature, and body weight intervals with arbitrary step sizes as an optional feature.
4. Creating a user-friendly graphical interface for training.
5. Developing a user-friendly graphical interface for entering data required for estimation.
6. The long-term goal is to publish the model on a platform that allows testing in everyday practice.

Summary of new scientific results

1. I created a machine learning-based model for PMI estimation using synthetic data. The model is easily adaptable to populations with different characteristics or living in different climatic zones.

2. I studied the effectiveness of various machine learning tools. The model using decision trees and SVM produced more accurate estimates than methods based on the Henssge formula or neural networks.

3. I developed a freely accessible Python script that implements the model and is suitable for PMI estimation. The model is continuously improvable, giving meaningfull results even when training with a low number of data, and provides low error rates.

4. I compared the created model with other machine learning-based methods. The model yielded more accurate results than the neural network-based method.

5. I compared the created model with empirical data. With the synthetic model, I provided a more convenient, modern, and accurate solution for PMI estimation than the Henssge nomogram.

Acknowledgements

I would like to express my gratitude to my supervisors, Dr. András B. Frigyik and Dr. Zsolt Kozma, for guiding, supporting, and contributing their expertise throughout my PhD work over the years.

I thank Prof. Dr. Miklós Nyitrai for initially supporting me as a supervisor and allowing me to join the program on the Investigating functional protein dynamics using biophysical methods.

I extend my gratitude to Dr. Gábor Simon, the director of the Institute of Forensic Medicine, for allowing me to conduct my research at the institute and for his unwavering support throughout my research journey.

I am thankful to Dr. Dénes Tóth for his assistance in my work and for the numerous discussions that expanded my knowledge in the initially unfamiliar field of forensic medicine, providing momentum to my research.

I express my gratitude to my family and loved ones for their support and patience, guiding me through this journey.

References

[1] H. Rainy, "On the cooling of dead bodies as indicating the length of time since death," *The Glasgow Medical Journal*, vol. 1, pp. 323–330, 1868.

[2] F. H. T. K. Marshall, "Estimating the time since death - the rectal cooling after death and its mathematical representation," *Journal of Forensic Sciences*, vol. 7, pp. 56–81, 1962.

[3] T. K. Marshall, "The use of the cooling formula in the study of post mortem body cooling," *Journal of Forensic Sciences*, vol. 7, pp. 189–210, 1962.

[4] T. K. Marshall, "The use of body temperature in estimating the time of death," *Journal of Forensic Sciences*, vol. 7, pp. 211–221, 1962.

[5] *Sigmoidal shape of the cooling curve.* [Online]. Available: `https://www.researchgate.net/figure/Sigmoidal-shape-of-the-cooling-curve-which-is-best-described-by-Marshall-and-Hoares_fig5_303796826`.

[6] C.Henssge, "Todeszeitschätzungen durch die mathematische beschreibung der rektalen leichenabkühlung unter verschiedenen abkühlungsbedingungen," *Zeitschrift für Rechtsmedizin*, vol. 87, pp. 147–178, 1981. DOI: `10.1007/BF00204763`.

[7] C. Henßge, "Die präzision von todeszeitschätzungen durch die mathematische beschreibung der rektalen leichenabkühlung," *Zeitschrift für Rechtsmedizin*, vol. 83, pp. 49–67, 1979. DOI: `10.1007/BF00201311`.

[8] C.Henssge, "Death time estimation in case work. i. the rectal temperature time of death nomogram," *Forensic science international*, vol. 38, pp. 209–236, 1988. DOI: `10.1016/0379-0738(88)90168-5`.

[9] C. Henssge, B. Madea, and E. Gallenkemper, "Death time estimation in case work. ii. integration of different methods," *Forensic Science International*, vol. 39, no. 1, pp. 77–87, 1988. DOI: `10.1016/0379-0738(88)90120-X`.

[10] C. Henssge, "Rectal temperature time of death nomogram: Dependence of corrective factors on the body weight under stronger thermic insulation conditions," *Forensic Science International*, vol. 54, no. 1, pp. 51–66, 1992. DOI: `10.1016/0379-0738(92)90080-G`.

[11] C. Henssge, E. Beckmann, F. Wischhusen, and B. Brinkmann, "Todeszeitbestimmung durch messung der zentralen hirntemperatur," *Zeitschrift fur Rechtsmedizin. Journal of legal medicine*, vol. 93, no. 1, pp. 1–22, 1984. DOI: `10.1007/bf00202979`.

[12] D. Zerdazi, A. Chibat, and F. L. Rahmani, "Estimation of postmortem period by means of artificial neural networks," *Electronic Journal of Applied Statistical Analysis*, vol. 9, no. 2, 2016.

[13] H. Muggenthaler, I. Sinicina, M. Hubig, and G. Mall, "Database of post-mortem rectal cooling cases under strictly controlled conditions: A useful tool in death time estimation," *Int J Legal Med*, vol. 126, no. 1, pp. 79–87, May 2011.

The article on which the thesis is based

Dani, Lívia Mária and Tóth, Dénes and Frigyik, Andrew B. and Kozma, Zsolt
Beyond Henssge's Formula: Using Regression Trees and a Support Vector Machine for Time of Death Estimation in Forensic Medicine.

Diagnostics 13(7):1260. (2023)
`https://doi.org/10.3390/diagnostics13071260`

Impact factor: 3.6

Presentation related to the thesis

Dani Lívia Mária, Frigyik Béla András, Tóth Dénes, Nyitrai Miklós, Kozma Zsolt
A halál matematikája, avagy az exponenciálisok csapdájában
MIOT 2018 Pécs, A Magyar Igazságügyi Orvosok Társasága XVI. Nemzetközi Konferenciája (in Hungarian)