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Research article

The influence of physiological parameters on game efficiency in team handball

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Abstract: In addition to the technical and tactical aspects, the influence of physiological parameters is an important aspect for the performance of handball players. In this paper, the authors aim to highlight and analyze the influence of specific indices on efficiency in the game. For this purpose, a methodology based on experimental physiological measurements and modeling with artificial neural networks (ANN) was used. The obtained results allow to conclude that the total efficiency coefficient in the game (CECG) is influenced by the measured values of the specific physiological indices. In addition, the use of the ANN can identify opportunities to improve CECG by changing these indices and, in this case, re-placing pre-game inactivity (PB) with a program (AB) to maintain physiological parame-ters at optimal levels.

Keywords: female handball; artificial neural network; physiological parameters; game analysis

1. Introduction

The requirements for female elite team handball (TH) players have changed as the game of TH has evolved substantially over the last decades [1]. Due to changed rules of the game and strategic tendencies towards higher game speed, the physical demands of major handball competitions seem to be increasing [2,3] and require a high level of physiological capacity which can enable the individual player to perform at a high pace [1]. The individual performance of a handball player is influenced by the effective interaction of physical, physiological, technical-tactical and psychological abilities, which in turn are determined by a large number of interrelated elements [4,5].

Handball is one of the most complex team sports games, due to the large number of players, different game tasks and different ways of cooperation and confrontation between players. During 60 minutes (two halves of 30 minutes) of fast-paced, intense, and dynamic activity, players face repetitive accelerations, sprints, jumps, shots, rapid changes of direction, and lots of physical contact [1,6–10]. These aspects make the individual and collective technical-tactical analysis of the players a very complex and complicated process. Currently, the efficiency of handball players reflects quantitative statistical data such as throwing efficiency percentage, number of decisive passes, number of interceptions, etc., which do not constitute a comprehensive model for objective evaluation. Some studies have developed calculation formulas to quantify player efficiency [11,12], but none of them consider the aspect of effort required by each recorded technical action. In our opinion such an approach should also refer to the efforts at that time to involve players in certain technical-tactical elements or processes that could help to complete the whole evaluation process and increase objectivity.

In addition to the technical and tactical aspects, the influence of physiological parameters is an important aspect of the performance of handball players. Depending on the sport, the objective assessment of some physiological indicators can provide important data that can help the coach plan training efforts to increase the player's biomechanical potential.

Monitoring heart rate (HR) in handball can be a valuable tool for assessing the physical demands of the sport on a player and tailoring training to ensure optimal performance and recovery. Handball is a fast-paced team sport with high-intensity intervals, sprints, jumps, and body contact [1,13], so the heart rate of players can give an insight into their physiological load and conditioning [14–17].

Body temperature can have a significant impact on an athlete’s performance [18–21] and therefore on the player efficiency in team handball. In most sports there is an optimal body temperature range within which maximum performance is achieved. This is typically around 38.5–39.5 degrees Celsius, which is slightly higher than the average resting body temperature (36.3–37.5°C) [22]. At these higher temperatures,the enzymes involved in energy production work most efficiently, improving muscle contractions and reaction times [22,23].

Blood lactate (BL) and blood glucose (G), along with hemoglobin, total protein, creatinine, urea, uric acid, etc., are two of the most important biochemical parameters studied to assess the functional state of the player’s body [24–28].

Evidence from previous studies suggest that the physiological demands differ depending on the playing positions [15] each requiring the performance of specific activities that vary in scope and intensity [13]. Numerous studies have found significant associations between physiological indices and players' physical performance [1,7,15–17], but none have been able to demonstrate an association between physiological indices measured just before the game and players' technical-tactical efficiency during the game.

Therefore, when observing, evaluating and interpreting player performances, all factors that influence the development of actions during the game must be taken into account: rules of the game, technique, tactics, ground dimensions, time and communication [4].

The integration of technology into healthcare, physical education, and sports has revolutionized these fields in many ways [29,30]. Many specialists use technology to collect data and given the sport's popularity in today's world, many organizations spend large amounts of money to achieve better results in sporting competitions. Therefore, predicting game outcomes has become an interesting topic for various sports organizations. However, performance predictions are still made using tools such as questionnaires, the Self-Regulation of Learning Self-Report Scale (SRL-SRS), the State Mindfulness Scale for Physical Activity (SMS-PA), and assessments by trainers [31]. On the other hand, currently most commonly used data mining techniques are artificial neural networks (ANNs), decision trees, Bayesian method, logistic regression, SVM and fuzzy methods [32].

The use of ANNs provide insight into how game analysis data can be used effectively. In handball, like in many other sports, ANNs are a part of a larger trend towards data-driven decision-making in sports and can be used for a variety of purposes. For example, ANNs can be trained on a dataset comprising the different parameters related to a player's performance. In a recent study, researchers analyzed in-game situations and, using deep learning methods, were able to recognize and track players and also recognize their actions [33].

By analyzing historical game data, ANNs can be trained to predict the outcome of future matches. By analyzing factors such as team rankings, player form, head-to-head records, home advantage, and more, ANNs can help professionals understand the key factors affecting the game outcome and create an advantage by designing better training programs. New methods have recently emerged in the literature to address the match outcome prediction. For example, one study [34] used the Modular Forward Neural Networks (MFNN) to predict the results of the 2015 World Handball Championship using match analysis and found that out of 18 analyzed variables from match events, the variables most influencing MFNN results were fast breaks and blocked shots.

From another angle, ANNs can be used to analyze game tactics and strategies. By examining the patterns of successful plays, they can help formulate effective strategies for future games. Previous studies analyzed the sequences of passes that often lead to a goal as well as offensive and defensive play patterns [35–37]. All of these results indicate that ANNs are suitable for modeling interactions between teams based on player positions.

From a sports science and medical perspective, success in team sports lies in effectively using evidence-based knowledge to develop the decision-making process to reduce the risk of injury and optimize athletes' performance [38]. This can be useful when planning training sessions and rest periods to prevent possible injuries. Along these lines, ANNs have previously been used to assess injury risk in soccer, basketball, American football, Australian football, and handball [38].

ANNs are used to analyze a player's physical metrics (such as heart rate, running speed, and temperature) along with game statistics (such as distance traveled, intensity, goals, errors, etc.) to predict injury risk, but to the best of our knowledge, the interaction between pre-game physiological capacity and in-game player efficiency has not previously been modeled.

Therefore, in this study, we investigated the use of ANN to provide a new method to predict overall effciency in handball games.

2. Materials and Methods

2.1. Subjects

The research included a number of 12 players, components of the women's handball team CSM Galați, from Romania. We analysed only field players (31.9 ± 4.05 years, 66.1 ± 5.8 kg, 173 ± 3.8 cm height and 2.2 ± 0.2 body mass index).

2.2. Physiological measurements

The physiological evaluation included four investigations, which aimed to identify the baseline values and the possible changes between two different situations: after warm-up (T1), and after 15 minutes of inactivity or passive break (T2). For heart rate (HR) investigation we used Garmin Fenix 5S smartwatches, body temperature (Tc) was recorded with infrared thermometer Veroval DS 22, blood lactate (BL) and serum glucose (G) were measured with Accutrend Plus device. The players were instructed not to have any food or coffee on the morning of the test, just water.

2.3. Game efficiency coefficient

Since we wanted to use a more comprehensive method for evaluating the technical-tactical efficiency of research players, we decided to use a calculation formula for a new coefficient: the global efficiency coefficient in the game (GECG) [39]. This formula includes both the efficiency coefficient (which relates to the efficiency of the players in the offensive phase, depending on both the goals scored and missed throws) and the difference between the coefficient of standardized positive actions and the coefficient of standardized errors, all related to the playing time (see equation 1).

$$GECG = \frac{EC+(CSPA-CSEG)}{GT} \quad (1)$$

Where:
GECG= overall efficiency coefficient in the game;
EC= efficiency coefficient (EC x UC) for all standardized actions in the game;
SEC= the effort coefficient of standardized actions;
SUC= the utility coefficient of standardized actions;
CSPA= the coefficient of standardized positive actions in the game;
CSEG= the coefficient of standardized errors in the game;
GT= effective game time play.

2.4. The artificial neural network

An artificial neural network (ANN) is a computational model based on the structure and functions of biological neural networks. Information that flows through the network affects the structure of the ANN because a neural network changes—or learns, in a sense—based on inputs and outputs. ANNs are considered nonlinear statistical data modeling tools whereby the complex relationships between inputs and outputs are modeled or patterns are found [38].

ANNs are a branch of machine learning that mimic the workings of the human brain to process data. ANNs are parallel, non-algorithmic calculation systems capable of identifying and reproducing complex relationships between an input-output data set, by making connections similar to those in the biological brain. An ANN consists of a number of elementary computing units – artificial neurons, interconnected in different architectures, depending on the purpose pursued. The most general architecture is "feed forward MLP" (Multi Layer Perceptron – neurons organized in multiple layers with information circulating from the input to the output), Figure 1.

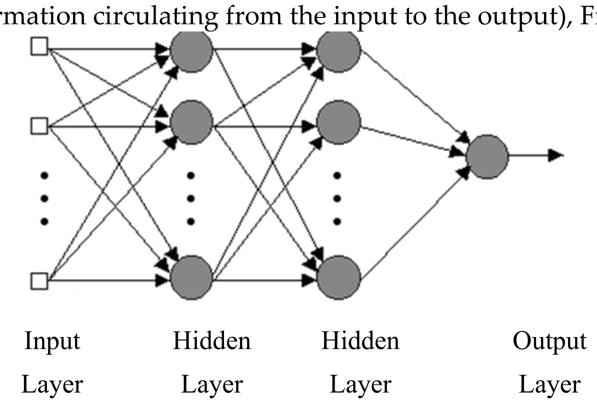


Figure 1. General architecture of MLP type neural networks

Each neuron receives information from the front ones, processes it using a specific transfer function and transmits it to the neurons in the next layer (Figure 1).

3. Results

3.1. GECG modeling using ANN

In order to model the evolution of the GECG, in the first phase, the specific indices that characterize this coefficient are identified, with the measurements being made immediately after the warm-up (T1) and 15 minutes after the warm-up or after passive break (T2), Table 1. These values are obtained both under passive break (PB) conditions and under active break (AB) conditions [39].

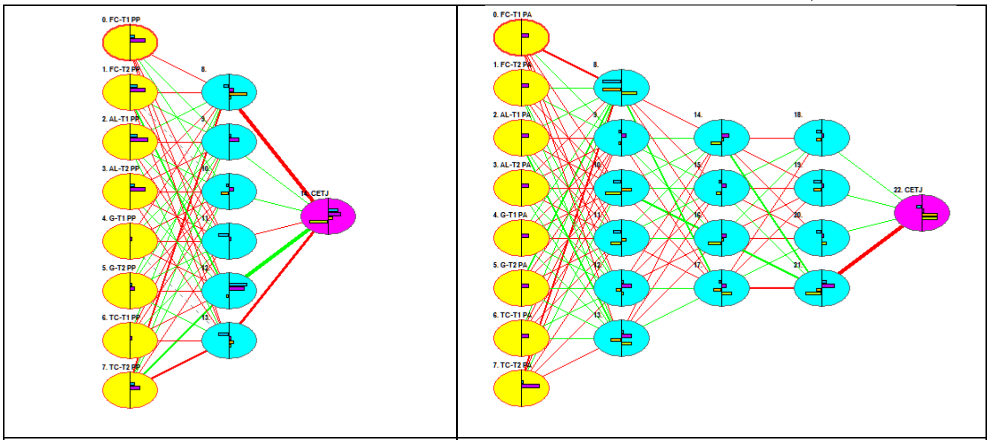
Table 1. Specific physiological indices of influence for CECG

HR [bpm]		BL [mmol/L]		G [mg/dL]		Tc [^{o}C]	
Heart rate		Blood lactate		Serum glucose		Body temperature	
T1	T2	T1	T2	T1	T2	T1	T2

The software package EasyNN [www.easynn.com]was used to create and use the neural model. It includes modules that allow the generation and optimization of the network architecture, this architecture being influenced by the structure and dispersion of the analyzed data. The resulting model can be used to analyze the importance of inputs to outputs, make predictions, and optimize output values.

In order to model the two pause scenarios, passive and active, respectively, the numerical values of the specific indices were used, obtained by the measurements performed in the two situations. Figure 2 shows the architectures corresponding to the two models.

As can be seen in Figure 2, although the structure of the data used is the same, the neural models for the two versions studied have different architectures, Table 1.



(a) (b)

Figure 2. Neural models: a) for PB version; b) for AB version

This difference arises from the different values of the specific indices in the two cases. In order to train and validate the two neural models, the accepted values for the training error and, respectively, validation [40] were determined, resulting in the data shown in Table 2.

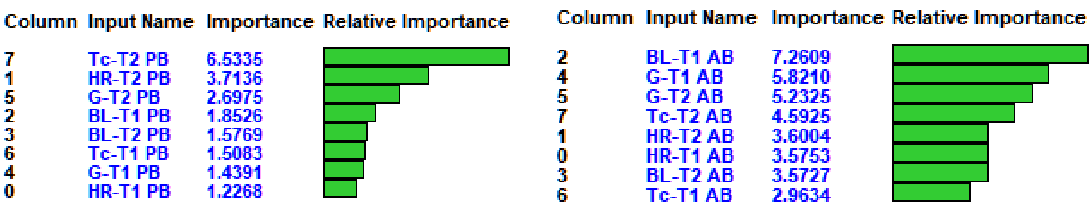
Table 2. CECG neural model parameters

PB Model		AB Model	
Training error	0.01%	Training error	0.01%
Number of hidden layers	1	Number of hidden layers	3
Number of neurons / layer	8-6-1	Number of neurons / layer	8-6-4-4-1
Number of training cycles	136	Number of training cycles	703
Number of validation sets	15%	Number of validation sets	15%
Validation error (R)	0.98	Validation error (R)	0.97

Once the models have been trained, they can be used to analyse, predict and optimize the values of the CECG.

3.2. CECG analysis

In this analysis, the aim is to identify specific indices with maximum influence on CECG. Figure 3 shows the hierarchies of the importance of the inputs, compared to the output, for the two models.



(a) (b)

Figure 3. Hierarchy of importance: a) for the PB version; b) for the AB version

It can be seen in Figure 3 that the importance of specific indices differs in the two scenarios: in the PB version on the first place is Tc-T2 PB, followed by HR-T2 PB and G-T2 PB, while in the first place AB version is BL-T1 AB, followed by G-T1 AB and G-T2 AB.

Based on the analysis of the importance of specific indices, it can be determined what measurements need to be taken to determine the possible evolution of CECG, depending on the option chosen, PB or AB.

3.3. Prediction of the CECG value

Based on neural models, predictions of CECG coefficient values can be obtained when the values of specific physiological indices are known, values that cannot be found in the initial data set. The only required condition is that these values be included in the minimum-maximum range corresponding to the values used in training. Table 3 shows an example for each version.

Table 3. The prediction of the CECG values for both PB version AB version

Indices	HR [bpm]		BL [mmol/L]		G [mg/dL]		Tc [°C]		CECG [points]
	Heart rate		Blood lactate		Serum glucose		Body temperature		Global efficiency coefficient in the game
Testing	T1	T2	T1	T2	T1	T2	T1	T2	
PB	128	94	2.2	1.8	86	87	37.5	36.2	-0.0772
AB	118	105.6	2.2	3.2	86	98	37.8	37	0.4001

3.4. Optimisation of the CECG value

Using the proposed models, the value of CECG can be optimized by finding the values of the specific indices that lead to reaching a maximum value of CECG, Table 4.

Table 4. Optimisation of the CECG value for both PB version and AB version

Measurements	HR [bpm]		BL [mmol/L]		G [mg/dL]		Tc [°C]		CECG [points]
	Heart rate		Blood lactate		Serum glucose		Body temperature		Global efficiency coefficient in the game
Testing	T1	T2	T1	T2	T1	T2	T1	T2	
PB	132	95	0.9	1.9	96	82	37.4	36.5	0.0284
AB	114	112.2	2.3	4.1	95	99	38.2	36.8	0.4225

Based on the results presented in Table 4, methods can be identified to bring specific indices to desired values, in order to obtain a higher CECG.

3. Discussion

Our research presents two neural models, built for two different situations, with passive break (PB) and with active break (AB), respectively.

The results of the present study show that artificial neural networks are able to determine the optimal player efficiency in team handball based on the players' physiological capacity before the game. To our knowledge this is the first study to address this topic in team handball. Additionally, the inclusion of a feature such as in-game player efficiency contributed to more accurate predictions.

Our dataset was comprehensive and compiled with the help of the team experts. Moreover, this study is based on data obtained from a previous research and present results support and complement those findings [39]. The mentioned study found significant changes in heart rate and body temperature before and after 15 minutes complete inactivity in handball players The hypothesis tested by the mentioned researchers was that the level of physiological capacity is significantly related to the game performance of substitutes. After a multivariate correlation analysis, based on Pearson's R-correlation coefficient, the presence of a statistically significant correlation between HR values (r=0.96, p <0.01), and Tc values (r=0.94, p <0.01), and the overall efficiency coefficient in the game (CECG) was observed. This means that CECG tends to be lower in players who have lower HR and Tc after 15 minutes of inactivity.

The interaction of pre-game players' physiological parameters and in-game player efficiency highlighted in our study represents an adequate model for the analysis match performance.

Our findings sheds light on a new approach to managing handball sideline time through the implementation of an active break protocol (AB), which significantly helps mitigate the negative effects of complete inactivity or passive rests (PB). The difference in the factors critical to achieving a higher CECG lies in the different organization of the time players spend on the sideline.This difference can be explained by the fact that muscle activity in the PB version is reflected in body temperature and heart rate. Because resting blood glucose and lactic acid concentrations are low, the ability to achieve a high CECG is directly proportional to the state of muscle activity. In AB, muscle activity is continuous, keeping lactic acid and blood glucose concentrations high, which also reflects the player's ability to achieve a high CECG.

5. Conclusions

In modern top-class handball, the physical and physiological performance of the players has a decisive influence on the game performance.

Physiological functions and game efficiency in handball are deeply intertwined. Performance in handball, like many sports, depends on a wide range of physiological parameters. Understanding these can help optimize a player's training regime and improve game efficiency. In terms of game efficiency, it's important to remember that physiological functions are only one piece of the puzzle. In addition to these physiological functions, technical skills, tactical understanding, psychological factors, and team coordination are also crucial for game efficiency in handball. A comprehensive training program for handball players should therefore aim to improve all these aspects. Moreover, individual physiological needs may vary depending on the player's specific role within the team.

Maintaining an optimal physiological capacity just before the game is important for the in-game handball performance. Strategies to manage Tc, HR or BL and G rates should be part of a player's overall game plan, including during the warm-up, during the game itself, and during recovery afterward. Coaches and sports scientists should work together to create personalized training regimes that take into account all these factors.

CECG coefficient values are influenced by a series of specific physiological indices but establishing the correlation between data is difficult as there is no suitable mathematical apparatus. Considering this, the possibility of experimentally establishing data sets (specific physiological index values-CECG values) creates the possibility of ANN-based modeling for this correlation. Based on the proposed models, specific physiological indices with the greatest influence on he CECG can be identified and thus its values can be optimized.

It's important to note, however, that while these systems can provide valuable insights, they should be used in conjunction with, not as a replacement for, the knowledge and expertise of coaches and sports professionals.

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