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A Survey on Applications of Statistical and Machine Learning Methods in Sport Physiology

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Abstract

This study has been carried out to give a detailed overview over several studies performed in literature during the past several years for predicting numerous sport physiology related metrics including upper body power (UBP), lower body power (LBP), endurance time and muscle strength. Despite the fact that for each of those metrics direct measurement methods exist and are highly accurate, the application of those methods requires expensive and sophisticated laboratory equipment, trained staff or an extreme amount of effort and energy to be performed. These disadvantages motivated researchers to propose alternative prediction models via various regression methods. Consequently, numerous prediction models have been developed using different sets of physiological, exercise and non-exercise (i.e. questionnaire) data, and a variety of machine learning and statistical methods including Multilayer Feed-Forward Artificial Neural Network (MFANN), Support Vector Machine (SVM) and Multiple Linear Regression (MLR). The survey results reveal that depending on the prediction field, the best performing statistical or machine learning method also varies. Physiological variables such as age, gender, height, body mass and body mass index (BMI) have been observed the be the mutual essential predictors influencing the accuracy of UBP, LBP, endurance time and muscle strength models. Considering the results of the studies overall, it can be concluded that the usage of data-driven prediction models proposed in sport physiology literature has the potential to produce quick predictions with acceptable error rates and can be used as alternative ways to direct measurement methods.

Keywords: Upper and lower body power; Endurance time; Muscle strength; Machine learning; Prediction

Introduction

Upper body power (UBP) represents the power that can be produced using the arm, shoulder and trunk muscles. Particularly, power generated by the upper body is transmitted through the poles and assists in forward motion [1]. A similar critical athletic quality is the lower body power (LBP) which is defined as the power generated by the musculature of the hips, thighs, and lower back [2,3], and in the musculature of the posterior lower leg [4]. The unit of UBP and LBP is given in Watt (W). Another popular metric related to the field of sport physiology is the endurance time which gives the maximum amount of seconds (s) that an individual can hold a perfect position of a physical form, pose or exercise. It provides a convenient means to assess muscle fatigue resistance [5]. Finally, muscle strength refers to the maximal amount of force that a muscle can apply against resistance in a single effort, the unit of which is given by Newton-Meter (Nm) [6].

The usage of UBP shows a special importance on sport branches that involve upper body activities, such as cross-country skiing, hitting, combat or any type of propulsion. LBP plays an essential role in sport branches that involve vertical jumping with and without a run-up, such as volleyball, basketball or high jump. Endurance time is widely used as a metric in physical training programs, most notably in core strengthening exercises, since maintaining the perfect posture as long as possible appears to be more important in those exercises, as a way to evaluate the success of muscle training which has been performed so far. Endurance time is viewed as an important component influencing the performance of athletes in various sport branches such as cycling, rowing, swimming and running. Finally, muscle strength is important to evaluate the strength of specific muscle groups (e.g. legs, chest and abdomen) rather than the strength of the whole organism during a physical activity.

Although the direct measurement methods provide the highest level of accuracy for each of these metrics, such methods are usually not the most favorable ways for a number of reasons. The tests of UBP in the research literature, for instance, have all been based upon custom-designed ergometers for individual research laboratories. Additionally, the measurement of UBP lacks standardization as it is still a relatively new physiological construct. For ski coaches and athletes, these limitations represent barriers to the design and tracking training program effectiveness. Many elite cross-country skiers, for example, have access to standard sports science laboratory testing such as tests of maximal oxygen uptake (VO_2max), maximal heart rate (HRmax), lactate threshold, as well as various measures of muscular strength and LBP. Test measures of UBP, however, are almost exclusively limited to sport research facilities with these custom-designed ergometers. Physical tests, in which the certain exercises are literally being performed by participants, are a common measurement

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Table 1: Summary of recent studies in literature that developed models for prediction of UBP. 6RM: maximum amount of body mass lifted for 6 consecutive repetitions; CCN: Cascade Correlation Network; MLR: Multiple Linear Regression; R: Multiple Correlation Coefficient; RPE: Self-Reported Rating of Perceived Exertion from Treadmill Test; SEE: Standard Error of Estimate; SVM: Support Vector Machine; UBP_{10}: 10-second Upper Body Power; UBP_{60}: 60-second Upper Body Power; Velmean: Mean Bar Velocity; VO_2max/VO_2peak: Maximal Oxygen Uptake; W: Watt.

Study	Year	Method	Predictor Variables	Metrics	Values
Wong et al [8]	2013	Pearson	6RM	R	0.93
Bautista et al [9]	2014	MLR	RPE, Velmean	R	0.94
Akay et al [10]	2015	SVM	Age, gender, height, body mass, VO_2max	R, SEE (W)	0.95, 18.11
Wang et al [11]	2017	MLR	Body mass, peek velocity	R, SEE (W)	0.92, 57

Table 2: Summary of studies in literature that developed models for prediction of LBP. ANOVA: two-way mixed-factor repeated measures analysis of variance; BJ: Broad Jump; ICC: Intraclass Correlation Coefficient; MVR: Multivariate Linear Regression; PCC: Pearson Correlation Coefficient; R: Multiple Correlation Coefficient; VJ: Vertical Jump Height; VJP: Vertical Jump Power; VJP/BW: Vertical Jump Power per Kilogram of Body Mass; VJP/FFM: Vertical Jump Power per Kilogram of Fat Free Mass.

Study	Year	Method	Predictor Variables	Metric	Value
Carlson et al [12]	2009	ANOVA	Body mass, vertical jump height	ICC	0.97
Smith et al [13]	2010	MVR	Age, height, body mass	R	0.9
Davis et al [14]	2011	Pearson	VJ, VJP, VJP/BW, VJP/FFM, BJ	R	0.94
Wright et al [15]	2012	Harman equation	System mass, jump height	PCC	0.94
Keller et al [17]	2015	Bland-Altman plot	Gender, femur length, body mass, chair stands	R	0.69

tool when evaluating both the endurance time and muscular strength. However, this way of measurement requires an extreme amount of effort, energy, time and trained staff for each participant taking the test. Thus, it can be concluded that the necessity of expensive and complex equipment, the time consumption when the measurement of a high amount of participants is needed and the existence of particular risks for some people due to the extreme exhaustion factors are the essential disadvantages of the direct measurement methods, inspiring the researchers to predict rather than to measure these metrics via various predictor variables in combination with promising statistical and machine learning methods.

Although UBP, LBP, endurance time and muscle strength are measured and evaluated as independent variables in different studies, they also are related to each other from different points of view. It's not uncommon to see that one of such metrics is used as an input variable for prediction of another metric in the literature. For example, in [1], the endurance time has been utilized as a predictor variable to predict the UBP of cross-country skiers using support vector machine (SVM) combined with the Relief-F feature selector. Beck et al [7] attempted to predict the maximal endurance time in a repetitive lift and carry task by using a particular type of muscle strength, called as "carry mass". Wong et al [8], used prediction models to estimate UBP by using the maximum amount of body mass lifted for 6 consecutive repetitions (6RM) as a predictor variable, which is an obvious metric representing the muscle strength.

The purpose of this survey paper is to give a detailed overview over several studies performed in literature during the past several years for predicting numerous sport physiology related metrics including UBP, LBP, endurance time and muscle strength. Particularly, for each study, a general description about the purpose is given along with some information about (a) the dataset, participants and exercise test; (b) the predictor variables chosen to create the prediction models; (c) the statistical and machine learning methods used to build the models; and finally (d) the numerical results and major conclusion.

The rest of the paper organized as follows. A summary of studies on prediction of UBP and LBP are discussed in Section 2. The studies related to the prediction of endurance time are summarized in Section 3. The studies for predicting muscle strength are presented in Section 4. Finally, the paper is concluded in Section 5.

Overview of Studies on Prediction of Body Power

Studies for predicting the upper body power (UBP)

Wong et al [8] carried out a study to predict UBP of physically active individuals using bench press load and Pearson correlation analysis. For the study, 29 physically active collegiate students between the ages of 22-25 were recruited. The maximum amount of body mass lifted for 6RM loads for bench press, barbell bicep curl, overhead dumbbell triceps extension, hammer curl and dumbbell shoulder press were measured for the intention of using those variables as predictors. It has been concluded that fitness professionals can use the 6RM bench press load as a time effective and accurate method to predict training loads for upper body assistance exercises.

Bautista et al [9] used prediction models in order to predict the power output of upper body. In total, 60 males between the ages of 21-25 voluntarily participated in the study. Rate of perceived exertion (RPE) and mean bar velocity (Velmean) have been used to perform linear regression analysis. It has been stated that the power output can be predicted using RPE-based prediction models with acceptable error rates.

Akay et al [10] proposed prediction models for estimating UBP_{10} and UBP_{60} of cross-country skiers using SVM. The dataset used in this study includes data of 77 subjects a minimum of 2 years of ski racing experience from the Montana State University ski team and junior racers from the Bridger Ski Foundation ski team. Age, gender, height, body mass, BMI, HRmax, VO_2max and exercise time are the predictor variables, and UBP_{10} and UBP_{60} are the target variables. 10-fold cross-validation was used to validate the prediction accuracy. The

Table 3: Summary of studies in literature that developed models for prediction of endurance time. BMI: Body Mass Index; ER: Error Rate; FT: Fatiguing Time; MFANN: Multilayer Perceptron; MLR: Multiple Linear Regression; PAR: Physical Activity Rating; R: Multiple Correlation Coefficitent; RPE: Self-Reported Rating of Perceived Exertion from Treadmill Test; S: Seconds; S_{init}: Initial Slope; SEE: Standard Error of Estimate; SVM: Support Vector Machine.

Study	Year	Method	Predictor Variables	Metric	Value
Lee et al [18]	2009	MLR	FT, S_{init}	ER (%)	30.4
Akay et al [19]	2015	SVM	Gender, BMI, RPE-8	R, SEE (s)	0.93, 19.91
Beck et al [7]	2016	Linear Mixed Models	Body mass, carry duration, oxygen consumption	R	0.92
Akay et al [20]	2017	MFANN	Gender, age, BMI, RPE-7, RPE-8, PAR	R, SEE (s)	0.92, 10.61
George et al [21]	2017	MLR	RPE-8	R, SEE (s)	0.93, 10.80

results show that SVM-based UBP prediction models can be safely used for the prediction of UBP of cross-country skiers. In a follow-up work, Akay et al [1], created various feature selection-based models to predict and identify the discriminative predictors of UBP_{10} and UBP_{60} of cross-country skiers with the help of SVM using the same dataset as in the previous work. As the conclusion, gender and age have been reported to be the most essential predictors of UBP_{10} and UBP_{60}.

Wang et al [11] investigated the reliability of the Ballistic Push-Up (BPU) exercise and to establish a prediction equation for both maximal strength (1 Repetition Maximum [1RM]) in the bench press exercise and UBP. For the study, 60 recreationally active men completed a 1RM bench press and 2 BPU assessments in 3 separate testing sessions. Peak and mean force, peak and mean rate of force development, net impulse, peak velocity, flight time, and peak and mean power were determined. Stepwise linear regression was used to develop 1RM bench press and power prediction equations. It has been concluded that peak velocity and flight time measured during the BPU can be used to predict UBP.

Table 1 gives an overview of studies on prediction of UBP. The studies have been sorted in chronological order. For each study, the most accurate model along with the utilized method and predictor variables are reported.

Studies for predicting the Lower Body Power (LBP)

Carlson et al [12] compared the effects of various training modalities on vertical jump, which is often used as an indirect predictor of LBP. Subjects were 37 intercollegiate athletes assigned to four training groups. Body mass and vertical jump height was used as predictor variables. As a result, it was stated that no difference was observed in vertical jump among strength training, plyometric training and jump training over a 6-week timeframe.

Smith et al [13] used multivariate linear regression-based equations to predict LBP in older adults using the 30-second chair-rise test. The data from a 30-second chair-rise test performed by 14 older adults (76 ± 7.19 years) have been used for this study. The average and peak LBP have been predicted with the usage of age, height and body mass. The results showed that LBP in fit older adults can be accurately evaluated using the data from the initial 20 seconds of a simple 30-second chair-rise test, which requires no special equipment, preparation or setting.

Davis et al [14] carried out a study about the relationship between LBP and sprinting performance of the college students. The data of 22 college-aged and trained males has been used for this study. The predictors for this study are vertical jump height, vertical jump power, vertical jump power per kilogram of bodyweight, vertical jump power per kilogram of fat free mass and broad jump. The study results showed that there is a positive relationship between jumping ability and sprinting ability in recreationally trained college males.

Wright et al [15] carried out a study to predict the LBP from vertical jump prediction equations for loaded jump squats at different intensities in men and women with the usage of models created by the Harman equation [16]. A heterogeneous group of 30 female and 30 male active college students were recruited from a university body mass training facility for this study. The system mass (body mass + applied load) and peak jump height for each participant have been used as predictor variables. It was stated that the Harman equation may be used to estimate the peak power of a loaded jump squat knowing the system mass and peak jump height.

Keller et al [17] predicted LBP in older adults using the 30-second chair stand. This study measured peak LBP among 14 men and 11 women over the age of 65 while performing the 30-second chair stand test. Independent variables of gender, femur length, body mass and the number of chair stands completed in 30 seconds were examined. It has been concluded that the predictions of the proposed models were within limits of acceptable accuracy to estimate the peak LBP.

Table 2 illustrates an overview of studies for prediction of LBP.

Studies for Predicting the Endurance Time

Lee et al [18] estimated muscle fatigue of the biceps brachii using high to low band ratio in EMG during isotonic exercise by using MLR-based models. The data from 10 subjects (5 male and 5 female) has been used for the study. The predictor variables forming the models are fatiguing time and initial slope of the high to low frequency band ratio. The results showed that statistical analysis can be used as a feasible tool for estimating the muscle fatigue.

Akay et al [19] attempted to generate SVM-based models that can accurately predict maximal endurance times involving isometric side-bridge exercises. The dataset created through the execution of the isometric side bridge exercise test included 80 healthy college-aged individuals. The predictor variables used to develop the prediction models included gender, BMI and the times to reach an RPE value of 4, 5, 6, 7 and 8, which are referred to as RPE-4 through RPE-8, respectively. 10-fold cross-validation was used to validate the prediction accuracy. It has been shown that SVM-based models can accurately predict maximum endurance times from RPE data along with the physiological variables gender and BMI.

In a follow-up work, Akay et al [20] developed prediction models

Table 4: Summary of studies in literature that developed models for prediction of muscle strength. 1RM: maximum amount of body mass lifted for 1 repetition; BF%: Body Fat Percentage; LBM: Lean Body Mass; MLR: Multiple Linear Regression; MVIC: Maximal Voluntary Isometric Contraction of Right Knee Extension; Nm: Newton-Metre; RDBP: Resting Diastolic Body Pressure; REPS55: 25kg Repetition Tests; REPS70: 31kg Repetition Tests; RHR: Resting Heart Rate; RSB: Resting Systolic Body Pressure; SVM: Support Vector Machine.

Study	Year	Method	Predictor Variables	Metric	Value
Abadie et al [22]	2000	MLR	Age, height, body mass, body density, body fat, RHR, RSBP, RDBP	R, SEE (Nm)	0.94, 2.30
Horvat et al [23]	2003	MLR	REPS55, REPS70, 1RM, height, body mass, LBM, BF%	R	0.91
Harbo et al [24]	2012	MLR	Age, gender, height, body mass, physical activity level	R	0.79
Muraki et al [25]	2013	Regression Analysis	Muscle thickness, muscle hardness, MVIC	R	0.57
Akay et al [26]	2017	SVM	sex, age, height, body mass, BMI, sport branch	R, SEE (Nm)	0.81, 15.55

to create new models to predict the maximum endurance time for the left-side bridge exercise using machine learning methods and hybrid data. Particularly, four different methods including MFANN, Generalized Regression Neural Network (GRNN), Radial Basis Function Neural Network (RBFNN) and Single Decision Tree (SDT) have been employed to develop the models. The dataset includes data gathered from 80 healthy college-aged individuals who were randomly assigned to perform the left-side bridge assessment. The study showed that GRNN-based and MFANN-based models can be used as a substitution for the direct measurement techniques in order to determine the maximal endurance time for the left-side bridge exercise.

Beck et al [7] aimed to investigate endurance time and oxygen consumption of a repetitive lift and carry task using linear mixed models. In total, 14 male soldiers (22.4 ± 4.5 years) conducted four assessment sessions that consisted of one maximal box lifting session and three lift and carry sessions. Carry mass, the duration of carry and oxygen consumption has been used as predictor variables. The results showed that the repetitive lift and carry task data can be used for estimating the endurance time.

George et al [21] developed MLR-based models to estimate maximal endurance time by using data from four core muscle endurance tests. 80 healthy university students (22.7 ± 1.9 years) performed the plank, right side-bridge, left side-bridge and back extension tests in a random order to generate data for the study. Age, gender, body mass, height, BMI and the elapsed times to reach RPE-4 to RPE-8 have been used as predictor variables. 10-fold cross-validation was used to validate the prediction accuracy. The results revealed that the usage of RPE-8 data can lead to accurate results in estimating maximal endurance time.

A summary of studies that developed models for prediction of endurance time is presented in Table 3.

Studies for Predicting the Muscle Strength

Abadie et al [22] built regression models for the prediction of one repetition maximal strength from a 5-10 repetition submaximal strength test in college-aged females. 30 healthy adult females (19-26 years of age) were tested for this study. The predictor variables were age, height, body mass, body density, body fat, resting heart rate, resting systolic body pressure and resting diastolic body pressure. The results of this study showed that the muscle strength can be predicted with an acceptable degree of accuracy in untrained female subjects.

Horvat et al [23] developed a regression equation capable of accurately predicting a 1RM bench press in collegiate women athletes. The data related to 65 women athletes from 9 different sport branches at University of Georgia NCAA Division 1 has been used for this study. The predictor variables for this equation were 25 kg repetition tests, 31 kg repetition tests, 1 repetition maximum, body mass, lean body mass (LBM), height and body fat percentage (BF%). The results showed that muscular endurance repetitions with LBM can be used to accurately predict 1RM bench press strength in collegiate women athletes.

Harbo et al [24] carried out a study to predict maximal isokinetic and isometric muscle strength of major muscle groups. The data from 178 healthy non-athletic individuals (93 male and 85 female) between the ages of 15-83 has been used for this study. Age, gender, height, body mass and physical activity level have been used as predictor variables. As a conclusion; age, height and body mass have been found to be related to the muscle strength of major muscle groups.

Muraki et al [25] predicted the muscle strength by the muscle thickness and hardness using ultrasound muscle hardness meter and regression analysis. 72 males and 33 females, whose ages ranged from 18 to 35 years, participated in this study. Muscle thickness and hardness in the right anterior region of the thigh without muscle tension and also the maximal voluntary isometric contraction of right knee extension have been measured for the usage as predictor variables. The study results showed that the combination of muscle thickness and hardness is capable of effectively estimating muscle strength especially in females.

Akay et al [26] created prediction models for predicting the hamstring and quadriceps muscle strength of college-aged athletes using SVM. The dataset included 75 athletes selected from the College of Physical Education and Sport, Gazi University, Turkey. The predictor variables of gender, age, height, body mass, BMI, and sport branch were utilized to build the hamstring and quadriceps muscle strength prediction models for various types of training methods. The generalization error of the prediction models was calculated by carrying out 10-fold cross-validation. The results showed that the SVM-based hamstring and quadriceps strength prediction models can be safely used to produce predictions regarding new data with acceptable accuracy.

Table 4 lists an overview of studies that developed models for prediction of muscle strength.

Conclusion

This study presented an overview about the data-driven modeling studies for prediction of UBP, LBP, and endurance time and muscle strength conducted within the course of the past several years. Numerous prediction models have been presented with the intention of predicting the mentioned metrics for different types of target audiences including physically trained individuals such as cross-country skiers, athletes, soldiers, and non-trained individuals such as college-aged students and elderly people, with the usage of statistical and machine learning methods. Representative examples of variables for the prediction of the given metrics range from physiological variables, such as gender, age, body mass, height, body density, BF% and BMI, to exercise variables such as RPE, 1RM, 6RM, jumping power and height values, to non-exercise data, i.e. questionnaire variables including PFA and PAR.

A number of conclusions can be reached considering the results obtained from the survey study. Firstly, the most commonly used and effective machine learning methods have shown difference for each prediction field. The SVM and MLR methods have appeared to be highly popular in the studies about the prediction of UBP, while MLR and MFANN are more commonly used in the studies related to the prediction of the endurance time. The most commonly chosen method has been seen as MLR when it comes to predicting the muscle strength. Similarly for prediction of LBP, the usage of the statistical analysis methods and equations highly dominated the machine learning techniques.

Secondly, with regard to performance-based comparison, SVM-based models led to more accurate prediction results for prediction of UBP, as compared to the rest of other methods such as MLR and Pearson correlation analysis. With respect to the studies about predicting the endurance time, MFANN and SVM have been observed to yield relatively better results than other methods, while the most favorable method for prediction of muscle strength was MLR. Among the statistical methods which are used for predicting the LBP, the ANOVA method has been reported to yield better results compared to the rest of methods.

Thirdly, when all prediction models presented in this study are investigated, it is observed that, on average, the usage of hybrid models, which are built by using both exercise-based and non-exercise-based predictors, is more commonly used and has provided better results than regular models including predictors from a single category. In addition, the comparison of the exercise-based predictor variables and non-exercise-based predictor variables with each other has not shown a great difference regarding the prediction performance and accuracy, since such differences have shown themselves more clearly in the method-based comparison.

Finally, predictor variables such as age, gender, height, body mass and BMI appear more commonly than any other type of predictor variables in the variety of accurately identified models, suggesting the high correlation of these physiological variables with the sport physiology related metrics.

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