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RESEARCH ARTICLE / ARAŞTIRMA MAKALESİ

The Comparison of Artificial Neural Network Approach and Response Surface Model for Evaluation Upper Limb Performance in Patients with Chronic Neck Pain

Kronik Boyun Ağrısı Olan Hastalarda Üst Ekstremite Performansının Değerlendirilmesi için Yapay Sinir Ağları Yaklaşımı ve Yanıt Yüzeyi Modelinin Karşılaştırılması

Leyla BAKACAK KARABENLİ[1], Serpil AKTAŞ ALTUNAY[1]

[1] *Hacettepe University, Department of Statistics, Beytepe, Ankara, Turkey*

Abstract
Response surface model (RSM) is used to detect the variable values that make the response variable maximum or minimum. Besides, the effect of exploratory variables on the response variable is determined. Thus, this method can be referred as a combination of regression analysis and optimization. RSM is mostly used in many fields such as industry and chemistry. However, it has limited application in the field of health. The upper limb performance assessment is a two-stage assessment of upper limb contributions to task performance. In this study, the upper limb performance of chronic neck pain patients is examined on 63 patients. The upper extremity functional index (UEFI-20) identifying the performance of upper limb is assigned as response variable. Input variables are taken as the variables related the pain-rating scales of patients at rest or in activity. The central composite model is implemented to estimate the model. The artificial neural network (ANN) approach is also applied to upper limb performance data. The mean absolute error, correlation coefficients, standard error of prediction are obtained from evaluating the experimental and predicted values of both models. The comparative analysis for both models is made on the prediction accuracy.
Keywords: Response surface model, optimization, artificial neural network, upper limb performance

Öz
Yanıt yüzey modeli (YYM), yanıt değişkenini maksimum veya minimum yapan değişken değerleri tespit etmek için kullanılır. Ayrıca, açıklayıcı değişkenlerin cevap değişkeni üzerindeki etkisi belirlenir. Dolayısıyla, bu yöntem, regresyon analizi ve optimizasyonun bir kombinasyonu olarak adlandırılabilir. YYM, çoğunlukla sanayi ve kimya gibi birçok alanda kullanılmaktadır. Ancak, sağlık alanında sınırlı bir uygulamaya sahiptir. Üst ekstremite performans değerlendirmesi, üst ekstremite ve onun görev performansı olarak iki aşamalı bir değerlendirmedir. Bu çalışmada, kronik boyun ağrılı hastaların üst ekstremite performansı 63 hastada incelenmiştir. Üst ekstremitenin performansını tanımlayan üst ekstremite fonksiyonel indeksi(UEFI-20) cevap değişkeni olarak belirlenmiştir. Girdi değişkenleri, istirahatte veya etkin durumdaki hastaların ağrı derecelendirme ölçekleriyle ilgili değişkenler olarak alınmıştır. Merkezi kompozit model, modeli tahmin etmek için uygulanmıştır. Yapay Sinir Ağı yaklaşımı da üst ekstremite performans verilerine uygulanmıştır. Hata kareler ortalaması, korelasyon katsayıları, standart hatası, her iki modelin de deneysel ve öngörülen değerleri değerlendirilerek elde edilmiştir. Her iki model için karşılaştırmalı analiz, tahminlerin doğrulukları üzerinden yapılmıştır.
Anahtar Kelimeler: Yanıt yüzeyi modeli, optimizasyon, yapay sinir ağları, üst ekstremite performansı

I. INTRODUCTION

Chronic neck pain is an important public health problem and, it affects one's daily life activities negatively. Besides, it causes functional disability, productivity loss and disability resulting in workforce and economic loss [1]. The upper limb performs extensive movements and movements that require motor skills. Performing life activities such as eating and hobbies such as painting are the task of upper extremity with the connections between the shoulder and the hand [2]. As the upper limb problems are one of the major problems in modern life and can affect all people in the world, in the literature, many kinds of researches have been carried out on the upper limb problems (eg. [3, 4, 5]).

Upper limb (extremity) performance assessment is a two-stage evaluation of the performance of the upper extremity and the motor factors such as muscle strength and sensory factors impacting on task performance. Upper limb function consists of main headings as sensation, muscle strength, coordination and arm stability. Under these headings, there are many subheadings. These factors enable the upper extremity to function and perform better. The variables used in this study are selected and evaluated by considering the important components of this function.

Corresponding Author: Leyla BAKACAK KARABENLI, Tel: +903122977900/110, e-posta: leylabakacak@hacettepe.edu.tr
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This scope of work is to analyze the upper limb performance of chronic neck pain patients in the field of physical therapy and rehabilitation using the Response Surface Models (RSM) and Artificial Neural Network (ANN) on a real data set which was collected in different clinics in Ankara. The performance of upper limb is assigned as the response variable. Input variables are taken as the variables related the pain-rating scales of patients at rest or in activity. The input variables are visual analog scale (VAS) at rest, at activity and at night, Copenhagen Neck Functional Disability Scale (NFDS), upper extremity power, upper extremity endurance. The RSM is implemented to estimate the most appropriate model. The ANN approach is also applied to upper limb performance data to estimate which variables are statistically significant on the upper limb performance. In recent years, ANN has become a widely used analysis, therefore it has been a matter of curiosity whether ANN or RSM, which is a classical method, will give better results in the evaluation of upper limb performance data in patients with chronic neck pain. In this study we compare six models and the results of ANN and RSS on a real data set.

II. MATERIAL AND METHOD

2.1. Response Surface Model

Response surface model (RSM) is used to reveal the effect of the factors (explanatory variables) on the response variable and to find the value(s) that make the response variable maximum or minimum [6]. This method consists of a series of mathematical and statistical techniques used to describe the relationship between response variable and explanatory variables. The first step in RSM is to determine the factors that are thought to have an effect on the response variables. After this step, experimental design, regression modeling and optimization techniques are used in the response surface method [7].

$$y = f(X_1, X_2, ..., X_k) + \varepsilon \tag{1}$$

where ε represents the noise or error observed in the response y and X's are observed values. The surface represented by $\eta = f(X_1, X_2, ..., X_k)$ is called a response surface and it is assumed to have a function of $X_i's$ $(i = 1,2, ..., k)$. Function f is response function of explanatory variables.

One of the aims of the response surface research is to determine the functional relationship between the explanatory variables and the actual response η according to the experimental results. Besides, the objective is to find the variables that make this function maximum or minimum. The response can be represented graphically, either in the three-dimensional space or as contour plots that help visualize the shape of the response surface. The application of RSM to design optimization is aimed at reducing the cost of expensive analysis methods and their associated numerical noise [8].

In general, the first-order model in terms of the coded variables is

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_k x_k + \varepsilon \tag{2}$$

the second-order model is

$$y = \beta_0 + \sum_{j=1}^{k} \beta_j x_j + \sum_{j=1}^{k} \beta_j x_j^2 + \sum_{i<j}^{k} \sum_{j=2}^{k} \beta_{ij} x_i x_j + \varepsilon \tag{3}$$

where, $\beta_0, \beta_1, \beta_2, ..., \beta_k$ are regression coefficients.
The estimation of regression coefficients for the first-order model is obtained by Least Square Estimation (LSE) method [9].

2.2. Artificial Neural Networks

The ANN have been developed by inspired by the biological nervous system. Biological nerve cells communicate with each other through synapses and a nerve cell send the information it processes to other cells via axons. Similarly, artificial nerve cells collect information with a sum function and pass through the activation function. Thus, these cells produce output and send it to other cells over the network's connections. ANN's are successfully applied in the following subjects, similar to the functional features of the human brain; learning, association, classification, prediction and optimization [10].

A typical ANN model is considered as nonlinear statistical data modeling tools where the complex relationships between inputs and outputs are modeled or patterns are found. They reveal the recognition of patterns in complex data sets that cannot be detected with conventional linear statistical analysis.

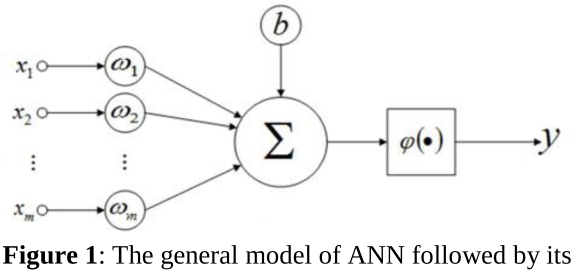


Figure 1: The general model of ANN followed by its processing [11]

The basic structure of ANN is given in Figure 1 and, it consists of an input layer, an output layer and, in between a hidden layer. The layers are connected via nodes and these connections from a network of interconnected nodes. In the ANN structure, $\mathbf{Y}$ is $n \times 1$ matrix of outputs, $\mathbf{W}$ is $n \times m$ matrix of weights, $\mathbf{X}$ is $m \times 1$ matrix of starting inputs and **Bias** is $n \times 1$ matrix of neuron biases and activation function is represented by $\varphi(.)$.

$$\begin{bmatrix} y_1 \\ y_2 \end{bmatrix} = \begin{bmatrix} w_{1,1} & w_{2,1} & w_{3,1} & w_{4,1} & w_{5,1} \\ w_{1,2} & w_{2,2} & w_{3,2} & w_{4,2} & w_{5,2} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \end{bmatrix} + \begin{bmatrix} Bias_1 \\ Bias_2 \end{bmatrix} \quad (4)$$

In a ANN model, the data received from external environment is connected to processing area via weights and these weights determine the effect of the relevant input. The sum function calculates the net input and this input is a result of the product of the weights associated with the inputs. The activation function calculates the net output during the process and this process also gives the neuron output [7].

ANN can also be displayed in matrix format, as in Equation (4). For example; w4,2 denotes the weight in the connection between Input 4 and Neuron 2.

The weights are selected in the neural network framework using a “learning algorithm” that minimizes a “cost function” such as the MSE, MAE or MAPE. Negative weights mean increasing this input will decrease the output. A weight decides how much influence the input will have on the output.

III. REAL DATA ANALYSIS

This study is based on a real data set which consists of upper limb performances. The upper limb performance is examined on 63 patients with chronic neck pain volunteer patients evaluated in different clinics in Ankara [12]. The response variable is taken as the Upper Extremity Functional Index (UEFI-20). This index measures disability in people and it takes the value between [0,80] [13]. A lower score “0” indicates that the person is reporting increased difficulty with the activities as a result of their upper limb condition. The input variables are related the pain-rating scales of patients which are visual analog scale (VAS) at rest [0,10], visual analog scale at activity [0,10], visual analog scale at night [0,10], Copenhagen Neck Functional Disability Scale(NFDS) [0,30], upper extremity endurance, upper extremity power. The first three variables are related to the VAS and in this scale, “0” represents that patient has no pain while 10 shows worst pain [14]. In Copenhagen scale, a value of 0 represents a minimal disability and 30 is a maximal disability [15]. Last two variables are upper extremity endurance and power; they are related two question “How long can you carry 1 kg?” and “How many kg can you carry?”, respectively. Thus, while endurance deal with time, power is concerned with maximum weight.

In this study, six models are constructed for the RSM and ANN. The First and Second models include all input variables and they are referred as full RSM and full ANN. Then, the significant variables obtained according to the RSM results are tested in the Third and Fourth models in RSM and ANN. They are called as “RSM and ANN with important variables from full RSM”. The last two models to be tested in the RSM and ANN are built by using important variables obtained from ANN. These models are expressed as “RSM and ANN with important variables from full ANN”. The models and variables used in the analysis are given in Table 1. The model results of these six models are compared in terms of R^2, R^2_{adj} and Mean Absolute Error (MAE).

In ANN, 70% of the data set is divided into training and 30% as test set according to the relative number of cases. While hyperbolic tangent is used as hidden layer activation function, identity was used for output layer activation function. In order to improve network training, scale covariates are rescaled and the type of this rescaling are standardized. Batch training type is used as it is more useful in small data sets. Besides these, optimization algorithm is scaled conjugate gradient.

The models given in Table 1 constructed with the help of relevant variables. The first model is RSM with all input variables and the result of this model is given in Table 2.

Table 1. Models for the RSM and ANN

Models	Variables used in the model
Model 1	VAS at rest, VAS at activity, VAS at night, Copenhagen NFDS, Upper extremity power, Upper extremity endurance
Model 2	VAS at rest, VAS at activity, VAS at night, Copenhagen NFDS, Upper extremity power, Upper extremity endurance
Model 3	VAS at activity, Copenhagen NFDS, Upper extremity power
Model 4	VAS at activity, Copenhagen NFDS, Upper extremity power
Model 5	Copenhagen NFDS, Upper extremity power
Model 6	Copenhagen NFDS, Upper extremity power

Table 2. Regression analysis of full RSM (Model 1) for UEFI-20

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	6	6611.5	1101.92	11.63	0.000*
Linear	6	6611.5	1101.92	11.63	0.000*
VAS at rest	1	350.1	350.08	3.69	0.060+
VAS at activity	1	470.1	470.07	4.96	0.030*
VAS at night	1	206.2	206.18	2.18	0.146
Copenhagen NFDS	1	2098.8	2098.85	22.15	0.000*
Upper extremity power	1	930.0	929.96	9.82	0.003*
Upper extremity endurance	1	1.2	1.22	0.01	0.910
Error	56	5305.9	94.75		
Total	62	11917.4			

UEFI-20=60.59+1.398*VAS at rest- 1.421* VAS at activity - 0.928*VAS at night- 1.324*Copenhagen NFDS + 0.0485*Upper extremity power+ 0.040* Upper extremity endurance

R^2 =55.48%, R^2_{adj} =50.71%, MAE=7.21

The important variables are "VAS at activity", "Copenhagen NFDS" and "upper extremity power". VAS at activity and Copenhagen NFDS have negative effect while upper extremity power has positive effect on UEFI-20. Since high values of VAS and NFDS mean that the patients have severe pain and maximum weakness, its inverse relationship with UEFI-20 indicates that these patients have difficulty moving. The interpretation of VAS at activity and Copenhagen NFDS coincides with the results of the study conducted by Özsoy, (2019). The author stated statistically significant negative relation between these two variables and UEFI-20. The positive relationship with power indicates that the more weight patients can carry, the more mobility they have.

The second model is ANN with all input variables and the results of this model given in Table 3.

According to the normalized importance, the variables with importance greater than fifty percent are Copenhagen NFDS and upper extremity power. These variables can be expressed as important variables that best explain the UEFI-20. Thus, these two variables are used in the following models.

Table 3. Independent variable importance of full ANN (Model 2)

	Importance	Normalized Importance
VAS at activity	0.111	36.3%
VAS at rest	0.113	37.2%
Copenhagen NFDS	**0.270**	**88.6%**
Upper extremity power	**0.305**	**100.0%**
VAS at night	0.095	31.2%
Upper extremity endurance	0.106	34.8%

R^2 =58.18%, R^2_{adj} =53.70%, MAE=6.80

In Figure 2, the comparison of RSM and ANN prediction is given by line graph. The line running close to the target line has better predictions. As given in Figure 2, the line of ANN prediction is moving closer to the target line, which means that the ANN predictions fit better than the RSM.

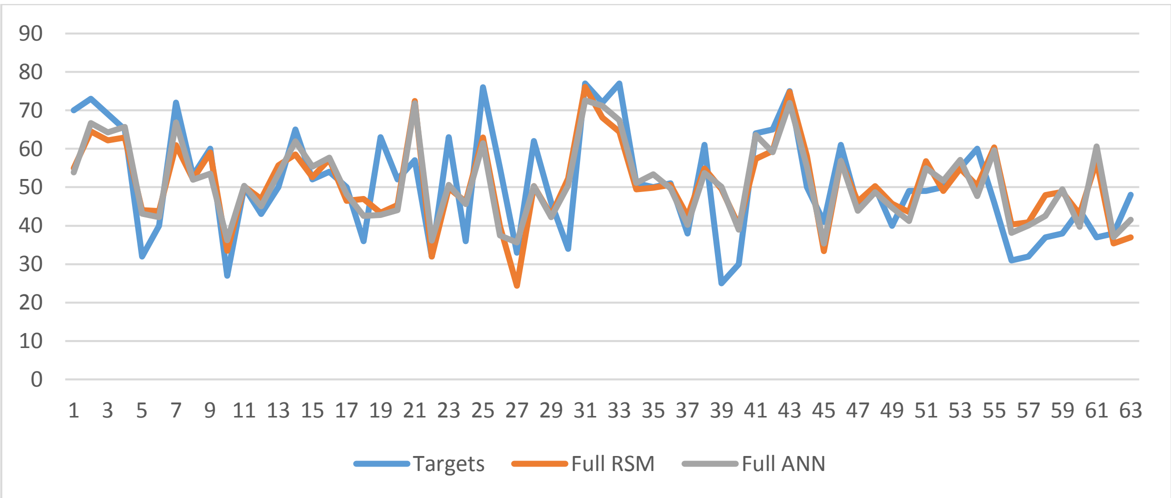


Figure 2. Comparison of full RSM and full ANN predictions

R^2 and R^2_{adj} of RSM (ANN) are 55.48% (58.18%) and 50.71% (53.70%), respectively. As visually indicated in Figure 2, the prediction of RSM model has a greater deviation than the prediction of ANN model (MAE of RSM=7.21, MAE of ANN=6.80). The high value of R^2 or R^2_{adj} and low value of MAE obtained for ANN model is indicative of its better fit.

Third model is constructed by the variables that are important in the RSM results created by using all variables.

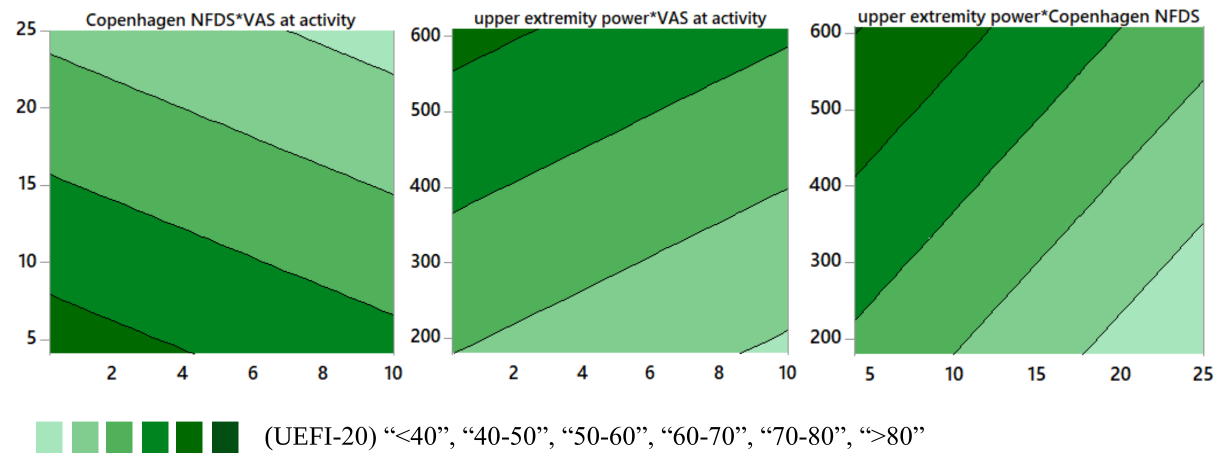
Table 4. Regression analysis of RSM with important variables from full RSM (Model 3)

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	3	6217.3	2072.44	21.45	0.000*
Linear	3	6217.3	2072.44	21.45	0.000*
VAS at activity	1	505.7	505.67	5.23	0.026*
Copenhagen NFDS	1	2281.0	2281.04	23.61	0.000*
Upper extremity power	1	1224.6	1224.63	12.68	0.001*
Error	59	5700.1	96.61		
Total	62	11917.4			

UEFI-20= 59.37 - 1.193* VAS at activity - 1.279*Copenhagen NFDS + 0.0531*Upper extremity power

R^2 =52.17%, R^2_{adj} =49.74%, MAE=7.31

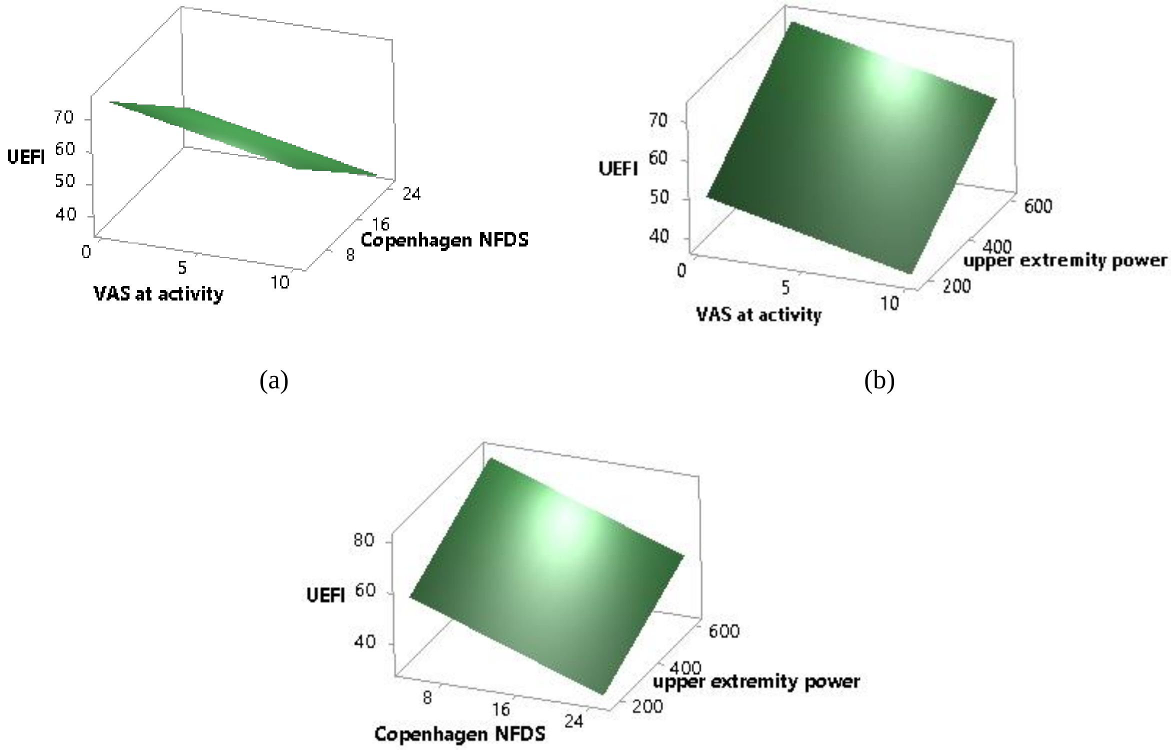
All variables used in this model are statistically significant and VAS at activity and Copenhagen NFDS have negative effect on UEFI-20 while upper extremity power has positive effect. As stated in the Model 1 results, patients who experience severe pain and maximum weakness during activity have difficulty during movement. The increase in the amount of weight that the patient can carry means that the mobility is also high.



(UEFI-20) “<40”, “40-50”, “50-60”, “60-70”, “70-80”, “>80”

(a) (b) (c)

Figure 3. Contour plots of UEFI-20 vs Copenhagen NFDS*VAS at activity (a), upper extremity power*VAS at activity (b) and upper extremity power*Copenhagen NFDS (c)



(c)

Figure 4. Surface plots of UEFI-20 vs Copenhagen NFDS*VAS at activity (a), upper extremity power*VAS at activity (b) and upper extremity power*Copenhagen NFDS (c)

In Figure 3 and Figure 4, the contour and surface plots of UEFI-20 vs other variables are given. UEFI-20 score is graded by color. A lower score 0 indicates that the person is reporting increased difficulty with the activities as a result of their upper limb condition. As the color is lightened, the patient's mobility is limited i.e. UEFI-20 score decreases. Where the Copenhagen score and VAS at activity are high, the UEFI-20 takes the minimum value. This means that the patient has difficulty in movement while having maximal disability and suffering worst pain at activity. Where the upper extremity power is low and VAS at activity is high, the UEFI-20 takes the minimum value. The patient experience maximum difficulty in movement when the weight that the patient can carry is low and the pain in activity is high. Where the upper extremity power is low and Copenhagen is high, the UEFI-20 takes the minimum value. If the weight that the patient can carry is low and the patient has maximum disability, the patient still has difficulty in movement.

In fourth model, ANN is constructed by the significant variables taken from full RSM and the results are given in Table 5. All three variables are more important since their percentage of importance greater than 50. In other words, VAS at activity, Copenhagen NFDS and upper extremity power make an important contribution in explaining the UEFI-20.

Table 5. Independent variable importance of ANN with important variables from full RSM (Model 4)

	Importance	Normalized Importance
VAS at activity	0.218	51.5%
Copenhagen NFDS	0.359	85.0%
Upper extremity power	0.423	100.0%

R^2 =57.94%, R^2_{adj} =55.80%, MAE=6.79

The line graph of predicted values of full RSM and ANN is given in Figure 5. Although the RSM and ANN predictions seem very similar, the model closer to target is ANN. MAE values are the biggest indicator of the line graph of prediction and the MAE value for ANN has a smaller value than that of RSM (MAE of RSM=7.31, MAE of ANN=6.79). The prediction of RSM model has a greater deviation than the prediction of ANN model. R^2 and R^2_{adj} of RSM (ANN) are 52.17% (57.94%) and 49.74% (55.80%), respectively. The high value of R^2 or R^2_{adj} and low value of MAE obtained for ANN model is indicative of its better fit.

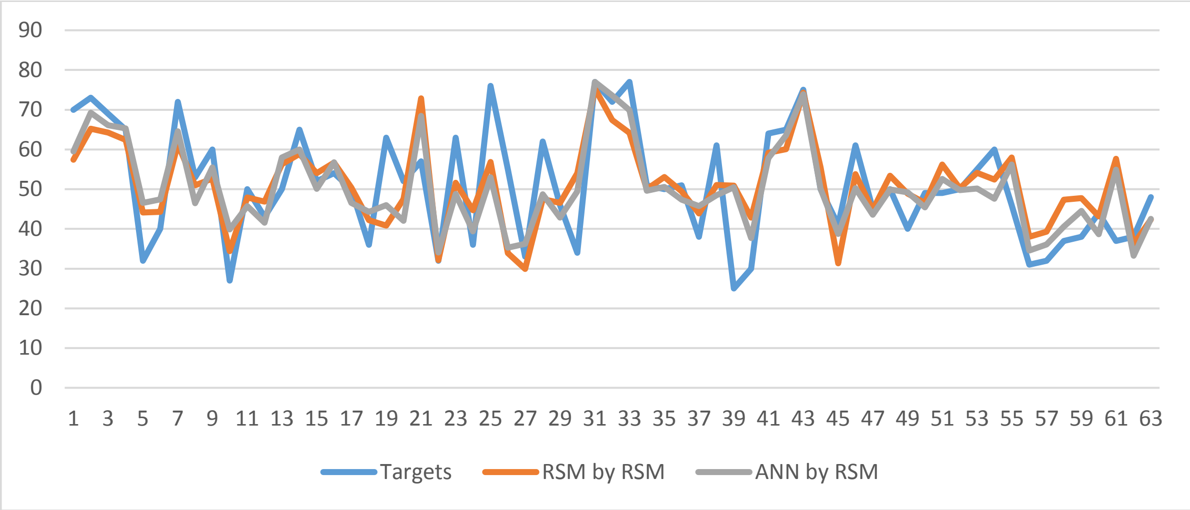


Figure 5. Comparison of RSM by RSM and ANN by RSM predictions

The fifth model is RSM obtained by the variables that are important in the model where all variables are used in ANN. The results from the fifth model are given in Table 6.

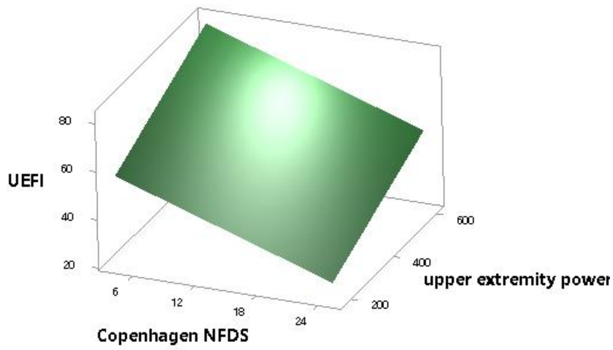
We can see from Table 6, all variables used in the model are statistically significant at %1 and Copenhagen NFDS has negative effect on UEFI-20 while upper extremity power has positive effect. In line with previous comments, as the amount of weight the patient can carry increases or the patient's weakness decreases, their mobility increases.

Table 6. Regression analysis of RSM with important variables from full ANN (Model 5)

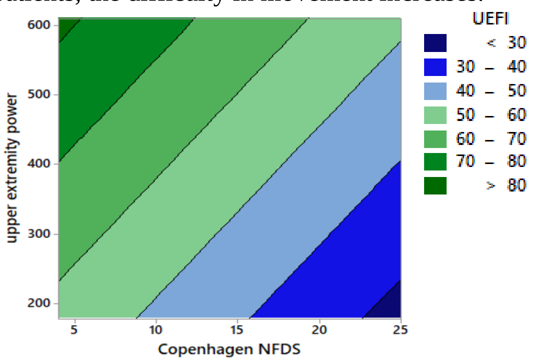
Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	2	5712	2855.8	27.61	0.000*
Linear	2	5712	2855.8	27.61	0.000*
Copenhagen NFDS	1	3101	3100.5	29.98	0.000*
Upper extremity power	1	1515	1514.8	14.65	0.000*
Error	60	6206	103.4		
Total	62	11917			
UEFI-20 = 52.24 - 1.438*Copenhagen NFDS + 0.0584*Upper extremity power					

R^2 =47.93%, R^2_{adj} =46.19%, MAE=7.76

The surface and contour plot of UEFI-20 are given in Figure 6. The minimum value of UEFI-20 score represents the difficulty with the activities. As the color in contour graph changes from blue to green means that the degree of difficulty with the activities is decreasing. Where the upper extremity power is low and Copenhagen NFDS is high, the UEFI-20 takes the minimum value. In other words, as the amount of weight carried is low or the level of disability increases in patients, the difficulty in movement increases.



(a)



(b)

Figure 6. Surface plot (a) and contour plot (b) of UEFI-20 vs upper extremity power and Copenhagen NFDS

In Model 6, the variables with a percentage of significance greater than fifty in full ANN are used. Copenhagen NFDS and upper extremity power are found as important variables. It can be expressed as important variables used to describe UEFI-20.

Table 7. Independent variable importance of ANN with important variables from full ANN (Model 6)

	Importance	Normalized Importance
Copenhagen NFDS	0.587	100.0%
Upper extremity power	0.413	70.4%

R^2 =52.17%, R^2_{adj} =50.57%, MAE=7.29

The prediction graph of the RSM and ANN models constructed by using important variables in ANN where all variables are used are given in Figure 7. As in Figure 5, the line graphs of RSM and ANN predictions are very close to each other. However, as can be understood from the MAE values, the ANN line fluctuates more similar to the target compared to the RSM.

The R^2 and R^2_{adj} of RSM (ANN) values are 47.93% (52.17%) and 46.19% (50.57%), respectively. The high value of R^2 and R^2_{adj} obtained for ANN model is indicative of its better fit. The prediction of RSM model has a greater deviation than the prediction of ANN model (MAE of RSM=7.76, MAE of ANN=7.29).

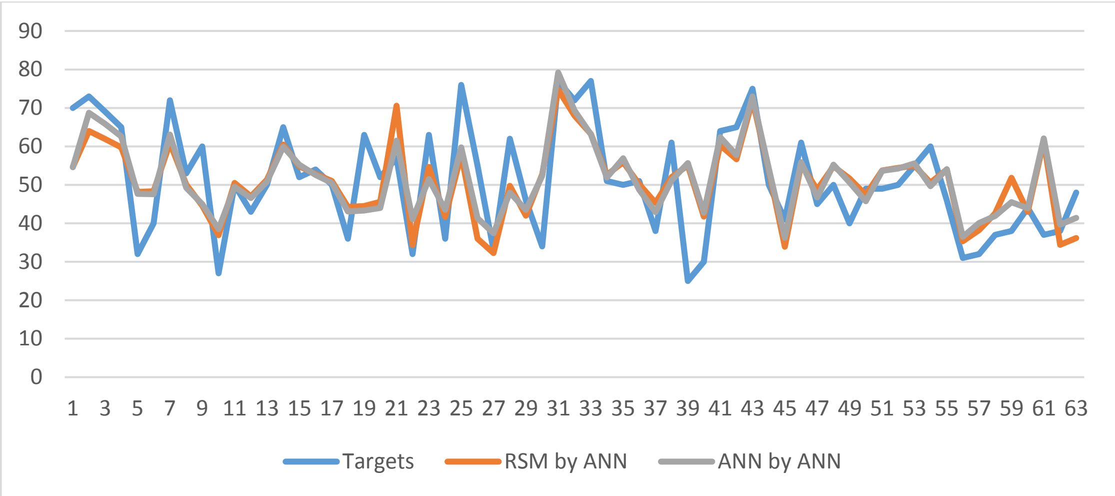


Figure 7. Comparison of RSM by ANN and ANN by ANN predictions

Table 8. Comparison of the model results

		R^2	R^2(adj)	MAE
Model 1	Full RSM	55.48%	50.71%	7.21
Model 2	Full ANN	**58.18%**	**53.70%**	**6.80**
Model 3	RSM with important variables from full RSM	52.17%	49.74%	7.31
Model 4	ANN with important variables from full RSM	**57.94%**	**55.80%**	**6.79**
Model 5	RSM with important variables from full ANN	47.93%	46.19%	7.76
Model 6	ANN with important variables from full ANN	**52.17%**	**50.57%**	**7.29**

The comparison of all models is given in Table 8. ANN models have high R^2 and R^2_{adj}, and low MAE; when all variables are used in Model 2, when the model is established on the important variables obtained as a result of RSM using all variables in Model 4, when the model is set up with variables with a percentage of significance over fifty in the ANN model where all variables are used. Briefly, it was concluded that the ANN models among the established models have high explainability and less deviation.

IV. RESULTS

In this study, RSM and ANN models are applied to a real data set to determine the important variables affecting UEFI-20. The variables used in the models are determined in following steps: First of all, all variables are put into the model and then new models are established according to the important variables (obtained from ANN and RSM, respectively) that are important in the results of these models. Finally, six model are implemented, and these models and their results are given in Table 8.

The results of this study support the results of the previous studies. For instance, Kiran et.al (2008) compared the ANN and RSM in fermentation media optimization and they showed the superiority of ANN in capturing the nonlinear behavior of the system [16]. It can be stated that ANN have worked better than RSM model in some studies [17, 18, 19, 20].

In this study conducted on patients with chronic neck pain, which is one of the common problems in daily life, the factors affecting the upper extremity functional index are examined. For this purpose, RSM and ANN are applied with the use of various variables in order to predict important variables and to decide which model gives better results. Thus, the performance of ANN and RSM models are evaluated by R^2, R^2_{adj} and MAE. According to the results of all six models, ANN predictions fit the targets line better than RSM since MAEs of ANN are smaller than those of RSM. Besides, R^2 and R^2_{adj} of ANN are greater than those of RSM. The prediction of ANN model has a smaller deviation than the prediction of RSM model. The predicted values by ANN has a low percent of error for predicting UEFI-20 values. The most significant variables on UEFI-20 score in all models are Copenhagen NFDS and upper extremity power.

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