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Research Paper

Developing a Radial Basis Function Neural Networks to Predict the Working Days for Tillage Operation in Crop Production

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Abstract

The aim of this study was to determine the probability of working days (PWD) for tillage operation using weather data with Multiple Linear Regression (MLR) and Radial Basis Function (RBF) artificial networks. In both models, seven variables were considered as input parameters, namely minimum, average and maximum temperature, relative humidity, rainfall, wind speed, and evaporation on a daily basis. The PWD was considered to be the output of the developed models. Performance criteria were RMSE, MAPE, and R2. Results showed that the R^2-value was 0.78 and 0.99 for MLR and RBF models, respectively. Both models had acceptable performance, but the RBF model was more accurate than the MLR model. The RMSE and MAPE values for the RBF model were lower than those for the MLR model. Thus, the RBF model was selected as the suitable model for predicting PWD. Moreover, the results of these models were compared to the prior soil moisture model. It was indicated that the results of the studied models had a good agreement with the results of the soil moisture model. However, the RBF model had the highest R^2 (99%). In conclusion, the developed RBF model could be used to predict the probability of working days in terms of agricultural management policies.

Keywords:
artificial neural network, multiple linear regression, probability of working days, redial basis function

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INTRODUCTION

Farm machinery management is one of the most expensive parts of agricultural production (Rotz & Harrigan, 2005). Management of this cost can largely help the productivity of farms. Weather is the most important factor in manager decisions with a key role to play in cost estimation. The effect of variability in weather conditions has an effective role in timeliness cost. Generally, agricultural operations, especially sowing, must be done in optimum time to prevent yield losses at harvest time and the resulting loss of profits. Accordingly, the determination of PWD can be an effective solution for this problem and the management of timeliness costs. The main factors for determining PWD include rainfall, air temperature, snow, air humidity, wind speed, and so on (American Society of Agricultural Engineers, 2000). The importance of this issue interested some researchers to focus on calculating PWD for various agricultural operations. Different ways have been used to determine the effective factors in PWD for a given operation. There were three main methods for this purposes: first, predicting the number of working days using weather parameters for weeds spraying in sugarcane fields (Kamali et al., 2011) and for harvesting paddy crop (Nesheli et al., 2012). Moreover, Saglam and Tobi (2011) calculated tractor available workdays over GAP area in Turkey based on rainfall, snowfall, and average daily temperature. Another research used weather data including rainfall, temperature, relative humidity to determine the suitable workdays in sugarcane harvesting in Ahvaz, Iran (Omrani et al., 2011). In this study, timeliness costs were calculated after determining the number of working days. The available working days for paddy harvesting operation by conventional and mechanized methods were estimated using weather parameters including relative humidity, air temperature, and rainfall (Kosari-Moghaddam et al., 2016). This method was largely applied to determine the working days except for tillage operation because soil moisture is an important factor in these operations. The second method is the estimation of PWD for tillage operation. In this method, PWD is determined based on daily soil moisture models and given criteria according to local conditions, weather parameters, and operation type such as harvesting switchgrass (Hwang, 2007), tillage and planting operations (Kosari-Moghaddam et al., 2015), tillage operation in semi-arid areas (Simalenga & Have, 1992) and the estimation of spring workdays (Selirio & Brown, 1972). In another research, Baier (1973) estimated field workdays in Canada from the versatile soil moisture budget. This study considered workday to be a day with no snow cover and with estimated soil moisture conditions in the upper three zones. Here, soil moisture criteria were 90, 95 and 97.5 percent of field capacity for different soil textures. Moreover, Witney et al. (1982) developed a model to calculate soil moisture content using soil water equations for Scotland, and then the number of working days for tillage was determined. Witney (1988) also developed a soil moisture content model based on the amount of water entrance and exit from the soil profile. In this research, the workability criteria were a moisture level of less than soil plastic limit and a rainfall level of less than 10 mm. Moreover, rainfall of less than 1.4 mm was defined as the criterion of working days for combine harvesting. Finally, the third method for the determination of PWD is based on various mathematical and modeling methods. This method has contributed the least to this subject. One of these methods is the Markov chain model used to determine field workdays (Hayhoe & Baier, 1974) and outdoor and machinery workdays (Ataíde et al., 2012). In this study, the model developed by Baier (1973) was used for soil moisture determination and workday criteria.

Multiple linear regression models have been widely used to model various types of problems in the agricultural sector, such as evaluation of regression techniques in tractor repair and maintenance costs (Rohani et al., 2010), energy audit of Iranian kiwifruit production using intelligent systems (Soltanali et al., 2017), and dryland wheat yield prediction using different regression models (Tatari et al., 2009). Wiljes and Zaat (1968) also determined the number of weather-working hours in combine harvesting in the Netherlands using multiple linear regression in terms of the number of dry days and mean daily rainfall for every half-monthly period. Table 1 shows some related studies on the determination of PWD in the agricultural sector by using different techniques.

Artificial Neural Network (ANN) is another method that has been used in recent studies for the prediction of various parameters in agricultural fields, such as intelligent modeling of material separation in combine harvester's thrasher by an ANN model (Mirzazadeh et al., 2012), a neural network approach for indirectly estimating farm tractor engine performance (Bietresato et al., 2015), and combined application of an artificial neural network and life cycle assessment in lentil farming in Iran (Elhami et al., 2017). Rostami et al. (2017) applied an ANN model to predict the yield, CO_2 emissions, and energy for basil production in Iran. Moreover, an ANN model was used to forecast Iran's rice import trend (Pakravan et al., 2011). To the best knowledge of the authors, no study has employed this method to predict PWD in the agricultural sector. So, the present research collected a comprehensive, invaluable set of all available data pertaining to the probability of working days for tillage operation. These data include a wide range of all parameters influencing PWD. After the review of numerous studies, the following objectives were set for the present work:

1- developing RBF and MLR models using weather variables influencing PWD,

2- using statistical criteria like means comparison, variance, and statistical distribution to assess and compare the models,

3- conducting sensitivity analysis and selecting the best input set based on 15 scenarios for the model,

4- Comparing models with another soil moisture model conducted in this area.

Table 1
The Related Studies on the Determination of the Probability of Working Days in the Agricultural Sector

Type of operation	Case study	Model inputs	Reference
Combine harvesting	Netherlands	Multiple linear regression model	Wiljes & Zaat, 1968
Cultivation and seeding	Canada	Soil moisture content	Selirio & Brown, 1972
Field-work	Canada	Snowfall and soil moisture content	Hayhoe & Baier, 1974
Tillage	Scotland	Soil moisture content	Witney et al., 1982
Tillage	Tanzania	Soil moisture content	Simalenga & Have, 1992
Switchgrass harvest	USA	Rainfall, snowfall, soil moisture content	Hwang, 2007
Field operation by tractor	Turkey	Rainfall, temperature, snowfall	Saglam & Tobi, 2011
Weeds spraying of sugarcane	Iran	Rainfall, temperature, wind speed, relative humidity	Kamali et al., 2011
Sugarcane harvest	Iran	Rainfall, temperature, relative humidity, evaporation	Omrani et al., 2011
Paddy harvest	Iran	Rainfall, relative humidity	Nesheli et al., 2012
Outdoor and operation of machinery in the field	Brazil	Rainfall, soil moisture content	Ataíde et al., 2012
Tillage and sowing	Iran	Rainfall, soil moisture content	Kosari-Moghaddam et al., 2015
Paddy harvest	Iran	Rainfall, relative humidity	Kosari-Moghaddam et al., 2016
Tillage	Iran	Minimum, average and maximum temperature, rainfall, wind speed, and evaporation on a daily basis	Current Study

METHODOLOGY

Study site and variables

The present study was conducted at the Research Station of the Agricultural Department of Ferdowsi University, Mashhad, Iran (36°15'N/59°36'E) between September and February in eight years (2002-2010). The weather data including daily minimum, maximum and average air temperature, wind speed, rainfall and relative humidity were collected from the meteorological stations in Mashhad. The FAO-Penman formula was also used to determine daily evapotranspiration (Allen et al., 1998). The number of working days were also gathered from a farm in Mashhad during 2002 and 2010. Generally, the average total rainfall and mean annual temperature were about 250 mm and 14.3°C in Mashhad. Seven independent variables were investigated to predict PWD as the dependent variable for the tillage operation in fall and winter. The variables are shown in Table 2.

Table 2
Variable Names and Symbols

Variable name	Symbol	Variable name	Symbol
T_{max}	x_1	Rainfall	x_5
T_{min}	x_2	Wind speed	x_6
T_{ave}	x_3	Evaporation	x_7
Relative humidity	x_4	Probability of working days	y_1

Multiple linear regression (MLR) model

MLR is a statistical analysis method used for determining the effect of some independent variables on a dependent variable in order to evaluate the linear dependency of the variables. This model, which describes the relationship between the unknown variable (y) based on known variables (x) , parameters, and random noise , is expressed in the following form (Fang & Lahdelma, 2016):

$$y_i=\beta X_i+\varepsilon_i \tag{1}$$

where is the predicted value, $X_i=(1,x_1, x_2,...,x_7)$ is a vector of explanatory variables, $\beta=(\beta_0,\beta_1,...,\beta_k)^T$ is the vector of the coefficient and is a random error term for ith observation.

We estimate parameters β by least square sense (LSQ), which minimizes the square sum of the error. Parameters $\tilde{\beta}=(\beta_0, \beta_1, \beta_2,\beta_{h(1)},..., \beta_{h(Ts)})^T$ are variables that minimize the square sum of errors variables:

$$\min \sum_{t=1}^{T} \varepsilon_t^2 \tag{2}$$

which can be written in matrix form:

$$\min \varepsilon^T \varepsilon \tag{3}$$

$$\varepsilon=\tilde{X}\tilde{\beta}-y \tag{4}$$

By substituting ε in the objective function, we have an unconstraint optimization problem:

$$\min(\tilde{X}\tilde{\beta}-y)^T(\tilde{X}\tilde{\beta}-y) \tag{5}$$

Forming the derivative and setting it to zero gives the solution as:

$$2\tilde{X}^T\tilde{X}a-2\tilde{X}^T y=0 \rightarrow \tilde{\beta}=(\tilde{X}^T\tilde{X})^{-1}\tilde{X}^T y \tag{6}$$

where $\tilde{X}=(\tilde{X}_1,\tilde{X}_2,...,\tilde{X}_7)^T, \tilde{\beta}=(\beta_0,\beta_1,\beta_2,\beta_{h(1)},...,\beta_{h(T_s)})^T$ and $y=(y_1,y_2,...,y_7)^T$

In this study, the elements of this regression model included seven independent variables ($x_1, x_2, ..., x_7$) and one dependent variable (y). Four different models (i.e. linear, interaction, quadratic and pure-quadratic models) were evaluated to find the best model whose general form is as below:

$$y = \beta_0 + \sum_{i=1}^{K} \beta_i x_i + \sum_{i=1}^{K} \beta_{ii} x_i^2 + \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \beta_{ij} x_i x_j \quad (7)$$

where is the dependent variable (PWD), β_0, β_i, β_{ii}, β_{ij} are constant coefficient, linear coefficient, quadratic coefficient and interaction coefficient, respectively, is the number of studied and optimized factors, and x_i, x_j ,$x_i x_j$,x_i^2 are independent variables, interaction and quadratic terms, respectively (Pishgar-Komleh et al., 2012).

Radial basis function (RBF) artificial neural network

RBF is a forward-feed network included three layers: input, hidden and output layers (Figure 1). The output of RBF is defined as (Ardabili et al., 2016):

$$y = h^T(x,t) \times W(t) \quad (8)$$

where h^T $(x,t)$is the radial basis vector of the RBF network and $W(t)$ is the vector of weights, and h_i is defined as Gaussian function as following:

$$h_i = exp(-\frac{\|x(t)-c_i\|^2}{2b_i^2}), i = 1, 2, \ldots m,$$

$$\begin{cases} c = [c_1, c_2, c_3, \ldots, c_m]^T \\ b = [b_1, b_2, b_3, \ldots, b_m]^T \end{cases} \quad (9)$$

where b and c are the base width and centric vectors, respectively. Also, m is the number of hidden layers neuron. The input layer neurons have propagation task of input layer features to the next layer. In the hidden layer, a kernel function associates each neuron of the hidden layer. The output layer is the summation of the hidden layer responses for respective inputs (Wen et al., 2012).

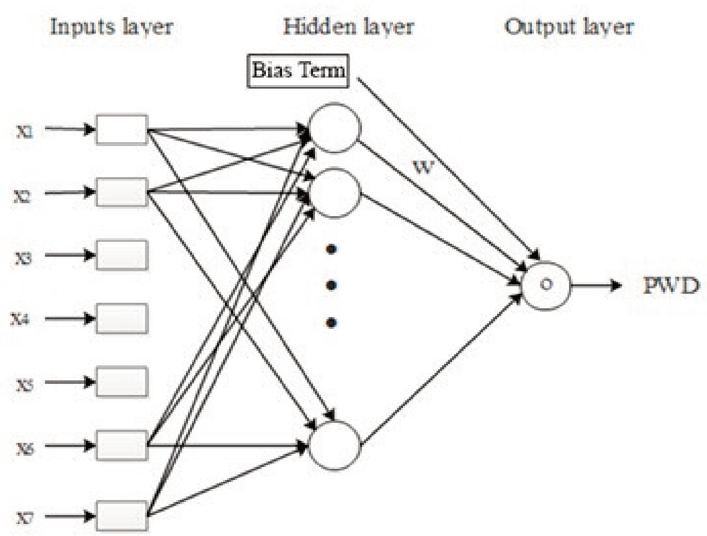

Figure 1. The RBF network structure

Initial data processing and finding optimum neurons and spread parameter

In this study, 13 algorithms existing in MATLAB were evaluated and the bayesian regularization back-propagation was selected as the best algorithm. The input data were normalized in the range [-1 1] to improve efficiency. In order to find the best performance of the RBF network, 15 scenarios were evaluated considering the combination of various independent variables (Table 3). Then, each scenario was investigated in networks with a combination of neuron numbers and spread parameters.

Table 3
Parameter Requirements of Each Scenario

Scenario No.	Symbol	Inputs of Network
1	S1	Min. temp., Max. temp, Ave. temp., RH, Rain, Wind Sp., Evap.
2	S2	Min. temp., Max. temp, Ave. temp., RH, Rain, Wind Sp.
3	S3	Min. temp., Max. temp, Ave. temp., RH, Rain, Evap.
4	S4	Min. temp., Max. temp, Ave. temp., RH, Wind Sp., Evap.
5	S5	Min. temp., Max. temp, Ave. temp., Rain, Wind Sp., Evap.
6	S6	Min. temp., Max. temp, RH, Rain, Wind Sp., Evap.
7	S7	Min. temp., Ave. temp., RH, Rain, Wind Sp., Evap.
8	S8	Max. temp, Ave. temp., RH, Rain, Wind Sp., Evap.
9	S9	Ave. temp., RH, Rain, Wind Sp., Evap.
10	S10	Min. temp., RH, Rain, Wind Sp., Evap.
11	S11	Min. temp., Max. temp., RH, Rain, Evap.
12	S12	Max. temp., Ave. temp., RH, Rain, Evap.
13	S13	Min. temp., Max. temp., RH, Rain, Evap.
14	S14	Min. temp., Ave. temp., RH, Evap.
15	S15	Min. temp., Rain, Evap.

Performance evaluation criteria

In this study, both the MLR and RBF models were evaluated using Root Mean Square Error (RMSE), Total Sum of Square Error (TSSE), Mean Absolute Percentage Error (MAPE), and coefficient of determination (R^2), which are shown in Equations 10-13.

$$RMSE=\sqrt{\frac{\sum_{i=1}^{m}(y_i-\hat{y}_i)^2}{m}} \quad (10)$$

$$TSSE=\sum_{i=1}^{n}(y_i-\bar{y}_i)^2 \quad (11)$$

$$MAPE=\frac{1}{m}\sum_{i=1}^{m}\left|\frac{y_i-\hat{y}_i}{y_i}\right|\times 100 \quad (12)$$

$$R^2=\frac{\left(\sum_{i=1}^{m}(y_i-\bar{y})(\hat{y}_i-\bar{\hat{y}})\right)^2}{\sum_{i=1}^{m}(y_i-\bar{y})^2 \cdot \sum_{i=1}^{m}(\hat{y}_i-\bar{\hat{y}})^2} \quad (13)$$

where y_i, $\hat{y}_i$, $\bar{y}$ are observed value, model output, and average observed value for ith observation, $\bar{y}$, $\bar{\hat{y}}$ are also average observed and predicted values, and m is the number of observations, respectively.

Finally, the statistical characteristics including average, maximum, minimum, skewness, kurtosis, and the sum of each independent and dependent variables and each model were calculated. In addition, the differences between model results were evaluated. All calculations and programming were done in MATLAB (R2016a, 9.0.0.341360).

Results and Discussion

The results of statistical analysis of independent and dependent variables are shown in Table 4. According to Table 4, the average PWD for the studied area and operations was about 88 percent varying between 51 and 100 percent based on different weather conditions. Moreover, the average rainfall in the studied period was about 14 mm and the total rainfall was 557.10 mm.

MLR model

Model selection

The results of evaluating four regression models including linear, interaction, quadratic and pure-quadratic models based on four performance criteria (i.e. RMES, TSSE, MAPE, R^2) are presented in Table 5. They showed that the quadratic model had the best performance among all models.

Table 4
Statistical Analysis of the Studied Variables

Descriptive statistics	x_1 (°C)	x_2 (°C)	x_3 (°C)	x_4 (%)	x_5 (mm)	x_6 (Km/h)	x_7 (mm)	y
Mean	17.15	4.30	10.51	52.93	13.59	6.66	2.64	87.66
Variance	82.20	45.14	63.72	348.62	190.39	4.89	3.53	136.53
Std. deviation	9.07	6.72	7.98	18.67	13.80	2.21	1.88	11.68
Min	-1.85	-13.28	-7.30	21.80	0.00	3.30	0.50	51.00
Max	31.06	15.23	23.30	80.10	47.74	12.20	6.90	100.00
Skewness	0.11	-0.07	0.11	-0.28	0.87	0.80	0.82	-1.26
Kurtosis	-1.27	-0.57	-1.11	-1.38	-0.17	0.26	-0.80	1.69
Sum	703.15	176.52	430.90	2170.00	557.10	273.20	108.30	35953.98

Table 5
The Results of Different Regression Models

Model	RMSE (%)	TSSE (%^{2})	MAPE (%)	R^2
Linear	9.70	3857.17	9.39	0.30
2FI	5.10	1065.69	4.18	0.80
Quadratic	**3.55**	**517.78**	**3.17**	**0.90**
Pure-quadratic	6.92	1964.29	5.95	0.62

*Bold numbers show the performance criteria for the best developed MLR model

After the appropriated model was selected, the best coefficients of the models were determined using stepwise and minimum *P*-value of coefficients methods. The results of analysis variance and estimated coefficients of the selected model are shown in Tables 6 and 7. According to Table 6, the dependent variable (PWD) was significantly ($p<0.01$) related to all independent variables, except x_7 to which it was related significantly at the $p<0.10$ level. The intercept of the model was also significant at $p<0.05$ level. R^2 for the final model was estimated at 0.78, which is not very high but acceptable.

Table 6
Analysis of Variance for the Selected Regression Model

Source	DF	SS	MS	Fval	Source	DF	SS	MS	Fval
Model	16	4295.31	268.46	4.95***	x_{26}	1	84.63	84.63	1.56***
x_2	1	13.37	13.37	0.25***	x_{34}	1	64.08	64.08	1.18***
x_3	1	559.58	559.58	10.31***	x_{35}	1	66.60	66.60	1.23***
x_4	1	221.76	221.76	4.09***	x_{36}	1	564.07	564.07	10.39***
x_5	1	806.93	806.93	14.87***	x_{67}	1	4.37	4.37	0.08***
x_6	1	82.40	82.40	1.52***	x_5^2	1	482.17	482.17	8.88***
x_7	1	5.18	5.18	0.10*	x_6^2	1	853.25	853.25	15.72***
x_{14}	1	47.60	47.60	0.88***	Error	24	1302.45	54.27	
x_{16}	1	169.91	169.91	3.13***	Total	40	5597.76		
x_{25}	1	269.41	269.41	4.96***					

*P<0.1, **P<0.05, ***P<0.01

Table 7

Estimated Coefficients of the Selected Regression Model

Source	Estimate	SE	t-stat	*P*-value	Source	Estimate	SE	t-stat	*P*-value
intercept	-189.84	72.66	-2.61	0.02	x_{25}	-0.74	0.26	-2.84	0.01
x_2	-33.72	10.69	-3.15	0	x_{26}	6.38	2.05	3.12	0
x_3	34.86	10.5	3.32	0	x_{34}	0.51	0.18	2.82	0.01
x_4	3.81	1.01	3.77	0	x_{35}	0.68	0.23	2.92	0.01
x_5	-7	1.52	-4.6	0	x_{36}	-10.96	3.3	-3.32	0
x_6	31.59	10.38	3.04	0.01	x_{67}	5.01	1.67	3	0.01
x_7	-27.9	14.87	-1.88	0.07	x_5^2	0.06	0.01	4.55	0
x_{14}	-0.47	0.15	-3.06	0.01	x_6^2	-2.03	0.51	-3.97	0
x_{16}	4.11	1.38	2.98	0.01					

$y \sim 1+x_2+x_3+x_4+x_5+x_6+x_7+x_1\,x_4+x_1\,x_6+x_2\,x_5+x_2\,x_6+x_3\,x_4+x_3\,x_5+x_3\,x_6+x_6\,x_7+x_5^2+x_6^2$

Diagnostics of the model adequacy

The model adequacy was evaluated to determine the performance of the model and whether the model would give poor or misleading results (Maran et al., 2013). The validation of the regression model was related to the validation of the assumptions of regression analysis. As depicted in Figure 2, we could be highly confident to the regression model for predicting PWD because the distribution of the studentized errors was very similar to normal distribution (Figure 2(a) and 2(c)), the variances of errors were approximately equal to the fitted values (Figure 2(b)), and the errors of the model were not auto-correlated (Figure 2(d)).

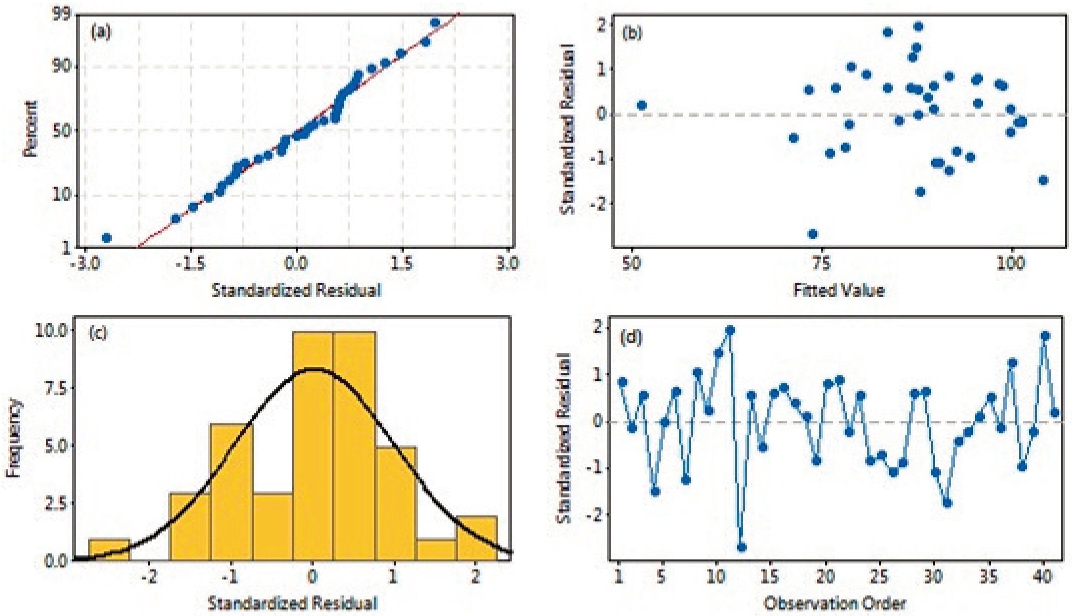

Figure 2. Diagnostics plots for the model adequacy

RBF model

Model selection

In order to estimate the best architecture of the RBF network, we evaluated the network using 15 scenarios with different combinations of inputs. The optimum number of neurons and the spread parameter was determined. Table 8 shows the selected scenario and the optimum number of neurons and spread parameters. The scenarios were ranked according to their performance in prediction based on three criteria including RMSE, MAPE, and R^2. As Table 8 shows, however, all scenarios had good performance and high R^2 value (99%) except S15. Scenario 5 was selected as the best due to its fewer input parameters. The inputs of this scenario included the minimum, maximum and average daily temperature, rainfall, wind speed, and evaporation. This scenario had the best performance on 19 neurons and a value of 0.1 for the spread parameter. Fig. 3 shows the performance of this scenario for various numbers of neurons and spread parameters for both train and test sets.

Table 8
Overall Results of the RBF Networks under Different Scenarios

Rank	Scenario	Hidden size	Spread	Train			Test		
				RMSE (%)	MAPE (%)	R^2	RMSE (%)	MAPE (%)	R^2
1	**S5**	**19**	**0.1**	**2.6E-9**	**1.2E-9**	**0.99**	**1.5E-9**	**1.3E-9**	**0.99**
2	S1	9	2	1.9E-7	1.34E-7	0.99	6.8E-8	5.6E-14	0.99
3	S2	19	2	5.6E-4	5.3E-4	0.99	5.1E-4	4.9E-4	0.99
4	S4	19	2	0.009	0.008	0.99	0.010	0.010	0.99
5	S3	7	3	0.014	0.010	0.99	0.008	0.006	0.99
6	S6	19	3	0.013	0.011	0.99	0.013	0.012	0.99
7	S7	21	2	0.022	0.019	0.99	0.018	0.018	0.99
8	S10	21	2	0.049	0.039	0.99	0.053	0.048	0.99
9	S9	15	5	0.057	0.058	0.99	0.038	0.034	0.99
10	S8	7	4	0.072	0.054	0.99	0.076	0.068	0.99
11	S11	21	2	0.095	0.096	0.99	0.081	0.081	0.99
12	S14	11	2	0.099	0.073	0.99	0.139	0.108	0.99
13	S12	11	5	0.301	0.279	0.99	0.255	0.222	0.99
14	S13	21	2	0.467	0.455	0.99	0.699	0.620	0.99
15	S15	19	1	1.150	0.418	0.98	2.477	1.107	0.98

*Bold numbers show the scenario characteristics and performance criteria for the best scenario

Sensitivity analysis of the RBF model

The outputs of the best RBF model and sensitivity analysis are shown in Table 9. The RBF model had a total efficiency of 99%. Sensitivity analysis indicated that the performance of the RBF model exhibited the highest sensitivity when rainfall (x_5) and wind speed (x_6) were excluded. The exclusion of these parameters from the model inputs resulted in 55% and 41% reduction in R^2 in the total phase and a significant increase in RMSE and MAPE in all three phases, respectively.

Generalization capability of the model

In this study, we analyzed the generalization capability of the RBF model using the variations in the number of train sets from 90 percent of total data to 80, 70, 60, 50, 40 and 30 percent of total data. The results of this analysis are presented in Table 10. According to these results, the selected RBF model had a good generalization capability and could keep its high performance in all data sets.

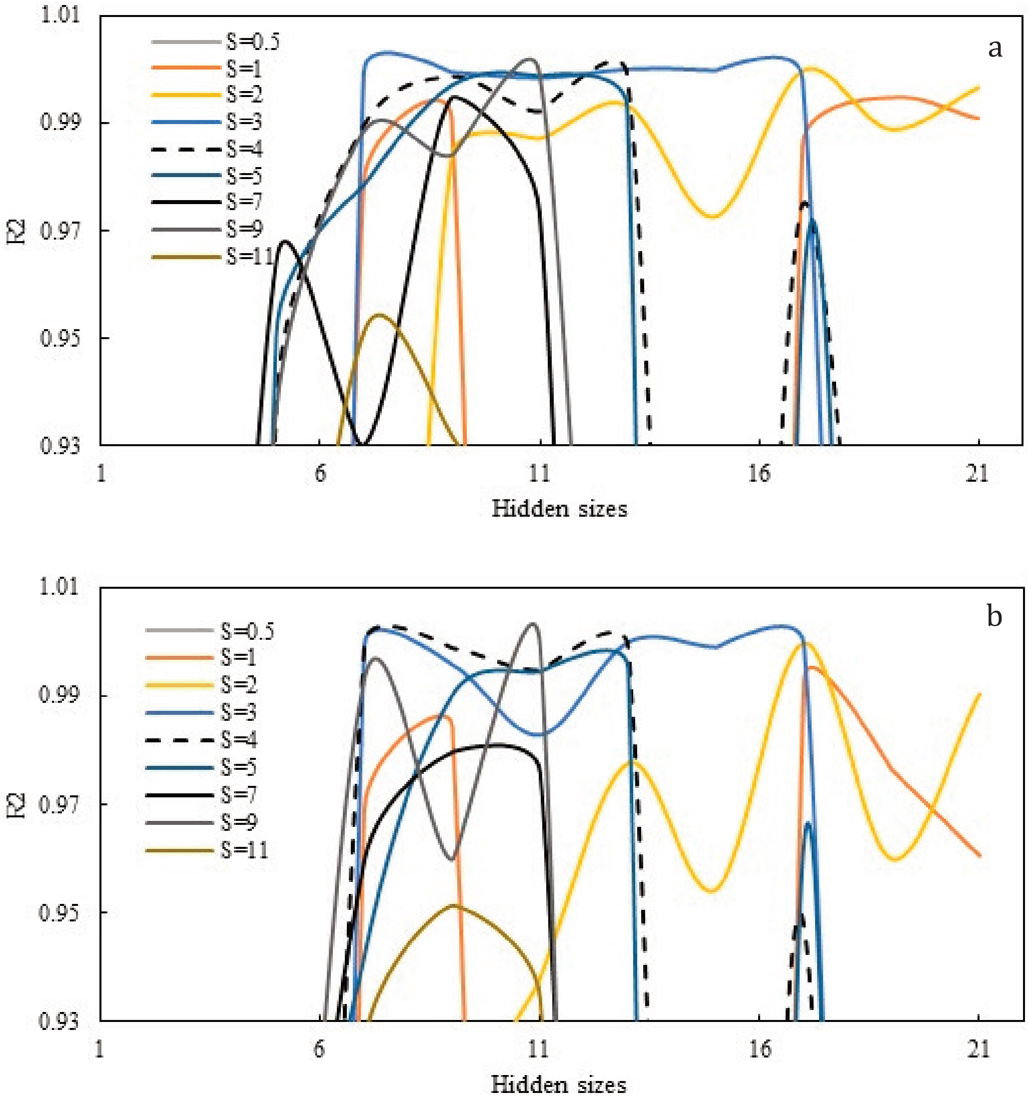

Figure 3. Diagrams of R2 vs. hidden sizes at different levels of spread for Scenario 5
a. Train set, b. Test set

Table 9
The Results of the Sensitivity Analysis of the Selected Scenario

	Train			Test			Total		
	RMSE(%)	MAPE(%)	R^2	RMSE(%)	MAPE(%)	R^2	RMSE(%)	MAPE(%)	R^2
All	2.64E-9	1.26E-9	0.999	1.50E-9	1.31E-9	0.999	2.46E-9	1.27E-9	0.999
All excluding *x1*	0.390	0.318	0.999	0.176	0.129	0.999	0.359	0.281	0.999
All excluding *x2*	3.73E-8	2.90E-8	0.999	2.51E-8	2.51E-9	0.999	3.53E-8	2.82E-8	0.999
All excluding *x3*	1.36E-8	1.99E-8	0.999	1.68E-8	1.19E-8	0.999	1.43E-8	1.27E-8	0.999
All excluding *x5*	9.320	7.373	0.609	8.416	8.455	0.014	9.150	7.852	0.550
All excluding *x6*	9.608	8.198	0.537	12.875	8.198	0.081	10.325	8.274	0.412
All excluding *x7*	4.91E-9	4.35E-9	0.999	6.18E-9	5.97E-9	0.999	5.18E-9	4.66E-9	0.999

Table 10

The Results of the Evaluation of the Selected Scenario Generalization Capability

TS	Train phase				Test Phase			
	RMSE(%)	MAPE(%)	TSSE(%^{2})	R^2	RMSE(%)	MAPE(%)	TSSE(%^{2})	R^2
90	1.92E-7	1.21E-7	1.37E-12	0.999	8.13E-8	7.34E-8	2.64E-14	0.999
80	2.64E-9	1.26E-9	2.30E-16	0.999	1.50E-9	1.31E-9	1.81E-17	0.999
70	0.759	0.610	16.72	0.996	0.649	0.442	5.065	0.996
60	6.43E-7	5.60E-7	1.03E-11	0.999	6.43E-7	4.68E-7	6.61E-12	0.999
50	2.12E-7	1.54E-7	9.45E-13	0.999	1.15E-7	1.03E-7	2.69E-13	0.999
40	1.20E-6	1.00E-6	2.37E-11	0.999	1.00E-6	8.64E-7	2.51E-11	0.999
30	0.455	0.332	2.485	0.997	0.597	0.461	10.36	0.997

Comparison of the results of models

The results of the models were compared with actual data and with the results of another study that had used the same weather data for the estimation of PWD based on soil moisture model (Kosari-Moghaddam et al., 2016).

Statistical characteristics for MLR and RBF

The results of evaluating the statistical characteristics of both MLR, RBF and soil moisture models versus actual values are shown in Table 11. This table presents that although the values of all parameters for both models did not significantly differ from the actual data, except for the skewness in the soil moisture model, these values were approximately equal to the actual ones in the RBF model, implying the good performance of this model.

Table 11

Statistical Properties of the Actual and Predicted Variables for the MLR, RBF, and Soil Moisture Models

	Statistical properties								RMSE	MAPE
	Mean.	Var.	Standard deviation	Min.	Max.	Kurtosis	Skew-ness	Sum		
Actual	87.66	139.94	11.83	51.00	100.00	4.34	-1.21	3593.97	-	-
MLR	87.50^{ns}	102.89	10.14^{ns}	50.60	100.00	5.45	-1.22^{ns}	3587.51	5.53	5.12
RBF-S5	87.65^{ns}	139.94	10.83^{ns}	51.00	100.00	4.34	-1.21^{ns}	3593.74	0.00	0.00
Sim. model	91.39^{ns}	181.90	13.65^{ns}	37.93	100.00	5.58	-2.17**	3747.12	16.17	14.15

* significant at 10%, ** significant at 5%, *** significant at 1%, ^{ns} not significant

The results of means comparison t-test

The means comparison t-test was used to evaluate the results of the MLR, RBF, and soil moisture models (Figure 4). This table shows that there was no significant difference between the results of all models and actual data. Moreover, the PWD predictions for all models and the actual data are shown in Figure 5. According to this figure, although all models predicted PWD between 70 and 100 percent, the soil moisture and MLR models predicted greater and smaller PWD values, respectively. Ahaneku and Onwualu (2007) developed a simulation model to predict suitable workdays for tillage operation in Nigeria based on soil moisture content. The results showed that the correlation coefficients between the observed and predicted data were 0.93 for both sandy loam and clay soils. Moreover, Babeir et al. (1986) determined the available field operation time for machinery based on weather and soil moisture conditions. They reported that the correlation coefficient of the observed and predicted soil tractability value was 0.95. The results of such models can be implemented as an input of the farm management simulation models to determine the costs of machinery operations. De Toro and Hansson (2004) calculated the daily soil workability based on a soil moisture model for plowing, secondary tillage, and sowing operations. These results were used as the input of a simulation model for the assessment of timeliness costs in Sweden. In another research, Savin et al. (2014) developed a profit maximization algorithm and general LP model for harvesting operation in which the loss of yield due to uncertain weather events were considered.

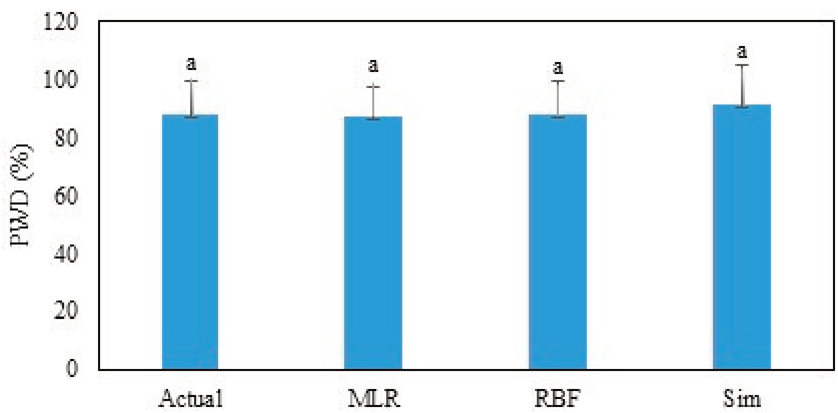

Figure 4. The comparison of three different models for determining the PWD values for tillage operation in Mashhad based on t-test

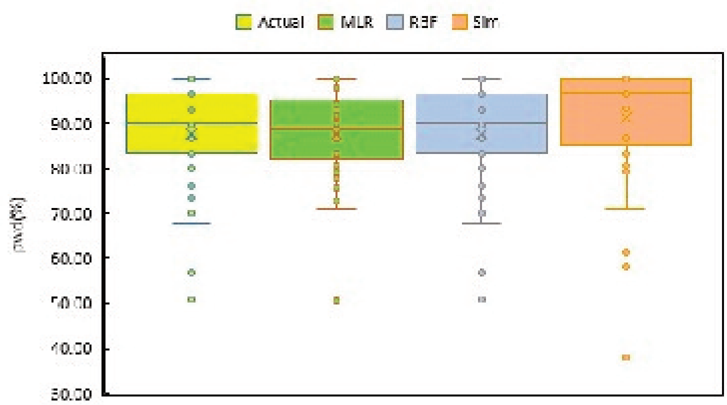

Figure 5. The comparison of the predicted PWD values for three models and actual data

CONCLUSION

The probability of working days is one of the most important parameters in agricultural machinery management, especially for the estimation of timeliness costs. This parameter is influenced by weather data such as daily temperature, rainfall, relative humidity, wind speed and so on which could be varied according to farm operation types. There are different ways to estimate PWD and we mentioned three main methods used in most research on this topic. In this research, we used the Multiple Linear Regression (MLR) and Radial Basis Function (RBF) network to estimate PWD for tillage operation in Mashhad, Iran. The performance criteria were RMSE, TSSE, MAPE, and R2. The results showed that R^2 were 0.78 and 0.99 for MLR and RBF models, respectively. The RBF model had a more acceptable performance and considered to be the best model. The results of RBF model implied that the scenario that included the maximum, minimum and average daily temperature, rainfall, wind speed and evaporation as input variables with 19 neurons and the value of 0.1 for the spread parameter exhibited the best performance among 15 suggested scenarios. Finally, the comparisons between actual and predicted data of all MLR, RBF, and soil moisture models presented that there were no significant differences between them.

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