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Predicting Auger Energy Consumption for Olive Orchards Using the Artificial Neural Networks

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Abstract: The present work aims to study the development and application of Radial Basis Function (RBF) networks for predicting auger energy consumption based on input energy. The study utilized RBF networks and explored the input energy with treatments 2 (Soil moisture content), 2 (Rotary speeds), 2 (Hole depths) and 4 (Replication) based on field operations. As indicated by the results, energy input differed between the treatments but was not significant. The highest input value in transaction soil moisture content was 14.75 %, rotary speeds of 235 rpm, and hole depths of 40 cm. In comparison, the lower input energy at transaction soil moisture content was 7.9%, rotary speeds of 235 rpm, and hole depths of 20 cm. Input energy in treatment (14.75 %, 235 rpm, and 40 cm) and treatment (7.9 %,235 rpm, and 20 cm) were 100.204 and 57.135 MJ. ha^{-1}, respectively. The highest input energy shares were recorded for diesel fuel at all treatments. Furthermore, the RBF network with one hidden layer had good convergence. The output results showed 10 and five hidden neurons in a hidden layer with high accuracy for treatment (14.75 %, 235 rpm, and 40 cm) and treatment (7.9%, 235 rpm, and 20 cm). In the treatment (14.75 %, 235 rpm, and 40 cm), the MSE for the training and testing sets was 0.0001 % and 0.01 % for data points with Ordinary RBF (ORBF type). The performance of the 3-10-1 architecture was better than other architectures. Finally, this research concluded that the RBF network method can forecast the input energy and energy expenditures related to the types of treatments.

Keywords: Auger, Hidden Layer, Human Energy, Rotary Speeds, Soil Moisture.

Introduction

Iraqi olive trees have grown in the region for more than five hundred years. Northern Iraq is the largest olive production area in the country. The latest data available from the Ministry of Agriculture, Iraq has a minimum of 600,000 fruiting trees concentrated in the Bashiqa area in Nineveh governorate, Iraq. In 2011, the Iraqi olive sector production ranged from 10,000 to 12,000 metric tons of table olives annually, constituting only 30% of domestic consumption (USAID, 2011). The current olive production reached 34.501 tons, with an annual production rate 19 kg. tree^{-1}. The Iraqi Central Statistics Office showed that olive trees came to 1.341.339 tree in northern and central Iraq (Al-Rubaie & Abdulhay, 2022). Until the last ten years, the olive has never been included as a strategic crop in the development plan for Iraqi production.

More recently, the Ministry of Agriculture recognized the potential for olive production and initiated several programs to develop nurseries to produce olive tree saplings to improve olive production practices throughout Iraq. It has distributed over one million Greek varieties of saplings to farmers to establish new groves to improve olive production practices throughout Iraq. As well as the Iraq Ministry of Agriculture (MoA) plans to plant 30 million olive trees. At the same time, the Iraqi olive industry began to grow and flourish. The farmers and the investors made plans to develop a sustainable olive oil industry. Therefore, Iraqi farmers and investors will have to the expand the olive production in the area by reducing production and packaging costs to make Iraqi olive oil more competitive with imported olive oil (Al-Rubaie & Abdulhay, 2022).

Growing olives in the fields is a slow and arduous process. Agricultural mechanization can reduce labor dependency, increase farm productivity, and hasten field operations (Balkan, 2019). The mechanical operation of olive orchard includes three to four stages such as, lining, holing for plantation, transporting the seedling from the nurseries to the farm, transporting the seedling to the planting hole, and finally planting the seedling to a hole (El-Gendy *et al.,* 2009; Lo Bianco *et al.,* 2021). Unfortunately, most of the olive cultivation operations in Iraq were done manually. For instance, the planting hole is either prepared manually with a hoe, which consuming a long time before planting the seedlings.

The most time-consuming operation for digging the planting hole was about 30.05% of the total time, whereas conveying the seedling was the least time-consuming. Introducing an auger for olives growing activities can facilitate the agricultural process, reduce the hard effort, and ensure the quality of nursery-grown plants (El-Gendy *et al.*, 2009). The hole depth and diameter by auger can well meet the standard of planting tree. The hole diameter and walls with a good verticality and quite regularly will improve the growth of the root system. It can work effectively on frozen and super hard soil, so the digging unearthed rate can achieve more than 90% (Su, 2016).

Energy consumption is the primary factor that affects crop yield. Farmers face challenges in selecting energy inputs for planting (Pokhrel & Soni, 2019). The auger consumes diesel fuel or gasoline to run the engine. However, it also uses other energy to operate, including human power and oil. In a drill, the primary factors that impact energy consumption are increasing the speed of the motor or PTO, hole cross-section, moisture content, soil strength, and hole depths (Joshi *et al.*, 2020; Khalilidermani & Knez, 2022).

Predicting is essential to model the energy consumption of the farming process. It gives the dynamic conditions of energy consumption in the agriculture operation. Recently, farmers and investors desperately need accurate forecasts. However, the current modeling of these predictions is far from convincing with these significant developments and challenges in agriculture. There is no well-defined forecasting method that considers the variables that drive the yield (Al-Rajabo *et al.,* 2021).

In a non-linear model, the problem becomes more complex when there are additional independent variables. In light of the complexity of these relationships, traditional data-processing techniques cannot satisfactorily investigate the process and product parameters because of non-linear relationships among the variables (Hilal *et al.,* 2021). Non-parametric model methods can address this issue as they are powerful predictive tools.

The popularity of artificial intelligence is related to its great benefits over conventional models. The use of models has increased rapidly over years, in a wide range of sectors (private strip, research, and government) and many various areas of application (natural sciences, agriculture and water management, energy and renewable energy, etc.). RBF is a branch of the science of science artificial intelligence and is a tool that to solve the problems, especially in fields that involve clustering and pattern recognition (Mirjalili, 2019; Kamir *et al.,* 2020). RBF networks are using calculations easier, so this method can learn faster and have a smaller error than the other neural networks (Rocha & Dias, 2019).

Exploratory research on auger processes and artificial intelligence revealed little research has published on the olives orchards. As indicated in the review, no study has been published in relation to energy analysis through using RBF neural networks, particularly about Iraqi olives planting. The objectives of this project were to (1) develop an RBF neural network model to predict energy consumption based on rotary speeds, hole depths, and soil moisture content, and (2) quantify the input energy for the auger processes based on the olives fields.

Materials & Methods

Experiments Site: The field investigations were conducted on an experimental plantation in Nineveh province, Iraq. These farms are located within 43°15'52.02"E longitude and 36°30'27.85"N altitude, as displayed in fig. (1). The soil texture at the site of experiment was a Loam (44.05 Sand, 14.45 Clay, and 41.5 Silt) and a soil pH of 7.6. Average climate characteristics during the experimental period are given in table (1).

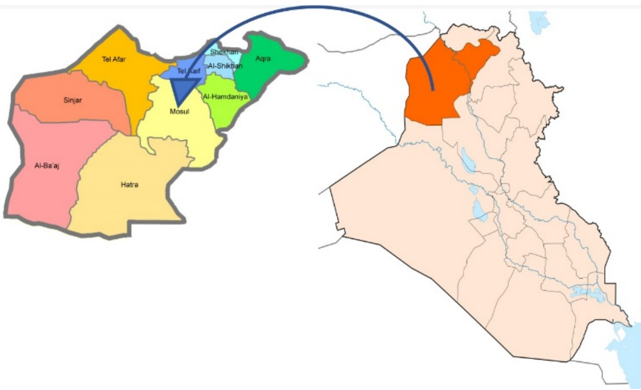

Fig. (1): The study sites (43°15'52.02"E, 36°30'27.85"N)

Table (1): Average monthly climate in most areas (World Weather Online, 2017–2021)

	Nineveh			
	Temperatures (°C)	**Precipitation (mm)**	**Average cloud (%)**	**Average Humidity (%)**
Jan	10	257.5	40	62
Feb	11	180.7	43	62
Mar	13	341.3	50	66
Apr	25	166.3	43	58
May	30	21.5	16	33
Jun	40	0.8	5	19
Jul	48	0	1	18
Aug	46	0	0	16
Sep	34	0.98	2	17
Oct	27	113.2	34	33
Nov	17	113.4	41	56
Dec	10	316.8	49	68

Olive machine and experimental design

The earth auger was selected according to considerations to be given to local olive patterns, timeliness factor of the olive cultivation area, soil type, farm size, plot size, and some different conditions. The study was conducted at one farm with one treatment of other olive planting methods. The number of 240 holes per hectare was chosen according to the cultivation method used in the region (Fig. 2). The auger specification was used for holes as described in table (2).

Fig. (2): Auger used in the field experiments.

Table (2): The specifications of earth auger.

Model No	GT-4350
Engine model	1E44F-5
Engine type	Single cylinder, air-cooling, 2-stroke
Gasoline, 2-cycle oil mixture ratio	58CC
Ignition system	C.D.I
Power	4.5kw
Fuel tank capacity	1.2L
Auger size (max)	300mm
G.W/N.W (without auger bit)	10.8Kg.9.7Kg^{-1}

The field layout's Randomized Complete Block Design (RCBD) was taken. The subjects were taken as blocks. The experiment field is divided into uniform units to account for any variation so that observed differences are mainly due to actual differences between treatments. The treatments (2×2×2×4) (Soil moisture content, Rotary speeds, Hole depths, and Replication) were randomized to minimize the effects of variation of different treatments due to other field conditions. The SAS® Visual Data Science Decisioning experiment was used to analyze the experiment's statistical package and statistically significant differences between the mean values (p-value 0.05).

Input energy data

This study estimate the energy consumed to dig a pit for planting olives has been assessed. The input energy was used to develop energy prediction models and select the essential variables in the energy utilized in Iraqi olive production. The input data was converted into forms of energy for the evaluation of the input analysis as presented in the equations (Table 3). Energy consumption for human labour, fuel, and lubricating oil was calculated per total hectare basis in each olive farm.

RBF Modelling: The RBF procedure treats the target vector ($Y^{(m)}$) as the dependent variable and the input vector (predictors, $X^{(m)}$) are factors.

$$X^{(m)} = X_1^m, \ldots\ldots x_P^{(m)}\ Input\ vector\ , patern\ m, m = 1, \ldots\ldots M.$$

$$Y^{(m)} = Y_1^{(m)}, \ldots\ldots y_R^{(m)}\ Target\ vector\ , pattern\ m.$$

The RBF neural network consists of three layers, including an input layer, an output layer, and a hidden layer called the radial basis function layer (Wu *et al.* 2021):

1- Define variables in the input layer: J_0=P units, $a_{0:\ 1\ldots}$, $a_{\ 0:\ J0}$; with $a_{\ 0:\ j}=x_j$.

2- Hidden layer**:** J_1 units, $a_{1:\ 1\ldots}$, $a_{1:\ J1}$; with $a_{1:}\ j=\varphi_j(X)$ and $\varphi_j(X)$.

3- Define variables and equation in the output layer:

J_2=R units, $a_{I:\ 1\ldots}$, $a_{\ I:\ J2}$; with: $a_{I:r} = w_{r0} + \sum_{j=1}^{J1} w_{rjQJ}(X)$. (2.1)

Ordinary RBF (ORBF) and Normalized RBF (NRBF) are two distinct types of Gaussian RBF architectures. In NRBF networks, the foundation function takes the form:

$$\varphi_j\left(X\right)=\exp\left(-\sum_{p=1}^{P}\frac{1}{2\sigma_{jp}^2}(x_p-\mu_{jp})^2\right)/\sum_{j=1}^{J_1}\exp\left(-\sum_{p=1}^{P}\frac{1}{2\sigma_{jp}^2}(x_p-\mu_{jp})^2\right) \quad (2.2)$$

As well, in ORBF, the Gaussian foundation function takes the form:

$$\varphi_j\left(X\right)=\exp\left(-\sum_{p=1}^{P}\frac{1}{2\sigma_{jP}^2}(x_p-\mu_{jp})^2\right)$$

(2.3)

The default RBF network settings and basic specifications as shown in fig. (3).

Table (3): Energy consumption equations and references

Equations	Energy equivalent references
Human energy = Farm labor hours x equivalent human energy input for a typical worker ($MJ.h^{-1}$)	(Ghasemi-Mobtaker *et al.,*2020)
Fuel energy = Fuel consumption by auger (l) x Energy equivalent ($MJ.l^{-1}$)	(Kitani & Jungbluth, 1999)
Oil energy = Oil consumption by auger (l) x Energy equivalent ($MJ.l^{-1}$)	(Al-Rajabo *et al.,* 2021)

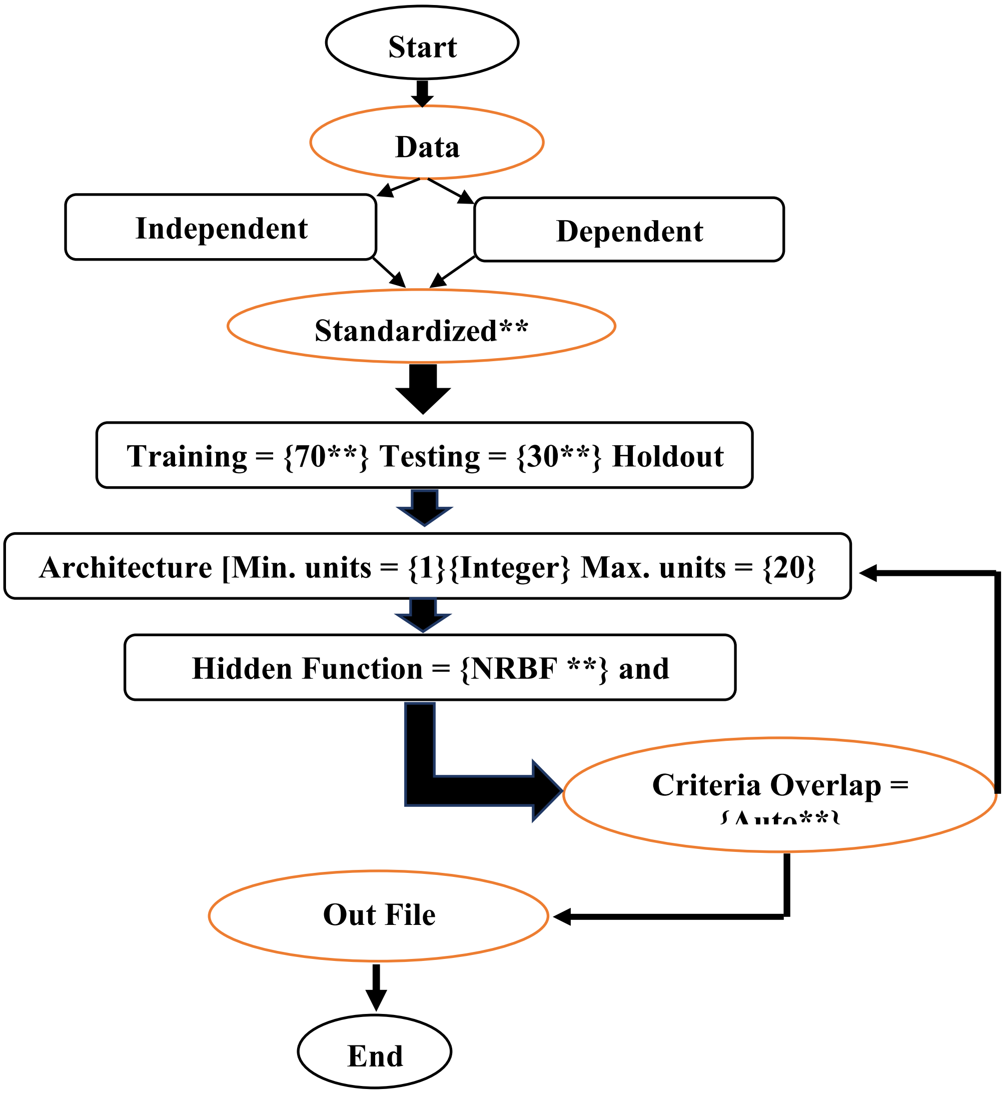

Fig. (3): Neural network settings (default settings in the program)**

Results & Discussion

Analysis of energy inputs used in digging a pit for olive cultivation

Three factors were statistically tested in the research work and the results drawn from these constitute the findings according to the overlapping transactions, as shown in table (4). The first factor speculated that soil moisture content would significantly affect work olive cultivation (fuel consumption, human labor, oil consumption). These results corroborated the finding of (Alzoubi *et al.*, 2020), who conducted a study on soil moisture content and found that soil moisture would play a significant role in determining energy consumption in an agricultural field.

The second result is that rotary speeds will not be a statistically significant factor affecting fuel and oil consumption. In contrast, rotary speeds played an essential element in human labor because auger rotation speeds significantly affected the effort of human labor. On the other hand, the result is that hole depths will be a statistically significant factor influencing the energy consumption of olive cultivation. These results are in line with Meselhy (2021) results, who found that a variable-depth tillage system has affected energy requirements.

Table (4): ANOVA for the energy input.

Source	DF	Fuel consumption MJ		Human labor MJ		Oil consumption MJ	
		F Value	Pr > F	F Value	Pr > F	F Value	Pr > F
Soil moisture content (a)	1	30.83	<.0001	383.82	<.0001	30.88	<.0001
Rotary speeds (b)	1	0.19	0.6645	196.23	<.0001	0.17	0.6828
Hole depths (c)	1	17.56	0.0004	412.17	<.0001	17.64	0.0004
block	3	0.39	0.7613	2.91	0.0587	0.38	0.7667
axb	1	2.66	0.1177	22.76	0.0001	2.69	0.1162
axc	1	6.38	0.0197	46.26	<.0001	6.37	0.0197
bxc	1	0.31	0.5859	0.00	1.0000	0.34	0.5655
axbxc	1	3.48	0.076	0.09	0.7637	3.55	0.0735
Error	21	MSE=167e-5		MSE=1.2e-7		MSE=3.52e-7	
Total	31						

Input energy types in digging a pit for olive cultivation by soil moisture content, rotary speeds, hole depths, and energy equivalents are shown in fig. (4). Diesel fuel consisted of the highest energy share of total energy input, followed by human labour and oil consumption. Input energy for diesel fuel was lower with the treatment of soil moisture content 7.9%+ rotary speeds 235 rpm + hole depths 20cm than soil moisture content 7.9%+ rotary speeds 335 rpm + hole depths 40cm. In treating soil moisture content of 14.75%+ rotary speeds 235 rpm + hole depths 40cm, diesel fuel (0.372 MJ) consisted of the highest energy share of total energy input. The most human labour energy for augers in the treatments of soil moisture content is 7.9%. According to fig. (4), energy shares for treatment of soil moisture content of 7.9%+ rotary speeds 235 rpm + hole depths 40cm and treatment of soil moisture content of 7.9%+ rotary speeds 235 rpm + hole depths 20cm showed the highest from total human labour. The treatment of soil moisture content 14.75%+235rpm+40cm + rotary speeds 235 rpm + hole depths 40cm was the highest from oil energy used in olive cultivation. Ozpinar (2022) showed that olive cultivation utilized a high level of required diesel fuel energy, especially in intensive systems, due to machinery being extensively used for soil tillage, spraying, transportation, weed control, pruning, harvesting.... etc.

Table (5) indicates no significant differences in all treatments included in the study. The total energy input for treatment (14.75%, 235rpm, and 40cm) in an olive pit was 100.204 MJ. $ha^{-1,}$ in which the highest shares were recorded for diesel fuel, human labor, and oil consumption, respectively (table 5).

Treatment (14.75%, 235rpm, and 40cm) was used for diesel fuel (89.4348 MJ. ha^{-1}), consisting of the highest energy share of total energy input, followed by human labor (6.6542 MJ. ha^{-1}) and oil consumption (4.1148 MJ. ha^{-1}). The consumption of diesel referred to soil cultivation, weed control, and harvesting are the cultural practices that require more fuel (Cappelletti *et al.,* 2014).

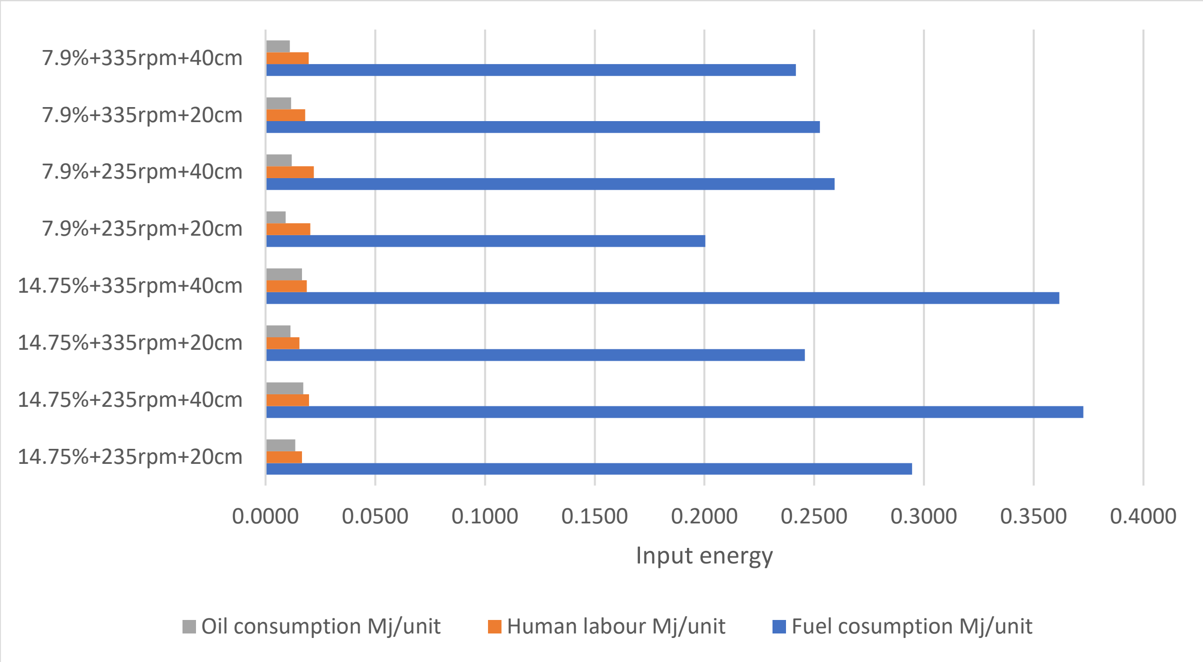

Fig. (4): Analysis of energy inputs used in an olive pit.

The lowest input energy value was recorded when the soil moisture content of 7.9 % interfered with the rotary speeds of 235 rpm, hole depths 20 cm, and reached 57.135 MJ. ha^{-1}. This treatment was used for diesel fuel, human labor, and oil consumption of 48.0851, 6.8371 and 2.2123 MJ. Hectare^{-1} of an olive pit, respectively. The results also showed that the lowest input energy of human work was recorded when the soil moisture content of 14.75 % interfered with the rotary speeds of 335 rpm, hole depths 20 cm, and reached 5.1679 MJ. ha^{-1}. Rajaeifar *et al.* (2014) studied the total energy consumption through the olive oil life cycle was 20 344 MJ.ha^{-1}, and expanding the use of machines results indicated that the total energy consumption was 8035 MJ. ha^{-1}. The results showed that the total energy input and output were 23 568 MJ ha−1.

Table (5): Analysis of total energy inputs used in an olive pit

Soil moisture content %	Rotary speeds rpm	Hole depths cm	Fuel consumption MJ. ha^{-1}	Human labour MJ. ha^{-1}	Oil consumption MJ. ha^{-1}	Total energy MJ. ha^{-1}
14.75	235	20	70.7026	5.5566	3.2529	79.512
14.75	235	40	89.4348	6.6542	4.1148	100.204
14.75	335	20	58.9680	5.1679	2.7130	66.849
14.75	335	40	86.8140	6.2883	3.9942	97.097
7.9	235	20	48.0851	6.8371	2.2123	57.135
7.9	235	40	62.2440	7.4029	2.8638	72.511
7.9	335	20	60.6060	6.0597	2.7884	69.454
7.9	335	40	57.9852	6.6085	2.6678	67.261

RBF networks models

Determine the optimum value of each parameter of a neural network by keeping the other parameter constant, is assumed different data for that parameter. In each case, the average value of error is calculated. Finally, the result with minimum error gives us optimum parameters. The most popular method for calculating error in RBF is Mean Square Error (MSE) (Pattanaik & Mohanty, 2022). The algorithm adjusts the biases and weights of the neural network to minimize the MSE. In the present research, the MSE is adopted to determine the error of the resulting models. As shown in figs. (5 - 8), the network was trained in two distinct Gaussian RBF architectures, Ordinary RBF (ORBF) and Normalized RBF (NRBF). It is obvious from these figures that the value of MSE in very high iterations is almost constant. This process took a short time, and the variation of MSE was too slight. In order to solve this problem and improve generalization, early stopping is a need.

It is evident in fig. (5) that the value of MSE is dropped very fast and suddenly from 0.078 to 0.0001, in Ordinary RBF (ORBF)and from 0.3 to 0.016 in Normalized RBF (NRBF). It was evident from this figure that for small training sets, convergence is perfect, also very fast, and error on the training set is driven to a small value. Still, the resulting error is significant when an increasing number of hidden neurons is presented to the network. The network has begun overfitting and has memorized the training examples (Wu *et al.* 2021).

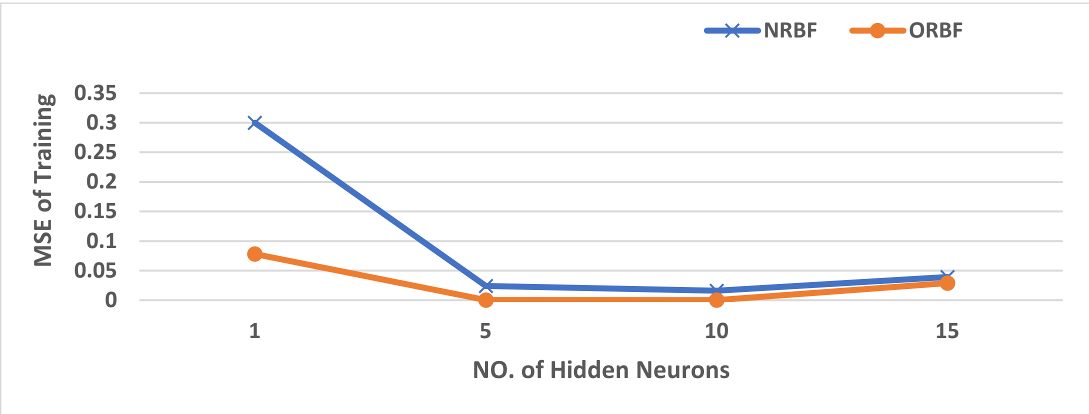

Fig. (5): MSE of training versus the number of hidden neurons in treatment (14.75%, 235rpm, and 40cm)

In the present case, good convergence could not be achieved after a few trials with the network with 5 to 10 hidden neurons. However, good convergence has been completed for treatment in a network with ten hidden neurons in ORBF (14.75%, 235rpm, and 40cm). Fig. (6) shows a variation between the MSE of testing and different numbers of hidden neurons. This research-based on the above observation decided to select the number of hidden neurons equal to 10 in both types of RBF. The training results of the architecture of the RBF model were shown after the models had been successfully built and trained.

The results in figs. (5 and 6) show that ORBF used the training with three inputs (10) neurons in hidden layers (1) output architecture has the best performance in obtaining the network model compared with other training in treatment (14.75%, 235 rpm, and 40 cm). The best mean value of MSE was close to zero. In addition, the performances of this model were virtually independent of the differences among the quantities of neurons in the hidden layers (Mirjalili, 2019). Based on the evaluations summarized in fig. (7), the training error was reduced by increasing hidden neurons. A large number of hidden neurons driving a neural network can easily memorize the correct response to each pattern in its training set rather than learning a general solution. Therefore, there must be a critical number of hidden neurons to reduce the error rate. Figs. (7 and 8) show the effect of different numbers of hidden neurons on the MSE of training and testing. As a result of training, figs. (7 and 8) show the best RBF models are obtained at 5 of a hidden neuron with the Normalized RBF type to consider the lagged values of both dependent and independent variables that have been considered for model building in the treatment (7.9%, 235rpm, and 20cm). In these, it can be seen that with an increasing number of hidden neurons, MSE is decreased, but variations in MSE values for more than 5 neurons increase. Wu *et al.* (2021) concluded that the prediction ability of the RBF is closely related to its number of artificial neurons. Therefore, the impact of the number of neurons on the prediction performance of the RBF model is investigated. On the other hand, utilizing more than 15 neurons in a network makes the computation process complicated and expensive in terms of time. Accordingly, both MSE in ORBF were more than NRBF in the treatment (7.9 %, 235 rpm, and 20cm).

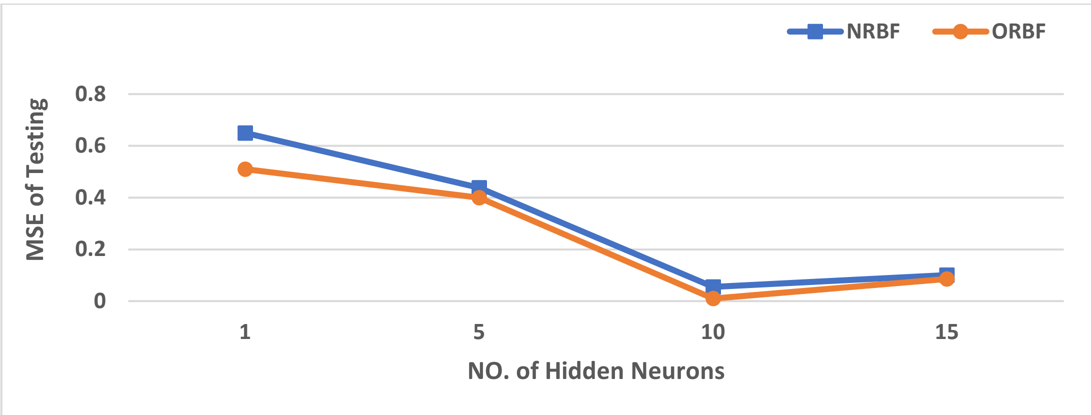

Fig. (6): MSE of testing versus the number of hidden neurons in treatment (14.75%, 235rpm, and 40cm).

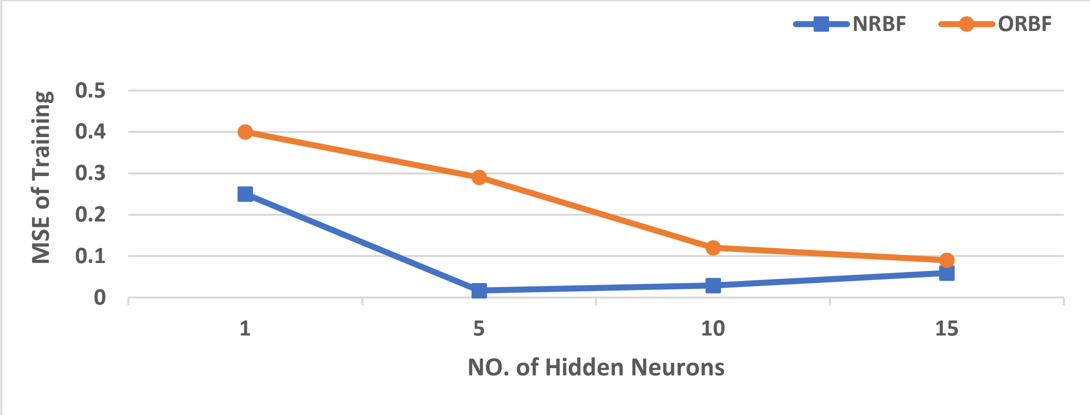

Fig. (7): MSE of training versus the number of hidden neurons in treatment (7.9%, 235rpm, and 20cm)

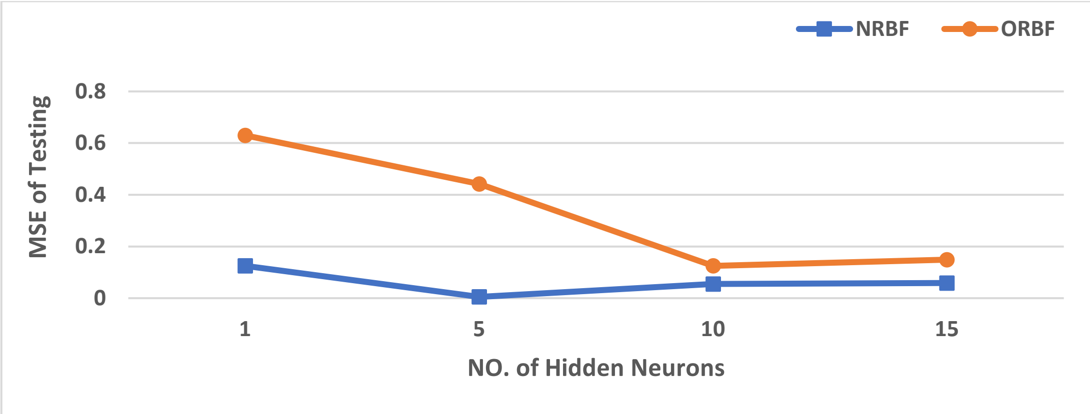

Fig. (8): MSE of testing versus the number of hidden neurons in treatment (7.9%, 235rpm, and 20cm)

Conclusions

A detailed study was carried out, considering one hidden layer and four numbers of hidden neurons for the architecture of the RBF net. The ORBF with 3-10-1 architecture performed was better than the other architectures for transaction soil moisture content was 14.75%, rotary speeds of 235rpm, and hole depths of 40cm. In this case, the MSE was lower than in another case. Errors in another case were high; this can be due to overgeneralization during training. Moreover, this study examined the effects of different agriculture treatments on energy indices. Treatment (14.75%, 235 rpm, and 40cm) resulted in the highest input energy, and treatment (7.9%, 235rpm, and 20cm) in the lowest. Consequently, the accurate model can be improved by using RBF networks for predicting auger energy and managing the energy used to reduce production costs and maintain energy inputs.

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Contributions of authors

O.M.M.T.: Conceptualization, methodology, resources, and data curation

Y.Y.H.: Software, validation, formal analysis, investigation, writing original draft preparation, writing review, and editing,

H.A. H.: Visualization, supervision, project administration and funding acquisition

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Conflicts of interest

The authors declare no conflict of interest.

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التنبؤ باستهلاك طاقة الة حفر جور لحقول الزيتون باستخدام الشبكات العصبية الاصطناعية

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المستخلص :يهدف العمل الحالي إلى دراسة تطوير وتطبيق شبكات دالة الأساس الشعاعي (RBF) للتنبؤ باستهلاك طاقة الة حفر الجور بناءً على مدخلات طاقة. استخدمت الدراسة دالة الأساس الشعاعي وتم تقدير طاقة المستهلكة عن المدخلات التي شملت محتوى رطوبة التربة وسرعات دوارة الة حفر الجور وأعماق الحفرة وبواقع اربع مكررات بناءً على العمليات الميدانية. يتضح من النتائج ، اختلفت مدخلات الطاقة بين المعاملات ولكنها لم تكن معنوية . سجلت أعلى قيمة مدخلات الطاقة عند المحتوى الرطوبي للتربة (14.75٪) ، وسرعة دورانية (235 دورة/الدقيقة) ، وعمق حفرة (40 سم). بينما كانت اقل طاقة للمدخلة عند المحتوى الرطوبي للتربة(7.9٪)، وسرعة دورانية (235 دورة/الدقيقة) ، وعمق الحفرة (20 سم) وسجلت كلا المعاملتين مدخلات الطاقة بمقدار 100.204 و 57.135 ميجا جول لكل هكتار على التوالي. تم تسجيل أعلى حصة من الطاقة المدخلة لوقود الديزل في جميع المعاملات. علاوة على ذلك ، فإن شبكة RBF ذات الطبقة المخفية الواحدة لديها تقارب جيد وأظهرت نتائج ان 5 و10 خلايا عصبية مخفية سجلت دقة عالية لكلا المعاملتين (14.75٪ ، 235 دورة في الدقيقة ، 40 سم) و (7.9٪ ، 235 دورة في الدقيقة ، 20 سم). وكان اقل خطا عند مجموعة التدريب والاختبار لمعاملة (14.75٪ ، 235 دورة/الدقيقة، و 40 سم) وبمقدار 0.0001٪ و 0.01٪ على التوالي. سجل هيكل الشبكة العصبية لدالة الأساس الشعاعي 3-10-1 أفضل اداء مقارنة مع الهياكل الشبكات الأخرى. أخيرًا، خلص هذا البحث إلى أن الشبكة العصبية ذات دالة الأساس الشعاعي يمكن أن تتنبأ بمدخلات الطاقة المستهلكة الى الة حفر الجور وعند جميع المعاملات الدراسة.

الكلمات المفتاحية: الة حفر الجور، الطبقة المخفية، الطاقة البشرية، سرعة الدوران، رطوبة التربة.