



ANALYSIS AND MODELING OF ENERGY INPUTS IN GREENHOUSES FOR DIFFERENT CUCUMBER VARIETIES

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ABSTRACT

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Cucumber is cultivated extensively in greenhouses and open fields worldwide, and is a key crop for greenhouse farmers in Iraq. This study aimed to analyze energy consumption and apply an Artificial neural network model (ANN) to predict the yield of three cucumber varieties: NEDDAL F1, SUPER HERO F1, and TOP GREEN F1, in Nineveh Governorate. The experiment was conducted in 18 greenhouses, and data collected included the types of equipment used in cucumber cultivation, working hours, fuel, number of workers, agricultural practices, fertilization methods, and pest control. The results showed that the total energy consumption for cucumber cultivation was 6251.88, 6201.88, and 6251.88 MJ house⁻¹, while the energy output was 4400, 5326.3272, and 5014.08 MJ house⁻¹ for the three varieties, respectively. Fertilizer and electricity consumption are key variables in cucumber cultivation, representing the highest energy inputs at 42% and 20%, respectively. The results showed that a neural network model is useful in predicting the energy output of three cucumber varieties, the minimum MSE and the highest R-value of model calibration were obtained by combining the LM training, the 10 and 12 of a hidden neuron, using the 25-10-1, 25-12-1, and 25-10-1 ANN architectures with LM training and a Log-sigmoid transfer function in NEDDAL F1, SUPER HERO F1, and TOP GREEN F1, respectively. The study demonstrated that the trained models achieved the lowest error rate, indicating the experimental model's ability to predict cucumber yield in Nineveh Governorate.

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INTRODUCTION

Protected agriculture, particularly greenhouses, is becoming increasingly widespread as a key approach to addressing global challenges such as population growth, water scarcity, and climate change. These structures offer precise control over weather conditions, enabling year-round production of high-quality crops and increased yields per unit area. However, these advantages come with high energy demands (Gruda *et al.* 2019; Batke *et al.*, 2026). Energy input estimation models are essential analytical and predictive tools for understanding and evaluating the energy efficiency of this complex system (Hanoum *et al.*, 2026). These mathematical and computational models allow for the simulation of greenhouse operations under various climatic and management conditions, enabling farmers and project planners to: (1) Assess environmental returns: calculate the carbon footprint and energy

efficiency of agricultural output. (2) Optimize economics: determine the equilibrium point between energy costs and returns to maximize profitability. (3) Plan for the future: assist in selecting the most suitable project sites, climate control systems, and thermal insulation technologies. (4) Foster innovation: virtually test the effectiveness of new technologies (such as geothermal heat exchangers or solar panels) before their costly field implementation (Chen and You, 2026; Amami *et al.*, 2026).

Despite significant advancements in greenhouse construction, a clear research gap remains in this field, which can be summarized as follows: The field still lacks integration with comprehensive designs. There is also a weakness in the simulation of smart systems and renewable resources (Laafer *et al.* 2026). Farmers and investors urgently need designs that can simulate the integration of energy sources in response to greenhouse needs and evaluate their feasibility under varying weather conditions. Furthermore, it often overlooks regional and climatic variations. (Golzar *et al.* 2018).

Energy productivity is used exclusively to indicate a unit of product per unit of energy applied, diverted, or depleted. Mostly, this term also refers to the agricultural production of each unit of land and the energy unit. The purpose of this definition is to measure the current performance of these resources and propose paths to improve productivity. The aims of the energy productivity analysis range from the assessment of agricultural production (tons of yield per unit of energy to the input of a crop in a field) to assessing the additional welfare of each group of input energy used in the agricultural sector. Since expressions of energy productivity vary in each context, it is essential to be clear about cucumber farming inputs and terms used (Kargwal *et al.*, 2022). Cucumber productivity depends on various factors, which include labor, electricity, fuel, seeds, different fertilizers, water, management factors, etc. Raising cucumber productivity denotes increasing the productivity of crops per unit of the level of other inputs consumed, but with the decline in the growth of tree yields globally, attention has shifted to the potential provided by improved management of input resources (Zhanbota *et al.*, 2021, Rashidi *et al.* 2024; Dekamin *et al.* 2025).

Environment and energy are two sides of the same coin. If energy use goes up anywhere, the environment will also be harmed more. People agree that burning fossil fuels releases greenhouse gases that cause air pollution, acid rain, and, most importantly, global climate change. Agriculture makes energy and then uses it. It uses a lot of energy that is available in the area, like seed, manure, and animal energy, both directly and indirectly. Fuels like diesel or gasoline, human power, fertilizers, and chemicals are all examples of direct energy. Indirect energy is released directly into the source of energy that is not directly put into agricultural activity, but is released through a conversion process. Machinery is an example of an indirect source of energy. Energy input for machinery is the energy needed to make the machine, not the energy needed to run it. Energy to run the machines can be thought of as energy input from people working (Nag and Gite, 2020; Hilal *et al.* 2023).

The primary obstacle in modeling cucumber yield and energy use is the difficulty of deriving the constants from the mathematical models. Because these linkages are so complicated, typical data-processing methods can't look into the process and product characteristics well enough because the variables don't have linear relationships. This problem can be solved with non-linear approaches because













they are very good at making predictions. Neural Networks (NNs) are a model-free way to estimate non-linear (accommodating multivariate) and non-parametric data (Musumeci *et al.* 2018). Exploratory research on artificial intelligence has shown that not much has been done on the yield of cucumbers and how much energy they use. NNs are a collection of different methods that were made to fulfill the different needs of forecast modeling. Neural networks can reliably predict intricate, nonlinear interactions, which is not the case with classic regression-based methods. The idea of NNs comes from the human brain, which has billions of neurons that are connected through synapses. Three important things about NNs are that they can learn, work in parallel, and generalize. The human brain is very parallel because each neuron can talk to many others at the same time (Koch,2025). The parallelism is perfect for difficult jobs like pattern recognition, which would be considerably harder to do in a series. NNs are set up in a way that makes them great for pattern recognition and other uses that can take advantage of parallelism. Another big plus for NNs is that they can learn by practicing. Training means giving the NN a lot of training samples, each of which has a set of inputs and the outputs that are expected. Researchers from several fields are very interested in neural networks because they can learn and generalize quickly. They use them to create and evaluate experimental data (Samek *et al.*2021). The major objectives of the research are to analyze and develop a NN model for predicting cucumber yield and energy consumption. The specific objectives are to develop and propose the preferred ANN architectures for the prediction of cucumber yield and output energy in greenhouses for different cucumber varieties, and to explore the input and output energy that will lead to the maximum cucumber production in northern Iraq.

MATERIALS AND METHODS

Collection of Input and output data for energy models

The input and output energy data were used for the development of models to predict output energy based on energy consumption in cucumber production operations in North Iraq. Energy consumption is defined as the energy used for the production of a cucumber until it leaves the greenhouses. The typical analysis of energy input and output is carried out by the direct and indirect energy sources. Identifying the data needed to determine key agricultural inputs and outputs requires a comprehensive survey design. Methods previously employed by researchers were carefully reviewed, and the most suitable for defining critical agricultural parameters was selected. Therefore, a series of experiments was conducted in 18 greenhouses (6 greenhouses for each cucumber variety), as shown in Table 1. The total data for each greenhouse consisted of 25 inputs and 1 output. Data were collected from February to June 2025. This study estimates the energy required for the on-farm production systems before the post-harvest stages. The energy consumption for cucumber production processes does not account for energy sources derived from renewable energy. In this study, direct energy was analyzed in the farm operations that include human power, diesel fuels, chemical fertilizers (Nitrogen, Phosphate, Potassium, Nutri gel calcium, Organic fertilizer, Humic acid, Liquid amino fertilizer and micronutrient fertilizer), electricity, water for irrigation, and seed. The direct energy source refers to the energy directly involved in performing an agricultural activity.

Table (1). Energy equivalent to estimating energy inputs and outputs

 Diesel fuel	L	56.31	Taki <i>et al.</i> (2018)
 Nitrogen	kg	66.14	Mostashari-Rad <i>et al.</i> (2019)
 Water for irrigation	M3	1.02	Karimi <i>et al.</i> (2008)
 Phosphate(P2O5)	kg	12.44	Mobtaker <i>et al.</i> (2012)
 Potassium (K2O)	kg	11.15	Unakitan and Aydn (2018)
 Micro fertilizers	kg	120	Mostashari-Rad <i>et al.</i> (2021)
 Pesticide	kg	199	Trotta (2019)
 Electricity	kWh	11.93	Naderi <i>et al.</i> (2019)
 Seed cucumber	kg	1	Rashidi <i>et al.</i> (2024)
 Machinery	hr	62.7	Azawi <i>et al.</i> (2024)
 Output	kg	0.8	Taki <i>et al.</i> (2018)
 Human labor	hr	1.96	Rashidi <i>et al.</i> (2024)

On the other hand, the indirect source of energy implies the energy source used via a conversion process, such as energy consumed through machinery and diesel fuel used in transporting the seeds and fertilizers. The energy consumption and output energy were calculated per total hectares' basis in each region, and these data were then converted to forms of energy for the evaluation of the output-input analysis. Energy equivalents shown in Table 1 were used for predicting output energy in cucumber production. The total input energy equivalent can be calculated by adding up the energy equivalences of all inputs in megajoules (MJ).

The total equivalent input energy is determined by fuel, human labor, water for irrigation, chemical fertilizers, electricity, micro fertilizers, seed cucumber, machinery, and pesticide consumption per operation for the greenhouse area, as shown in the equations in Fig. 1. The energy use efficiency, specific energy, energy productivity, and net energy were calculated according to the equations described in Mousavi *et al.* (2023), and Rashidi *et al.* (2024), respectively.

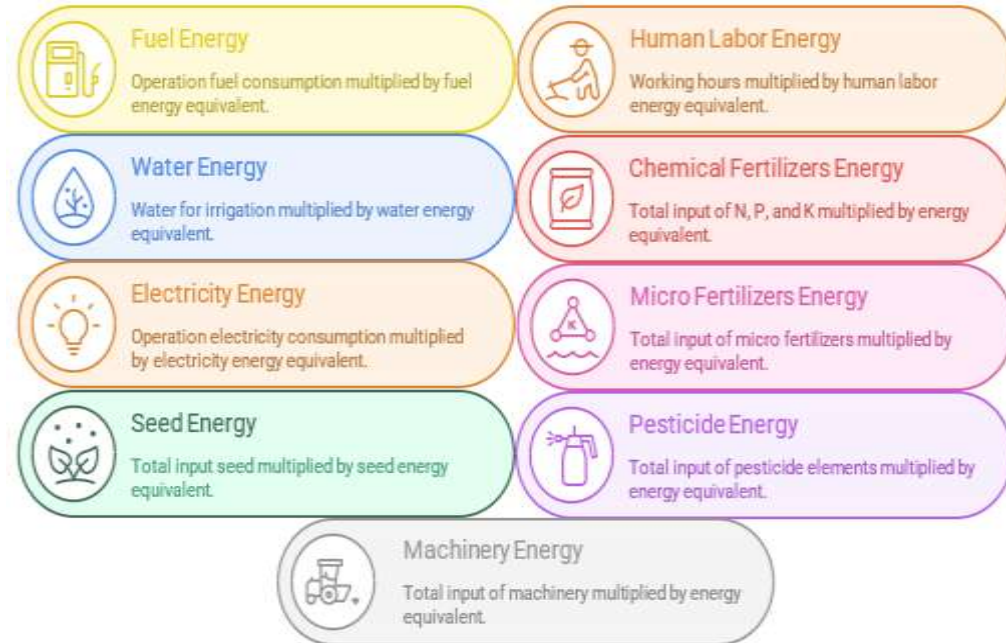


Figure (1). Equations for calculating the equivalent energy inputs for cucumber farming operations

Validation and exploration of data

After the data is gathered and sent to the spreadsheets, the next steps are to check and process the data that was received. Data validation is the process of checking all the data collected to ensure it is complete, makes sense, and free of errors (Mishra and Datta-Gupta, 2017). This step turns raw data into validated data that is then processed to make the summary reports needed for analysis. There are three main types of data processing: data exploration, data cleaning, and data transformation. Data cleaning is necessary in this study because the data analyzed by data mining techniques can be incomplete, inconsistent, and erroneous; for example, certain tuples may require inference due to missing values for specific attributes (Demuth *et al.*, 2014). Therefore, data cleaning tasks: (i) fill in missing values, (ii) identify outliers and smooth out noisy data, (iii) correct inconsistent data, and (iv) resolve redundancy caused by data integration.

Development of ANN Models for Crop Yield and Energy

The model built in this study falls into the category of prediction. It may be classified into modeling using an ANN to predict crop yield and energy in cucumber production. The ANN method is expected to provide a better prediction of cucumber production as a function of the characteristic parameter. The non-linear nature, which is the strength of other artificial neural networks, can overcome the shortcomings of

conventional methods that are cumbersome and unpopular when entering the non-linear model.

In this study, several network structures were examined to find the best model. Specifically, the influence of (i) the number of neurons at input layers, (ii) the number of neurons at hidden layers, (iii) the learning algorithm (training function), (iv) the type of transfer function in each neuron in the hidden layers and the output layer in the model. Types of network structure were studied to approximate the actual cucumber yield and energy output.

The research was conducted in four phases, as follows:

1. The ANN model was constructed under 25 types of input. The output targets were plantation productivity and output energy, as shown in the figure. 2.
2. The optimal model was obtained through the learning of the neural networks. The proposed ANN model used in this work employed two supervised training algorithms, namely, Levenberg–Marquardt (LM), and resilient BP (RP). These algorithms were used to evaluate suitability.
3. Multiple layers of neurons with nonlinear transfer functions enabled the network to learn nonlinear and linear relationships among the input and output parameters. The linear output layer enabled the network to take any value, even those outside the range of -1 to $+1$. Meanwhile, the outputs of the network were in a limited range when the last layer of a multilayer network possessed sigmoid neurons. The weights and bias on these links are referred to as input-hidden layer weights and bias. Using the following equation (Du and Swamy, 2013).

$$v = \sum_{i=1}^m (w_{i_{input}} * x_i) + \beta_{i_{input}} \dots \dots \dots 1$$

This represents the amount inclusive of the values of the variables involved, multiplied by weights in addition to the value of bias.

$$net = \beta_{i_{output}} + \sum_{i=1}^n (v_i * w_{i_{output}}) \dots \dots \dots 2$$

Where i input neurons, m neurons in the first hidden layers, n neurons in the second hidden layers, w_i is the weights representing the strength of the connection between the node and β_i is the bias associated with the node.

4. The models were tested. The step model test is a method for testing the weight obtained at the time of training. The consistency of the best models acquired during the training process was verified through the use of different input data. In this research, we used two transfer functions, namely, log-sigmoid (LS) and tangent-sigmoid (TS).

The final part of the neural network, that is, the function approximation (regression), included the sigmoidal function, log-sigmoid, and tan-sigmoid (Kyurkchiev and Markov, 2015). The most popular transfer function for a nonlinear relationship is the sigmoidal function (Schmidhuber, 2015). The general Log-sigmoid form of this function is indicated below:

$$y_{FFB} = \frac{1}{1 + e^{-net_{FFB}}} \dots \dots \dots 3$$

The general Tan- a sigmoid form of this function is indicated below:

$$y_{FFB} = \tan \text{sig}(\text{net}) = \frac{2}{(1 + \exp(-2 * \text{net}_{FFB}))} - 1 \dots \dots \dots 4$$

After training a random sample (70%) for training and a sample (15%) for cross-validation, the latter was used for testing. Then 6, 10,12 and 14 hidden nodes were suggested for this network topology.

5. ANN model simulation was performed.

The network and simulation performances were evaluated, and the acceptable results were finally obtained. In this work, the following performance measurement functions were employed:

1. Mean square error (MSE):

$$MSE = \frac{1}{N} \sum_1^N (XI - YI)^2 \dots \dots \dots 5$$

2. Coefficient of correlation (R).

The best ANN model simulations using hypothetical data were conducted to forecast energy and to examine the effects of input data on the productivity of cucumber plantations. ANN programmers were using MATLAB's Neural Network Toolbox (Haykin,2009; Erdemir and Ayata,2017).

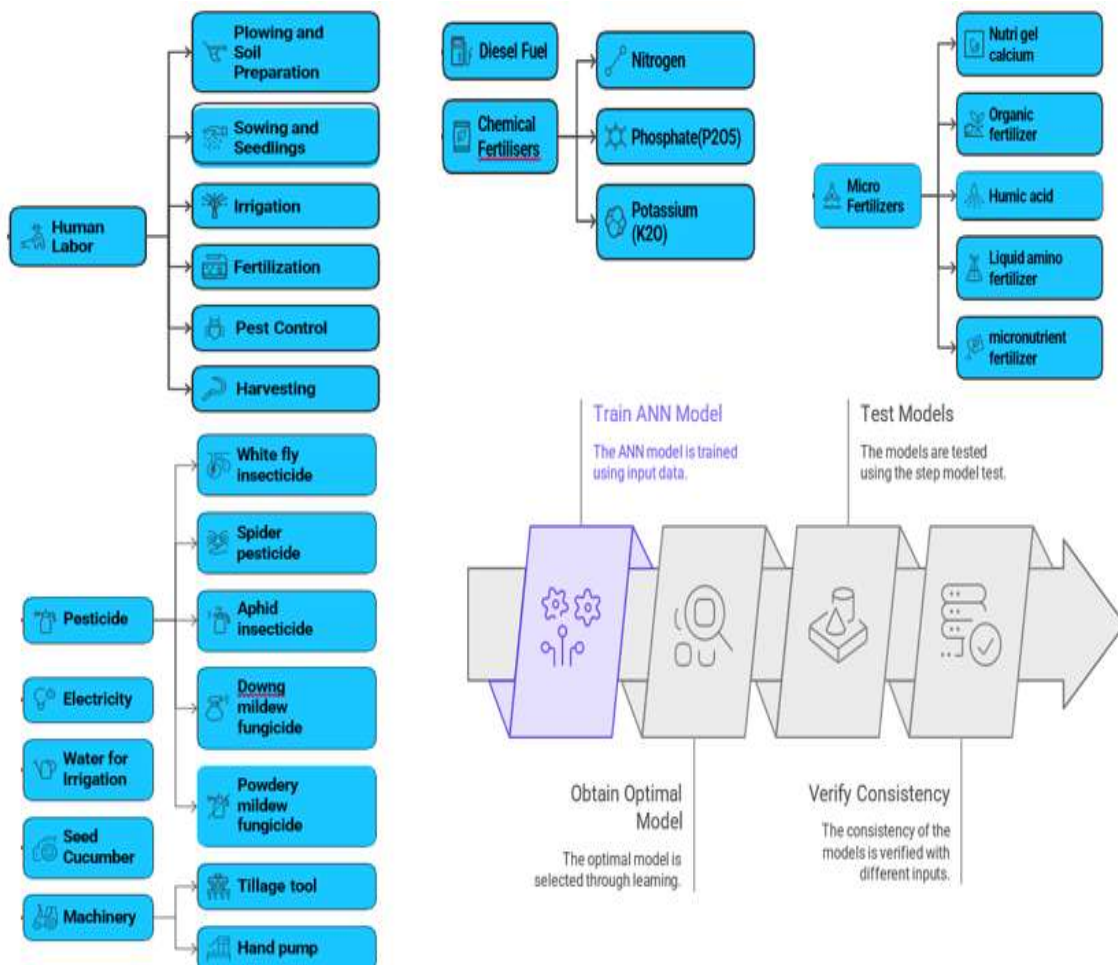


Fig 2. Energy inputs and outputs and the development of ANN models

RESULTS AND DISCUSSION

Energy Indicators Analysis for the Three Cucumber Varieties

In this section, the input and output quantities and their equivalent energies were first calculated, along with the energy indicators. Table 2 shows the energy input and output per greenhouse for the production of the three cucumber varieties. The results indicate that the total energy input for producing one greenhouse of cucumber varieties NEDDAL F1, SUPER HERO F1, and TOP GREEN F1 was 6251.88, 6201.88, and 6251.88 MJ house⁻¹, respectively, while the total energy output was 4400, 5326.3272, and 5014.08 MJ house⁻¹. An analysis of the contribution of each input shows that the largest share of energy input is attributed to fertilizers, electricity, and agricultural machinery, while the smallest is attributed to cucumber seeds and diesel fuel. The large share of fertilizers among the inputs (2792.2 MJ house⁻¹ and 45%) is mainly attributed to the depletion of greenhouse soils and the prevailing belief in agricultural areas that using this quantity of fertilizer will lead to increased production, thus improving economic returns. Conversely, the small share of diesel fuel among the inputs (168.93 MJ house⁻¹ and 2.72 %) is mainly attributed to the fact that the use of agricultural machinery in various farming operations was limited to plowing. Çebi *et al.* (2019), in their study "Energy Efficiency and Economic Analysis of Cucumber Cultivation in Greenhouses in Turkey: The Case of Thrace," reported that the energy analysis in greenhouses showed that energy consumption resulting from nitrogen and phosphate fertilizers, in addition to fuel and electricity, was high, noting that chemical fertilizers play a major role in increasing indirect energy consumption. Eskandari and Mosavian (2023), in a study conducted in Gutvand, southwestern Iran, examined the energy consumption of two cucumber production systems: field production and greenhouse production. The results indicated that the energy inputs for the two systems were not significantly different. In both systems, the majority of the energy input was allocated to nitrogen fertilizers (57% and 53% for field and greenhouse, respectively). Table 2 shows that Nutri-gel calcium fertilizer and organic fertilizer accounted for up to 19% of the total fertilizer used in this study, consistent with the findings of (Adekiya *et al.* 2022, Luo *et al.* 2026, and Halshoy *et al.* 2026). Since using organic fertilizer in agriculture has more effective nutritional effects compared to chemical fertilizers, and because its production requires significantly less energy, replacing chemical fertilizers with organic fertilizer can reduce energy consumption, improve input utilization, and benefit the production system (Liu *et al.* 2026). Furthermore, increasing nitrogen use efficiency according to the product's needs and choosing the appropriate time for fertilization can reduce environmental impacts and nitrate runoff (Veres *et al.* 2026 and Atapattu *et al.* 2026).

From an environmental perspective, consuming approximately 20% of electricity inputs is highly desirable, as it encourages the use of non-renewable energy sources in cucumber production and enhances the sustainability of the agricultural ecosystem. Most studies indicate that the high consumption of chemical fertilizers, especially urea, in cucumber production not only increases energy consumption but also poses numerous environmental risks. Therefore, replacing animal manure with various chemical fertilizers not only reduces costs and energy consumption but also improves environmental health by minimizing pollutant emissions.

Table (2). Energy input and output analysis of cucumber varieties

Items (unit)	Unit	NEDDAL F1		SUPER HERO F1		TOP GREEN F1	
A. Inputs		Total energy equivalent (MJ)	Percentage of total energy input (%)	Total energy equivalent (MJ)	Percentage of total energy input (%)	Total energy equivalent (MJ)	Percentage of total energy input (%)
1. Human labor	hr						
(a) Plowing and Soil preparation		23.52	0.3762	23.52	0.3792	23.52	0.3762
(b) Sowing and seedlings		35.28	0.5643	35.28	0.5688	35.28	0.5643
(c) Irrigation		78.4	1.2540	78.4	1.2641	78.4	1.2540
(d) Fertilization		78.4	1.2540	78.4	1.2641	78.4	1.2540
(e) Pest Control		39.2	0.6270	39.2	0.6320	39.2	0.6270
(f) Harvesting		98	1.5675	98	1.5801	98	1.5675
2. Diesel fuel	L	168.93	2.7020	168.93	2.7238	168.93	2.7020
3. Chemical fertilisers	kg						
(a) Nitrogen		529.12	8.4633	529.12	8.5316	529.12	8.4633
(b) Phosphate(P ₂ O ₅)		149.28	2.3877	149.28	2.4070	149.28	2.3877
(c) Potassium (K ₂ O)		133.8	2.1401	133.8	2.1574	133.8	2.1401
4. Micro fertilizers	kg						
(a) Nutri gel calcium		600	9.5971	600	9.6744	600	9.5971
(b) Organic fertilizer		600	9.5971	600	9.6744	600	9.5971
(c) Humic acid		480	7.6776	480	7.73958	480	7.6776
(e) Liquid amino fertilizer		180	2.8791	180	2.9023	180	2.8791
(d) micronutrient fertilizer		120	1.9194	120	1.9348	120	1.9194
5. Pesticide	kg						
a) White fly insecticide		49.75	0.7957	49.75	0.8021	49.75	0.7957
(b) Spider pesticide		99.5	1.5915	99.5	1.6043	99.5	1.5915
(c) Aphid insecticide		49.75	0.7957	49.75	0.8021	49.75	0.7957
(d) Downg mildew fungicide		149.25	2.3872	149.25	2.4065	149.25	2.3872
(e) Powdery mildew fungicide		149.25	2.3872	149.25	2.4065	149.25	2.3872
6. Electricity	Kwh	1193	19.0822	1193	19.2361	1193	19.0822
7 Water for irrigation	M ³	326.4	5.2208	326.4	5.2629	326.4	5.2208
8-Seed cucumber	kg	200	3.1990	150	2.41862	200	3.1990
9.Machinery	hr						
(a) tillage tool		376.2	6.0173	376.2	6.0659	376.2	6.01738
(b) hand pump		344.85	5.5159	344.85	5.5604	344.85	5.5159
Total energy input	MJ house ⁻¹	6251.88	100	6201.88	100	6251.88	100
B. Output							
Yield	kg	5500		6657.909		6267.6	
Total energy output	MJ house ⁻¹	4400	100	5326.3272	100	5014.08	100

After fertilizers, electricity, and machinery, the energy consumed for pest control (497.5 MJ house⁻¹ and 8.021761143%) ranks fourth among the most energy-intensive inputs. The increased use of pesticides stems from the misconception among farmers that excessive pesticide uses leads to increased production. This has resulted in increased pesticide resistance, negatively impacting agricultural practices in the experimental area.

According to Table 3, the SUPER HERO F1 variety recorded the best results for energy use efficiency, energy yield, specific energy, and net energy, with values of 0.858824614, 1.073530768 kg MJ, 0.931505672 kg MJ, and -875.5528 MJ, respectively. The TOP GREEN F1 variety recorded the second-best results compared to the NEDDAL F1 variety. In a study conducted in Alborz province, the energy ratio, energy yield, energy intensity, and net energy added per hectare of cucumber production were 0.11, 0.14 kg/MJ, 7.3 MJ/kg, and -865,665.55 MJ, respectively. The high energy intensity in Alborz Province is attributed to the large electricity consumption required for groundwater extraction, as well as the excessive use of agricultural machinery and chemical fertilizers (Hosseini-Fashami *et al.*, 2019). Given the role of nitrogen fertilizers and chemical pesticides in exacerbating environmental impacts, it is suggested that organic production methods, biological control, and integrated pest management be employed in cucumber production (Raman *et al.* 2024). Research has shown that consumers are willing to pay more for organic products (Brambila-Paz *et al.* 2025).

Table (3). Energy indicators for the production of different varieties of cucumbers in Nineveh Governorate

	Unit	NEDDAL F1	SUPER HERO F1	TOP GREEN F1
Energy use efficiency	-	0.7037883	0.858824614	0.802011555
Energy productivity	kg MJ ⁻¹	0.879735376	1.073530768	1.002514444
Specific Energy	MJ kg ⁻¹	1.136705455	0.931505672	0.997491863
Net energy	MJ house ⁻¹	-1851.88	-875.5528	-1237.8

Development of Energy Models

One of the most significant methods of forecasting plant production is the energy. A model of energy is a type of quantitative forecasting. The goal is to find models in historical energy data and the sequence data to predict the pattern of future energy data. The results can be used as a reference for future forecasting. Forecasting should be based on the analysis of the pattern of existing data. Investigation and forecasting the impacts of input energy on cucumber production by computational intelligence techniques. This section of the discussion explains these criteria, examines their relationships, and explores their impact on the accuracy of prediction models in obtaining a clear view of the data and the process of generating the choice for the three categories. Furthermore, the selection of the most important factors, with acceptable correlations between them, confirms the reliability of the data collection process. Additionally, this information was used to select the input variables for the ANN models.

Finding high-precision models for energy inputs and outputs is very useful for organizing the production and planning processes. As shown in Tables 4,5,6 and 7

for the performance of the ANN models in NEDDAL F1, SUPER HERO F1, and TOP GREEN F1, the MSE and R-value show variations across the evaluation and training algorithms LM and RP under Log-sigmoid and Tan-sigmoid, with different numbers of neurons in the hidden layers of the ANN models.

Table (4). The performance of the ANN models in NEDDAL F1

Training function	No. of hidden neuron	Output Energy model for NEDDAL F1							
		Log sigmoid				Tan sigmoid			
		Coe. Correlation (R) %				Coe. Correlation (R) %			
		Tr.	Te.	Val.	All	Tr.	Te.	Val.	All
Train LM	6	0.928	0.919	0.899	0.898	0.898	0.797	0.898	0.898
	10	0.999	0.999	0.999	0.998	0.999	0.998	0.999	0.989
	12	0.898	0.970	0.970	0.970	0.980	0.974	0.976	0.898
	14	0.928	0.919	0.929	0.928	0.939	0.950	0.968	0.928
Train RP	6	0.895	0.887	0.797	0.880	0.558	0.631	0.897	0.852
	10	0.798	0.890	0.889	0.785	0.779	0.799	0.899	0.785
	12	0.667	0.698	0.788	0.876	0.792	0.886	0.896	0.585
	14	0.590	0.837	0.699	0.677	0.839	0.559	0.789	0.779
Tr. =Training Te. =Test Val.= Validation									

In the training process, weights and biases are constantly adjusted to minimize the error between the actual and the desired outputs. Although the R-value varied, the highest was also the MSE, the very highest. Calculation of MSE for training set data shows that the artificial neural network predicts the output energy with a minimum error. For more confidence, the capability of the trained network in predicting the output energy, choosing the minimum MSE implies that the ANN is successful in training. The best performance of the network model is obtained when using the training function LM compared with RP training functions for energy models to the three categories. The minimum MSE and the highest R-value of model calibration were obtained by combining the LM training, the 10 and 12 of a hidden neuron. Therefore, the best performance of the ANN architecture is 25-10-1 and 25-12-1 and 25-10-1 with LM training and Log-sigmoid a transfer function in NEDDAL F1, SUPER HERO F1, and TOP GREEN F1, respectively. Although train LM does require more memory than other algorithms, it is regularly the fastest backpropagation algorithm in the toolbox. Train LM is extremely recommended as a first optimal supervised algorithm. For arriving at a network that generalizes well, validation vectors are used to stop training early if the network's performance on the validation vectors fails to improve or remains the same for max_fail epochs in a row. It is very complicated to define which training algorithm will be the fastest for a specific problem.

Table (5). The performance of the ANN models in SUPER HERO F1

Training function	No. of hidden neuron	Output Energy model of SUPER HERO F1							
		Log sigmoid				Tan sigmoid			
		Coe. Correlation (R) %				Coe. Correlation (R) %			
		Tr.	Te.	Val.	All	Tr.	Te.	Val.	All
Train LM	6	0.958	0.929	0.939	0.939	0.922	0.929	0.949	0.959
	10	0.972	0.967	0.929	0.928	0.929	0.957	0.979	0.937
	12	0.997	0.996	0.999	0.997	0.998	0.999	0.998	0.995
	14	0.928	0.939	0.929	0.946	0.912	0.920	0.929	0.940
Train RP	6	0.863	0.787	0.797	0.768	0.858	0.831	0.897	0.852
	10	0.893	0.782	0.885	0.768	0.779	0.899	0.899	0.885
	12	0.699	0.769	0.892	0.778	0.892	0.686	0.896	0.685
	14	0.897	0.899	0.894	0.896	0.883	0.759	0.789	0.879

Tr. =Training Te. =Test Val.= Validation

Table (6). The performance of the ANN models at TOP GREEN F1

Training function	No. of hidden layers	Output Energy of TOP GREEN F1							
		Log sigmoid				Tan sigmoid			
		Coe. Correlation (R) %				Coe. Correlation (R) %			
		Tr.	Te.	Val.	All	Tr.	Te.	Val.	All
Train LM	6	0.958	0.940	0.925	0.926	0.958	0.940	0.955	0.967
	10	0.997	1	0.999	0.997	0.929	0.928	0.923	0.907
	12	0.903	0.935	0.928	0.909	0.899	0.898	0.898	0.881
	14	0.898	0.829	0.799	0.845	0.867	0.948	0.950	0.921
Train RP	6	0.849	0.825	0.899	0.871	0.885	0.899	0.799	0.859
	10	0.748	0.887	0.799	0.760	0.739	0.898	0.878	0.876
	12	0.793	0.889	0.777	0.882	0.780	0.796	0.795	0.882
	14	0.895	0.886	0.770	0.853	0.892	0.895	0.873	0.888

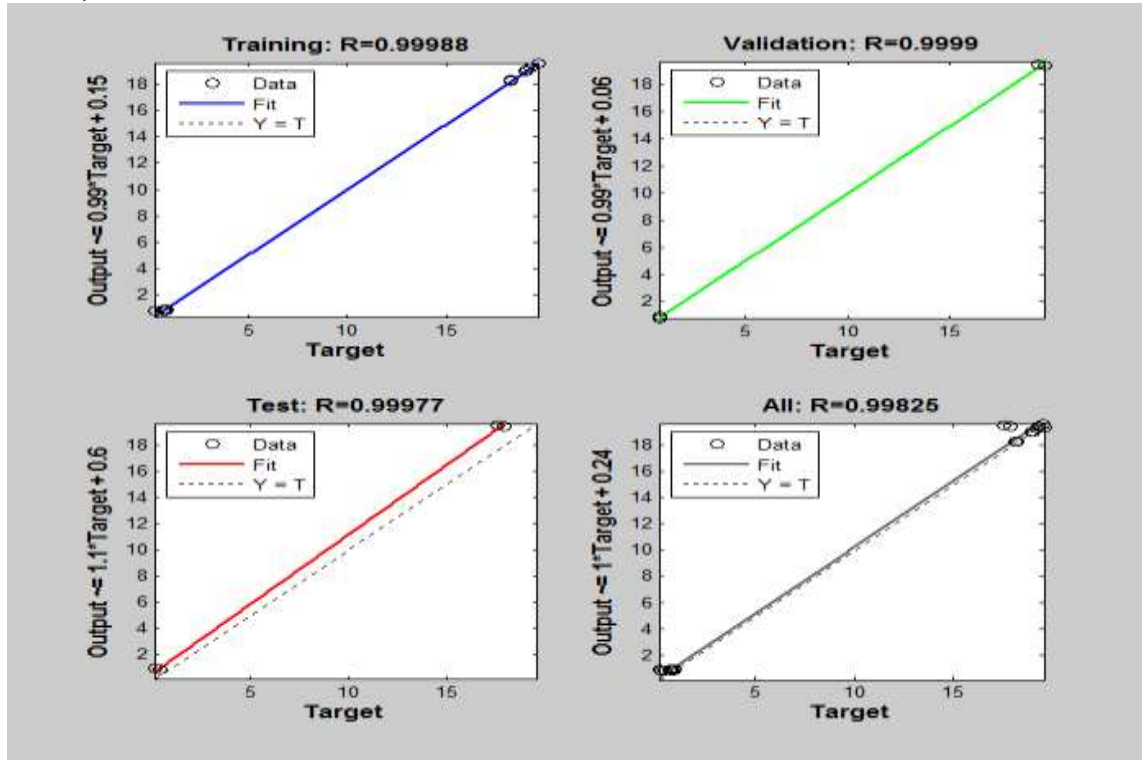
Tr. =Training Te. =Test Val.= Validation

It depends on many factors, including the error goal, the complexity of the issue, the training set, and the number of data points in this set, the number of weights and biases in the network, and whether the network is being used for discriminant analysis or regression (Du & Swamy, 2013; Rashidi *et al.*, 2024).

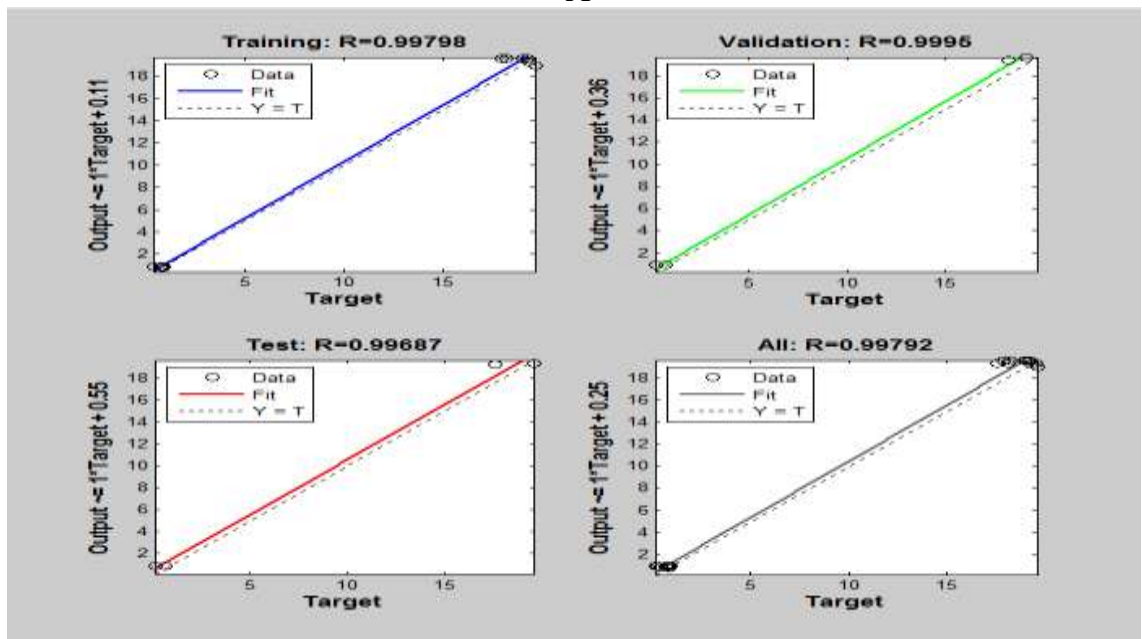
Table (7). The MSE of the ANN models for NEDDAL F1, SUPER HERO F1, and TOP GREEN F1

Training function	No. of hidden neuron	MSE of the ANN models							
		Log sigmoid		Tan sigmoid		Log sigmoid		Tan sigmoid	
		MSE %	MSE %	MSE %	MSE %	MSE %	MSE %		
Train LM	6	0.1034	0.1224	0.2409	0.4254	0.1625	0.1728		
	10	0.0936	0.0998	0.1936	0.1874	0.1001	0.1023		
	12	0.2409	0.1145	0.1021	0.4424	0.1667	0.1392		
	14	0.1519	0.0995	0.1519	0.2686	0.1543	0.2716		
Train RP	6	0.1719	0.2416	0.1719	0.2416	0.1045	0.1075		
	10	0.6136	0.2072	0.6136	0.1046	0.1462	0.1364		
	12	0.3412	0.1021	0.3412	0.1121	0.1074	0.1960		
	14	0.1378	0.1452	0.1378	0.1452	0.1934	0.3134		

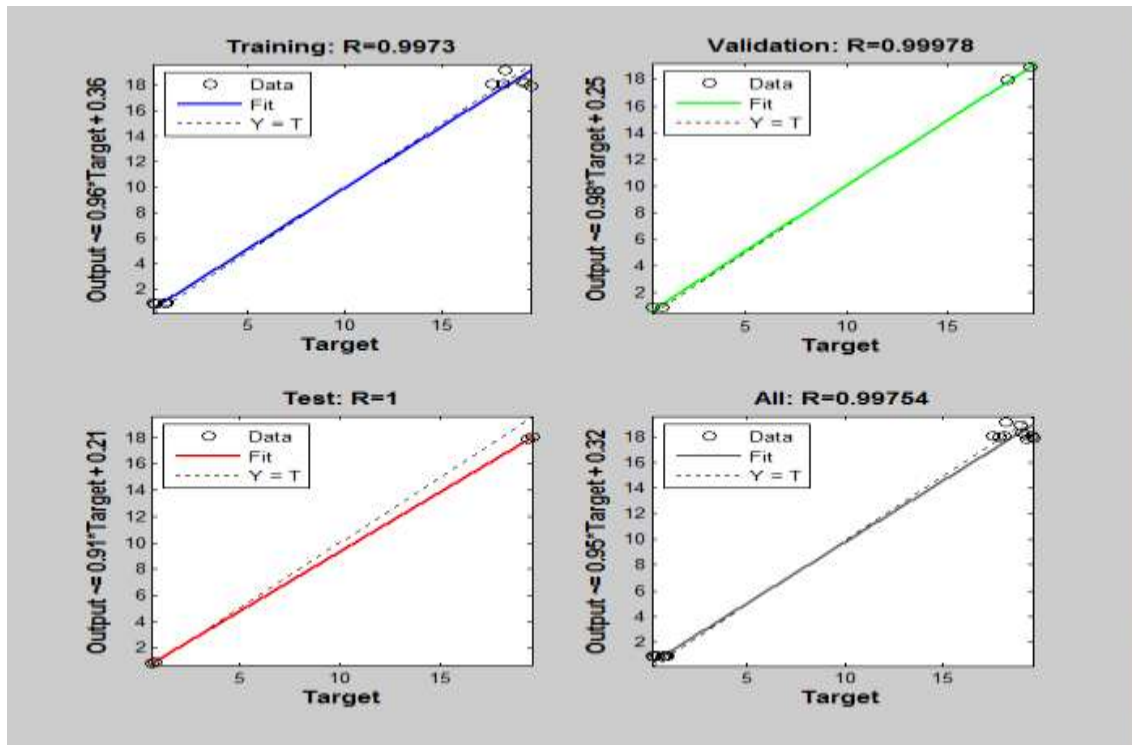
The best ANN models are presented in Figure 3. It can be clearly seen that the actual output energy and predicted energy are visually represented, strongly suggests very close to a line between the actual and predicted for the training, validation, and all sets for models, with a slight deviation is clear for the testing set. This justifies the efficacy of the model, although the best energy models are given in the equation of output in fig 3 at all datasets for ANN in NEDDAL F1, SUPER HERO F1, and TOP GREEN F1, respectively. The error in equations may be because of the high MSE values, as shown in Table 7.



A



B



C

Figure (3). The scatter plots of ANN models predicted vs. actual energy values, scatter plots A for NEDDAL F1, scatter plots B for SUPER HERO F1, and scatter plots C for TOP GREEN F1

CONCLUSIONS

This study critically evaluated energy indicators and developed artificial neural network models for a cucumber production system using different cucumber varieties, including NEDDAL F1, SUPER HERO F1, and TOP GREEN F1. The results indicate that nitrogen fertilizers (45%) and electricity (20%) are the main energy inputs, significantly impacting emissions and sustainability. Diesel fuel accounted for the smallest energy input, at only 2.72%, and optimizing diesel fuel inputs is crucial. These findings highlight the potential for improved farm management and tillage practices to effectively reduce diesel consumption and enhance overall energy and environmental performance. The SUPER HERO F1 variety demonstrated the highest yield and energy efficiency. Analysis of the neural network-based prediction models revealed that these models achieved accuracy of over 0.998, 0.997, and 0.997, with experimental errors of 0.0936, 0.1021, and 0.1001 for each of the three varieties, respectively, achieving full efficiency. This indicates potential for improvement in this sector, and the application of these models could lead to a significant reduction in input usage. The results also showed that the number of dilution layers significantly impacted model accuracy, with the highest accuracy recorded at layers 10 and 12. For farmers and policymakers, this research proposes strategies for identifying energy inputs and their impact on production, which can help control output and provide guidance on promoting sustainable agricultural practices. Future research should focus on open-field applications and compare them with the findings of this study to provide more effective recommendations for stakeholders in the agricultural sector.

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CONFLICT OF INTEREST

The authors state that there are no conflicts of interest with the publication of this work.

تحليل ونمذجة مدخلات الطاقة في البيوت البلاستيكية لأصناف الخيار المختلفة

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الخلاصة

يُزرع الخيار على نطاق واسع في البيوت المحمية والحقول المفتوحة حول العالم، ويمثل محصولاً رئيسياً لمزارعي البيوت المحمية في العراق. هدفت هذه الدراسة إلى تحليل استهلاك الطاقة وتطبيق نموذج الشبكة العصبية الاصطناعية (ANN) للتنبؤ بمحصول ثلاثة أصناف من الخيار: NEDDAL F1، SUPER HERO F1، وTOP GREEN F1، في محافظة نينوى. أُجريت التجربة في 18 بيتاً محمياً، وشملت البيانات التي جُمعت أنواع المعدات المستخدمة في زراعة الخيار، وساعات العمل، والوقود، وعدد العمال، والممارسات الزراعية، وطرق التسميد، ومكافحة الآفات. أظهرت النتائج أن إجمالي استهلاك الطاقة لزراعة الخيار بلغ 6251.88، و6201.88، و6251.88 ميغا جول لكل بيت بلاستيكي بينما بلغ ناتج الطاقة 4400 و5326.3272 و5014.08 ميغا جول لكل بيت بلاستيكي للأصناف الثلاثة على التوالي. يُعد استهلاك الأسمدة والكهرباء من المتغيرات الرئيسية في زراعة الخيار، حيث يُمثلان أعلى مدخلات الطاقة بنسبة 42% و20% على التوالي. أظهرت النتائج أن نموذج الشبكة العصبية مفيد في التنبؤ بمخرجات الطاقة لثلاثة أصناف من الخيار، وقد تم الحصول على أقل قيمة لمتوسط مربع الخطأ (MSE) وأعلى قيمة لمعامل التحديد (R^2) لمعايرة النموذج من خلال دمج تدريب نموذج التعلم (LM)، وعشرة واثني عشر عصبوناً مخفياً، باستخدام بنى الشبكات العصبية الاصطناعية 1-10-25 و1-12-25 و1-10-25 مع تدريب باستخدام نموذج التعلم الآلي ودالة نقل دالة سيجمويد (Sigmoid) في أصناف NEDDAL F1 وSUPER HERO F1 وTOP GREEN F1 على التوالي. أثبتت الدراسة أن النماذج المُدرّبة حققت أقل معدل خطأ، مما يدل على قدرة النموذج التجريبي على التنبؤ بمحصول الخيار في محافظة نينوى.

الكلمات المفتاحية: الأسمدة الكيميائية، مدخلات الطاقة، الآلات الزراعية، نموذج الشبكة العصبية، المبيدات الحشرية.

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