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Modeling energy use and economic productivity of different fish production systems using artificial neural networks

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ABSTRACT

This study aimed to use artificial neural networks (ANNs) to predict output energy and economic indicators. So, data on two fish breeding sites were collected with a questionnaire, directly from the site owners and administrators, and from the records. Then, the input and output energy of cold-water and hot-water fish were calculated. The cold-water fish were found to have a more favorable energy ratio (ER) (2.24), energy productivity (EP) (0.04 kg MJ^{-1}), specific energy (SE) (26.83 MJ kg^{-1}), and net energy gain (NEG) (33222.16 MJ kg^{-1}). According to the results, fish feed and electricity are two factors among energy consumption inputs whose proper management will increase energy efficiency. The benefit-to-cost ratio was positive for cold-water fish (1.54) and hot-water fish (2.45). The productivity of cold-water and hot-water fish was 0.58 kg $\$^{-1}$ and 0.52 kg $\$^{-1}$, respectively. The results of ANNs showed that R^2 varied from 0.947 to 0.993 overall, from 0.912 to 0.964 for the training stage, and from 0.978 to 0.980 for the testing stage in the case of cold-water fish. Regarding hot-water fish, these values were 0.885-0.998, 0.923-0.952, and 0.952-0.995, respectively. So, ANNs can be used to predict output energy and economic productivity.

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Introduction

The importance of aquatic food consumption for the health of society and its role in healthy human nutrition is growingly acknowledged with the increase in human knowledge (Hilmarsdóttir et al., 2022). Fish farming techniques refer to the solutions by which fish is produced at the maximum sustainable level using various tools and methods that are based on scientific principles (Ögmundarson et al., 2020). The main goal of aquatic production management is to achieve profitability by integrating basic production factors including fish hatchery, water, environment, scrod, investment, and labor (Cashion et al., 2017). Decreased growth and physiological deficiencies in aquaculture are due to imbalances in dietary components, which leads to environmental problems (Leštan et al., 2008). Not only does maximum growth depend on the diet formula, but production costs are also reduced by minimizing dietary costs and saving on protein sources. Energy issues are very important in deciding on the use of different inputs. The main purpose of a system is to produce animals and plants. In terms of energy, production should exceed the input (Schau et al., 2009). Therefore, a systematic system deals with the rational use of production resources. Energy is one of the basic needs of sustainable production (Esengun et al., 2007b). Energy consumption has increased in response to population growth and better living standards. The rising demand for food has intensified the consumption of inputs and other natural resources (Soltani et al., 2013). Increasing energy consumption in recent years has posed problems for human health and environmental issues. Effective use reduces environmental problems and prevents the destruction of natural resources (Thrane, 2004).

Trout is a valuable food that has 20% protein and 9% fat and is resistant to environmental changes such as oxygen, carbon dioxide, low pollution, and climate change. It also has a good growth rate (White et al., 2006). In suitable areas of Iran, fish farming has growingly been increased through the construction of fish hatcheries. Due to the biological conditions, cold-water fish are among the best animals for farming. Trout are easily adapted to artificial production conditions and different densities (Pelletier and Tyedmers, 2007). This fish has a good taste among consumers. It is also compatible and cost-effective with artificial feeding conditions. The fish can be raised in clear, cold water at temperatures between 12 and 18°C with a dissolved oxygen rate of 6-10 ppm (Guilpart et al., 2012). The most suitable temperature for feeding and growing this fish is 14-16°C. In trout farming, the volume of water required is one of the factors underpinning the reproduction rate. The requirements for the production of one ton of fish are an area of about 50 m^2 and a water flow of 7-10 L/s in normal conditions with no use of mechanized tools for production (Harvey et al., 2003). Common species of warm-water fish farming include common carp, silver carp, and herbivorous carp. Non-food competition species in the pool are effective in using different weight sizes of scrod (Pincinato and Asche, 2016). In farmed specimens, the growth rate of fish is about twice that of wild specimens. Carp typically weigh between 2 and 14 kg but can grow up to 40 kg (Pelletier and Tyedmers, 2007). Carp production in the world is reported to be 5.67 million tons, which is equivalent to 4.7% of the total fish production in the world (FAO, 2020).

The fisheries sector faces limited production resources and provides food security for the growing population. The process of using production resources must contribute to the food needs of the current generation and the food security of the next generation (Pishgar-Komleh et al., 2011). The goals of energy analysis include reducing the consumption of energy inputs, replacing renewable energy sources, reducing production costs, and using nature-friendly production methods as part of an optimal management system (Iriarte et al., 2010). Energy is influential because of its multiple roles or functions in each area of our lives. Energy resources are expensive and limited, so improving energy efficiency is essential for sustainable agriculture (Esengun et al., 2007a). The study of energy indices helps to find methods for optimizing energy consumption. Energy analysis allows energy costs to be modified. Very little data have been provided on aquaculture energy and fisheries production in Iran. The data reported in the literature are from previous studies from other countries (Dallemand et al., 2015; Schau et al., 2009). Optimal resource allocation is one of the most basic concepts in economics. Therefore, economic evaluation is done using different techniques and calculations. On the other hand, artificial neural networks (ANNs) simulate the concept of biological neural networks to identify pattern determination, data building, and modeling. Many researchers have used ANNs to model energy-economic and environmental impacts (Antanasijević et al., 2015; Najafi et al., 2018). Nabavi-Pelesaraei et al. (2018) modeled environmental impact categories and yield in paddy production. Their results indicated that the adaptive neuro-fuzzy inference system (ANFIS) with multi-levels was a useful planning tool for managers to predict environmental indices and energy output of agricultural production systems. The ANFIS model needed less computation time whilst the ANN model attained more accurate results.

Aquaculture projects are considered one of the most important production and employment sectors due to their potential (Elhendy and Alzoom, 2008). Research on fish farming economics has revealed that the net efficiency of decentralized systems is higher than that of centralized systems (Obasi, 2005). Ahmed et al. (2014) evaluated the economics of fish farming and the costs of production of tilapia fish farming using cross-sectional data from 23 centralized fish farms. The minimum average production cost was 201 tons of fish per year and the maximum profit was 200 tons per year. All farms operated on a scale below the maximum, and most operated below the minimum yield scale. The low quality of fish input and the low level of farm management skills were the reasons for inefficiency. Oladimeji et al. (2018) showed that fuel, feed, and water inputs formed the overcoming share of energy inputs accounting for 91% and 83% in earthen and concrete fish production systems. The energy use efficiency in both fish production systems was found to be 0.879 and 0.697, respectively. In a study on energy efficiency and environmental impacts of rainbow trout in Iran, Elhami et al. (2019) estimated total energy inputs and rainbow trout yield at 60483.50 MJ ton^{-1} and 281.78 ton ha^{-1}, respectively, while the counterpart values were 77,183.63 MJ ha^{-1} and 210.50 kg ha^{-1} in the Lordegan region, respectively.

Fish farming production systems should adopt an approach by which energy dependence can be reduced, which can be partially achieved by changing economic value. To achieve such goals, methods are used to produce different aspects of the system process. The present study conducts an energy-economic analysis of two types of fish farming systems. Also, the study uses ANNs to predict energy consumption and economic productivity.

Methodology

Study site

The lack of water resources and people's need for healthy protein sources have led to the dual or multi-purpose use of water resources. Fish farming is one of the important resources. Farmed fish are divided into cold-water and hot-water groups in terms of the temperature tolerance range (Ayer and Tyedmers, 2009). Topographic maps, geology, hydrology, soil science, land use of the area, and access roads to the study site were examined for sampling. The sampling stations were selected according to natural conditions and access to the river by taking natural and human features into account. Sub-tributaries of the river, changes in geological structures, and pollution sources including fish hatcheries, agricultural lands, the establishment of residential centers, and existing industries were considered. The most important measures after providing the desired location for the construction of the site are to specify the type of system in terms of density (dense, semi-dense, super-dense), determine the capacity of the building based on the amount of incoming water and the type of system, and design and plan the place and its facilities according to the abovementioned features and capital.

Alborz province (5715 m^2), which accounts for 0.3% of the total area of Iran, has a population of 2.8 million and is one of the most populous provinces with a high population density. The province is apt for aquaculture due to its favorable climate, access to major aquatic markets, the availability of many rivers, and fish farmers' reception of the latest technology in the field of fish production. The fish production rate in this province amounts to 1550 tons of cold-water fish from 100 fish hatcheries and 80 tons of warm-water fish from 9 fish hatcheries. Management programs include increasing the efficiency of aquaculture production per unit area by guiding breeders toward the use of modern aquaculture equipment, aquaculture production in combination with agricultural water (with the participation of soil and water management) to increase water productivity, and the use of the maximum capacity of water resources for production (Ministry of Jihad-e-Agriculture of Iran, 2020). Also, the approximate number of fish production ponds in Alborz province was determined. To collect information about the type and amount of inputs and outputs consumed, the number of samples was determined by Equation 1 (Cochran, 1977).

$$n=\frac{\frac{z^2pq}{d^2}}{1+\frac{1}{N}\left(\frac{z^2pq}{d^2}-1\right)}$$

where N is the population size, z is the reliability coefficient, p is the estimated proportion of an attribute that is present in the population, q is 1-p, and d is the permitted error ratio deviation from the average population.

Energy

Different forms of energy including non-renewable, direct, and indirect energies have a positive effect on the output surface. The study of energy consumption patterns in production systems is inevitable and necessary due to limited resources and the misuse of non-renewable energy, e.g., fossil fuels, on the environment and human health (Singh et al., 2002). The amount of energy consumed in different production systems depends not only on the type of product but also on the type of materials used in production (Ghorbani et al., 2011). The behavior of different systems in the use of inputs and energy sources is different, and energy efficiency is different in each production system (Singh et al., 2007). The required data were collected after the samples were identified. Data were calculated by Excel software. The equivalents of energy inputs for fish production are shown in Table 1.

Table 1
Energy Conversion Coefficients Used to Energy Inputs for Smoked Fish Production.

Inputs and output (Unit)	Energy equivalent (MJ Unit^{-1})	References
A. Inputs		
1. Human labor (h)	1.96	(Ghasemi-Mobtaker et al., 2020)
2. Fish (kg)	55.60	(Butler et al., 2017)
3. Water (m^3)	1.02	(Kaab et al., 2019)
4. Electricity (kWh)	11.93	(Acaroğlu and Aksoy, 2005)
5. Feed Consumption (kg)		
a) Starting feed	18.40	(Muir, 2015)
b) Growth feed	17.57	(Muir, 2015)
c) Fattening feed	16.72	(Muir, 2015)
B. Output		
1. Fish (kg)	60.05	(Muir, 2015)

Study indicators

Various inputs are used as raw materials or energy during a production process. Inputs have energy content. The energy content of the inputs consumed and produced during the production process is called the input and output energy for a production system (Yuan and Peng, 2017). Energy indices are good criteria for determining yield and efficiency of input consumption. Calculating energy indices is one of the main steps in the energy analysis process (Hosseini-Fashami et al., 2019). The ratio of the output energy to the energy of the consumable inputs is called energy use efficiency (EUE). Equation 2 describes the energy ratio. The ratio of product weight to the total energy of inputs is called energy productivity (EP). Energy productivity expresses the amount of product per unit of energy consumed, which is obtained using Equation 3. The ratio of the total input energy to the weight of the output product is the specific energy (SE) and is determined in MJ/kg. In fact, specific energy is the inverse of energy productivity, which is obtained using Equation 4. Net energy gain (NEG) is the difference between the gross energy produced and the total energy required to produce in the system. A negative NEG indicates the high energy consumption that has been reported using Equation 5 (Aghaalikhani et al., 2013).

Comparative factors are defined to evaluate the design and provide accurate analysis. These baseline indicators examine the significance of system production. The calculation of economic indicators helps to have a good estimate of the economic situation of the producers in the region (Oladimeji et al., 2018). Indicators include the total cost of production, gross return (GR), net return (NR), productivity (P), and benefit-to-cost ratio (BC). The cost of inputs that manufacturers buy from the market can be calculated. The cost of using inputs that are not bought from the market (human labor and land rent) is another part of the calculation. The value of the inputs is equal to the cost of the missed opportunities (Taherzadeh-Shalmaei et al., 2021). NR is obtained by reducing the total cost of production, and GR is obtained by reducing the variable cost of gross income. BC index can also be calculated by dividing total income by total production cost. Economic indicators are obtained using Equations 6, 7, 8, and 9 (Elhendy and Alzoom, 2008)

$$\text{Energy use efficiency} = \frac{\text{Output energy (MJ)}}{\text{Input energy (MJ)}} \tag{2}$$

$$\text{Energy productivity} = \frac{\text{Production (kg)}}{\text{Input energy (MJ)}} \tag{3}$$

$$\text{Specific energy} = \frac{\text{Input energy (MJ)}}{\text{Production (kg)}} \tag{4}$$

$$\text{NEG} = \text{Output energy (MJ)} - \text{Input energy (MJ)} \tag{5}$$

$$\text{GR} = \text{Gross production value } \left(\frac{\$}{\text{ton}}\right) - \text{variable costs } \left(\frac{\$}{\text{ton}}\right) \tag{6}$$

$$\text{NR} = \text{Gross production value } \left(\frac{\$}{\text{ton}}\right) - \text{Production costs } \left(\frac{\$}{\text{ton}}\right) \tag{7}$$

$$\text{BC} = \frac{\text{Gross production value } (\$ \text{ ton}^{-1})}{\text{Production costs } (\$ \text{ ton}^{-1})} \tag{8}$$

$$\text{P} = \frac{\text{Yeild (kg)}}{\text{Production cost } (\$)} \tag{9}$$

Artificial neural networks (ANNs)

ANNs are a kind of simplistic modeling of real neural systems that are widely used in solving various problems in science. The field of application of these networks is very wide from classification to such applications as interpolation, function estimation, and signal detection and compression. Perhaps the most important advantage of these networks is their high capacity in addition to their ease of use (Abiodun et al., 2018). ANNs, by modeling the neural network of the human brain, can investigate complex and unknown phenomena well. These networks are part of intelligent dynamic systems that, by processing observational data, transfer the hidden law behind the data to the network structure, so these systems are called smart. In other words, ANN is a type of mathematical model that has a high ability to model and create non-linear relationships for interpolation (Prieto et al., 2016). ANN models are a strong nonlinear modeling branch of science, which can facilitate the establishment of links among input and output parameters via adequate weights and activation functions. In this study, Matlab software is employed to implement and train a back-propagation feed-forward neural network with different activation functions, number of neurons, and number of hidden layers (Khatib et al., 2012). The networks are built with seven input variables (energy equivalents of human labor, fish, water, electricity, starting feed, growth feed, and fattening feed) and outputs (output energy and economic productivity). For supervised training of the ANN, the datasets are randomly subdivided into three subsets, namely, training (70%), testing (15%), and validation (15%). The differences between the observed data and the computed ANN results are used for the performance evaluation of these ANN models. Eq. (10) gives the error function used in performance evaluation (Kiani et al., 2010):

$$E = \frac{1}{p}\sum_{p}\sum_{k}\left(t_{pk} - z_{pk}\right)^{2} \quad (10)$$

where is the index of the output vector, is the index of input vectors, is the *k*th element of the *p*th target pattern vector, and is the *k*th element of the output vector under input pattern *p*.

2.4.1. Performance assessment of models

Several statistical metrics, namely, mean absolute percentage error (MAPE), root mean square error (RMSE), and coefficient of determination (R^2), are employed to evaluate the performance of models, as shown in Eqs. (11)-(13) (Safa and Samarasinghe, 2011; Renno et al., 2016):

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left(\frac{\left|(P_i - A_i)\right|}{A_i}\times 100\right) \quad (11)$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{\mathrm{n}}\sum_{i}^{n}\left(P_i - A_i\right)^2} \quad (12)$$

$$R^2 = 1 - \sqrt{\frac{\sum_{i=1}^{n}(P_i - A_i)^2}{\sum_{i=1}^{n} A_i^2}} \quad (13)$$

where *N* denotes the number of training vectors and and denote the observed and simulated output for the ith training vector, respectively

Results and Discussions

Highlights of energy analysis

Factors such as the amount of input can be controlled by producers, but in fish, it is necessary to be aware of the importance of each factor in the fish production process and their impact on output. The results of the energy analysis of cold-water fish and warm-water fish are shown in Table 2. The total input energy of cold-water fish (26827.84 MJ ton^{-1}) is less than the total input energy of hot-water fish (33901.40 MJ ton^{-1}). It is found that hot-water fish consume more energy. As a result, it is necessary to reduce energy consumption in the production stages. The production energy for both types of fish was estimated to be 60050 MJ ton^{-1} due to the similarity of the fish energy equivalent. The calculations are based on the consumption of 1000 kg of fish. The consumption of each of the inputs and energies is shown in Table 2. The use of raw materials and fuel to produce hot-water fish is more than cold-water fish. Figure 3 shows the share of energy consumption of the inputs. The fish feed includes starting feed, growth feed, and fattening feed which have different energy intensities. The energy consumption of each type of fish feed was compared. Feed energy consumption is higher for hot-water fish production (74.81%). In the initial stage, energy consumption is equal, but in the fattening feed, cold-water fish (21%) consume less energy. Growth feed after fattening feed is in the second rank of energy consumption due to its effect on the beginning of fish growth and the amount of energy per unit. High energy consumption in fish production is also related to electricity consumption. The results showed that 22% more fossil fuel is used for cold-water fish production, but it is not much different from the fuel consumption of hot-water fish production. The high consumption of electricity is due to the fact that devices such as aeration pumps, electric motors of wells, and lighting and heating systems are constantly active. Hamilton et al. (1992) calculated energy consumption for several types of seafood, estimating it at between 2 and 192 kcal. They found that most of the fish protein produced was herring, which needed 2 kcal of fossil energy to produce 1 kcal of protein. The highest consumption of fossil energy was 192 kcal per kcal of protein. d'Orbcastel et al. (2009) compared two salmon farming systems. One of the two systems was based on operational data from a fish farming site that used the system through flow (FTF), and the other was based on an experimental pilot with a low head recirculating system (RSF) in the same area. They found that the RSF system consumed 57659 MJ ton^{-1} of fish, which was 24-40% more than the FTF system. The RSF system has great potential for reducing energy through the design of biofilters and improving air circulation. Fuel consumption in Danish fisheries has the most significant potential effect, and improving consumption patterns and increasing consumption efficiency should be considered (Thrane, 2004). Aubin et al. (2009) reported that the systems studied required a lot of energy. Low-emission electricity can replace more polluted energies. Efficient use of energy and use of renewable energy was reported as a way to achieve sustainable aquaculture in Finland (Grönroos et al., 2006).

Energy and economic indicators reports

Table 2
Energy inputs and output of different fish production.

Inputs and output	Cold-Water Fish			Hot-Water Fish		
	Quantity (Unit ton^{-1})	Total energy equivalent (MJ ton^{-1})	Percentage (%)	Quantity (Unit ton^{-1})	Total energy equivalent (MJ ton^{-1})	Percentage (%)

A. Inputs						
1. Human labor	25.78	50.52	0.18	29.75	58.31	0.17
2. Fish	22.11	1229.38	4.58	32.50	1807.00	5.33
3. Water	150.22	153.23	0.57	213.25	217.52	0.64
4. Electricity	499.11	5954.40	22.19	540.75	6451.15	19.02
5. Feed Consumption						
a) Starting feed	384.00	7065.60	26.33	486.67	8954.67	26.41
b) Growth feed	376.00	6606.32	24.62	497.36	8738.62	25.77
c) Fattening feed	345.00	5768.40	21.50	458.98	7674.15	22.63
Total energy input	**-**	**26827.84**	**100**	**-**	**33901.40**	**100**
B. Output						
1. Fish	1000.00	60050.00	-	1000.00	60050.00	-

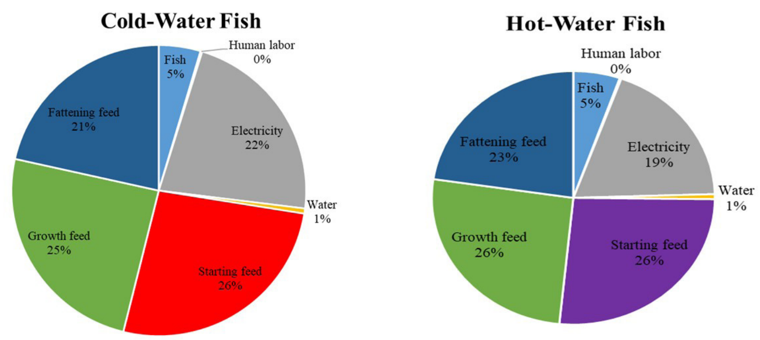

Figure 1. The share of energy input of different fish production

Energy and economic indicators of fish production are compared in Table 3. The energy ratio of cold-water fish (2.24) indicates a greater difference in energy consumption and energy production. The positive ER of hot-water fish (1.77) indicates that the output energy is higher than the input energy. EP, EI, and NEG of cold-water fish are 0.04 kg MJ^{-1}, 26.83 MJ kg^{-1}, and 332222.16 MJ kg^{-1}, respectively. The desired results are due to the lower energy consumption per unit of fish production. To increase fish production and reduce energy consumption, action should be taken to optimize consumption. The relationship between fish feed and electricity is in oxygen supply by electricity. If enough oxygen is not supplied by electricity, the fish will not feed on the available feed, resulting in lower fish production. In this case, a solution must be adopted to provide adequate oxygen and reduce the amount of electricity consumption (White et al., 2006). Calculation of the efficiency of compact and semi-compact systems showed that the effects of food production, use of electricity, and production of contaminants on the surface of the breeding pond were identified. Developing policies to change the composition of food, management of breeding ponds, and water treatment before evacuation is essential to achieve sustainability in this sector (Cao et al., 2011). The benefit-to-cost ratio of cold-water and hot-water fish production was 1.54 and 2.45, respectively. As a result, the costs of cold-water fish production (1715.31 \$ ton^{-1}) are lower than that of hot-water fish production (1904.06 \$ ton^{-1}). Productivity was calculated to be 0.58 Kg \$$^{-1}$ for cold-water fish and 0.52 Kg \$$^{-1}$ for hot-water fish. In general, the results of this study showed that the construction and development of fish farming have positive economic effects. The results of the present study and the majority of previous studies have acknowledged that aquaculture increases the income of individuals and improves the economic situation. Brummet et al. (2008) reported that if fish farming is accompanied by government protectionist policies, it will boost economic growth and food security. A study in Vietnam showed a positive and significant relationship between the amount of investment in fish farming units and the increase in producers' incomes, and investment in the study area improved the economic situation of farmers (Nhan et al., 2007).

Evaluation of ANNs

Table 3
Energy and economic indices in different fish production.

A. Energy indices	**Unit**	**Cold-Water Fish**	**Hot-Water Fish**
Energy ratio	ratio	2.24	1.77
Energy productivity	kg MJ^{-1}	0.04	0.03
Specific energy	MJ kg^{-1}	26.83	33.90
Net energy gain	MJ kg^{-1}	33222.16	26148.60
B. Economic indices			
Gross value of production	\$ ton^{-1}	4360.35	4680.44
Variable cost of production	\$ ton^{-1}	1333.87	1452.84
Fixed cost of production	\$ ton^{-1}	381.44	451.22
Total cost of production	\$ ton^{-1}	1715.31	1904.06
Gross return	\$ ton^{-1}	3026.48	3227.60
Net return	\$ ton^{-1}	2645.04	2776.38
Benefit to cost ratio	ratio	1.54	2.45
Productivity	Kg \$$^{-1}$	0.58	0.52

The statistical measures of the most accurate ANN models in predicting output energy generation and economic productivity for different fish production are shown in Table 4. The results of MAEP, RMSE, and R^2 are computed for the networks. It can be observed that the R^2 values vary in ranges of 0.947-0.993 overall, 0.912-0.964 for the training stage, and 0.978-0.980 for the testing stage in cold-water fish. In hot-water fish, the corresponding values are 0.885-0.998 overall, 0.923-0.952 for the training stage, and 0.952-0.995 for the testing stage. Matlab (R2016b) is employed for model implementation and data training. Feed-forward back-propagation neural networks with the Levenberg-Marquardt training algorithm are employed for the ANN models. Sigmoid and linear functions are adopted as activation functions in hidden and output layers, respectively. For the two types of fish production, the developed ANN models are different. A 7-11-3-2 structure is adopted as the predictive ANN model for cold-water fish, i.e., two hidden layers are adopted with seven neurons in the input layer, eleven and three neurons in hidden layers, and two neurons in the output layer. The best ANN structure for hot-water fish is 7-9-8-2, with again two hidden layers, but with seven neurons in the input layer, nine and eight neurons in hidden layers, and two neurons in the output layer. Elhami et al. (2017) employed an ANN model to predict environmental impact categories and yield of lentil cultivation. The selected ANN architecture consisted of two hidden layers with nine neurons in the input layer, ten and six neurons in the hidden layers, and eleven neurons in the output layer. Chen and Jing (2017) predicted the yield by using ANN and estimated MAPE, RMSE, and R^2 at 10.38%, 979 kg ha^{-1}, and 0.61, respectively.

Table 4

The results of different arrangements of ANN models in different fish production.

Types of production (best topology)	Items	Statistics indices	Independent variables	
			Output energy	Economic productivity
Cold-water fish (7-11-3-2)	Overall	R^2	0.993	0.947
		RMSE	0.112	0.089
		MAPE (%)	0.035	0.116
	Train	R^2	0.964	0.912
		RMSE	0.325	0.149
		MAPE (%)	0.036	0.049
	Test	R^2	0.980	0.978
		RMSE	0.158	0.036
		MAPE (%)	0.114	0.118
Hot-water fish (7-9-8-2)	Overall	R^2	0.998	0.885
		RMSE	0.213	0.119
		MAPE (%)	0.089	0.073
	Train	R^2	0.952	0.923
		RMSE	0.251	0.113
		MAPE (%)	0.008	0.008
	Test	R^2	0.995	0.952
		RMSE	0.216	0.356
		MAPE (%)	0.084	0.039

Conclusions

The sustainability of the current rate of the aquaculture industry development requires a way to increase environmental, social, and economic acceptance. The amount of production in terms of energy should be more than the amount of input. Therefore, systematic and purposeful fish farming always deals with the rational use of production resources. The total energy use of cold-water and hot-water fish is 26827.84 MJ ton^{-1} and 33901.40 MJ ton^{-1}, respectively. Starting feed, growth feed, and fattening feed contributed significantly to energy consumption. Electricity consummation in different fish production with 22% in cold-water fish and 25% related to hot-water fish. The total cost of producing cold-water fish (1715.31 \$ ton^{-1}) and hot-water fish (1904.06 \$ ton^{-1}) showed that fish production is profitable in these sites as its income exceeds the costs. The ANN results showed that values of R^2 vary in ranges of 0.947-0.993 overall, 0.912-0.964 for the training stage, and 0.978-0.980 for the testing stage in cold-water fish. Regarding hot-water fish, the corresponding values are 0.885-0.998 overall, 0.923-0.952 for the training stage, and 0.952-0.995 for the testing stage. According to the results, ANN can predict output energy and economic productivity. The purpose of this work was to determine the best fish farming system. It is necessary to optimize the fish feed and maximize feed utilization through the use of combined breeding systems and water recirculation. It is recommended to minimize the load of waste products in the effluent by using appropriate drainage techniques during fishing.

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