Chapter 7
A Neuro-Fuzzy Approach to Selecting Crops in Vertical Irrigation

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Abstract Uncontrolled use of land resources and an ever increasing population has led to a scarcity of land in many countries, especially in Asia where population is higher than in other parts of the world. Also, the recent growth in urban populations has induced the use of forest land for agriculture or for residential purposes. In some countries governments are encouraging people to opt for vertical residences (multistoried apartments) where a single area is used to accommodate more than one family. In countries like China and Japan, where land scarcity is acute, people practice agriculture in multistoried structures. But irrigation requirements for this kind of agricultural practice are different from those of conventional procedures. Not all crops can be cultivated inside apartments due to the controlled nature of the inside environment. Thus the present study will try to find a methodology for selecting suitable species of crop for indoor cultivation ensuring the desired level of yield under minimum uncertainty.

Keywords Vertical irrigation • Fuzzy logic • Neuro-genetic model

7.1 Introduction

This investigation aims to formulate a procedure for selecting crops that would be suitable for cultivation under vertical irrigation systems. Advances in neurogenetic models and fuzzy logic are used to identify and predict the suitability of crops for the considered conditions.

The recent demand for land by burgeoning populations and requirements to ensure food security for those populations make the system of vertical crop cultivation the easiest and most useful solution to the current crisis of land availability.

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The scarcity of land has forced farmers to encroach on forest land and even riverbeds to satisfy the rising demand for food.

To prevent such land use, the cultivation of crops under vertical irrigations systems to maintain the food supply has been found to be the easiest and most reliable solution. But the problem with such a system is that not all crops support vertical irrigation systems. The following factors must be considered for the cultivation of crops under vertical irrigation methods:

1. Length of roots (L_R)
2. Spread of roots (R_S)
3. Nutrient absorption (N)
4. Temperature tolerance (T)
5. Water tolerance (W)
6. Parasite tolerance (Pa)
7. Space requirements (A)
8. Profitability compared with conventional agricultural practices (P)

Short crops whose roots do not spread out very much can absorb nutrients from water and do not depend on the soil for their daily nutrient requirements, and crops that are temperature tolerant and do not attract parasites or other pests can be used for cultivation under vertical irrigation systems.

Because the cultivation will be performed in vertical systems, the weight of the crop is a major factor when selecting crops for such systems. The crops must not be highly water intensive because excess water will increase the weight requirement. That is why drip or sprinkler irrigation is used in such irrigation methods, where water is channelized from a reservoir situated on a roof. A proper drainage system must also be used so that water is not stored anywhere within the irrigation system. Because soil increases the weight requirement and can attract different hazardous species, hydrophilic plants are generally preferred. But plants with minimum requirements for soil or that can be cultivated in sandy soil also are harvested under vertical irrigation systems. Plants must also be odorless and not attract insects or other parasites because this can create disturbances to other residents of the vertical dwelling. Generally fruits like tomatoes, vegetables like lettuce, cabbage, and brinjal, and crops like rice and maize are popular species known to be cultivated under vertical methods of irrigation.

The success of a vertical irrigation system thus mainly depends on the capacity of the crop to tolerate a controlled and closed environment and the efficiency of the farmer in meeting the daily requirements of the crop. Proper selection of crop species also reduces maintenance requirements.

Not only the environment, but the profitability of crops raised in a vertical irrigation system compared to those raised in conventional irrigation systems must also be considered. Only if profit is maximized or loss minimized compared to old irrigation systems can a species of plant be cultured in a vertical irrigation process.

That is why the present investigation uses neuro-fuzzy techniques to estimate the nonlinear interrelationships that exist in the prediction of crop suitability under such specialized irrigation systems.

7.1.1 Brief Methodology

Fuzzy logic, a recent innovation in searching for optimal solutions to complex problems, is used to determine the weighting of each variable according to its importance in determining the suitability of a crop being cultivated under a vertical irrigation systems.

The weighting was used to determine the weighted average of the variables, which is directly related to the suitability of a particular plant species for cultivation under a nonconventional irrigation system.

The weighted average and value of all the input variables are categorized such that each category represents the level of suitability of the crop due to the quantitative or qualitative situation of the variable. For example, the length of the root can be encoded into nine categories from Extremely Small to Extremely Large. The category Extremely Small will have the highest level of suitability with respect to other categories of the variable. Again, for the variable parasite tolerance, Extremely High will represent the higher suitability of the crop compared to the other categories for cultivation in a vertical irrigation system.

The categorized data of the variables will help to create a combinatorial data matrix considering each possible combination that may exist among the input and output variables. Each of the categories was rated according to its impact on the selection mechanism. The rankings were then used to determine the weighted average. This weighted average was also categorized in such a way that Extremely High represents greater suitability of the crop than other categories and Extremely Small represents the opposite characteristic of the sample species.

A neurogenetic model was then used to formulate the relationship between input and output variables in such a way that if the category of the input variables is given, the model predicts the level of suitability of the plant species for cultivation under a vertical irrigation system. Because the neurogenetic model will be trained by the combinatorial data matrix, the model can predict the suitability of any combination of input variables. The model is validated by performance metrics like precision, sensitivity, specificity (CEBM 2012), and kappa index of agreement (GANFYD 2012).

7.1.2 Fuzzy Logic

Zadeh et al. discovered the benefit of following fuzzy logic in solving practical decision-making problems. Fuzzy logic nowadays is applied in various field such as the selection of a reservoir operating mechanism, watershed management, dam break analysis, and other optimization and clusterization problems.

Fuzzy logic was used in this study to determine the weighting that represents the role of variables in identifying species' suitability for cultivation under a vertical irrigation system.

7.1.3 Neurogenetic Models

Neural network models follow the signal-transmission mechanism of the human nervous system. The capability of the human nervous system to identify complex, nonlinear, and uncertain situations is mimicked in solving real-life decision-making problems. Analysis of recent studies shows that neural networks have been applied to various topics in engineering, medicine, science, and the arts (Table 7.1).

Such networks were used either separately or coupled with other sophisticated and high-end linear, nonlinear, and metaheuristic algorithms for prediction, clusterization, and function approximation problems (Table 7.2)

The problem independency, data flexibility, and efficiency in mapping complex collinearity has made the neural network one of the most sought-after modeling techniques, and it was thus applied in the present investigation for the assessment of crop suitability.

Neural networks are often referred to as black boxes and, due to the requirements for large amounts of data and computational infrastructure, applications of neural networks are generally limited to problem domains where a satisfactory database is available and supported by high-end computational facilities. The selection of network topology and activation function along with algorithms for updating the weights is made using either a trial-and-error method or by the application of various search algorithms like genetic or swarm or simulated annealing, as shown in Table 7.2. As was correctly pointed out by Duin (2000) and Jain and Nag (1998), no universally accepted methodology is available yet to guide a developer of such models in the selection of the three most important parameters (network topology, activation function, and input weights), which inherently affect the accuracy level of the developed models.

7.1.4 Genetic Algorithm

A genetic algorithm (GA) is a popular search algorithm that replicates the crossover mechanism of meiotic cell division where traits of the parent are transferred to the new cell. Some traits become dominant, some dormant, but few new traits are formed due to mutation. In practical problem solving, GAs are applied to searching for the optimal solution from among the many available ones. Available solutions are compared with genes that are transferred to the child cell and from the available solution 100 or 1,000 new solutions are randomly generated. Among the newly generated solutions, the five or ten best solutions are selected with the help of fitness functions. The selected optimal sets of solutions are then used in crossing over where traits of one solution are combined with other traits of another solution to generate a new solution. The optimal solution is identified with the help of the same fitness function, but from the new set of generated solutions. The crossover mechanism is not mimicked when optimal solutions are identified with asexual GAs.

Table 7.1 Examples of neural network applications in different fields of science, arts, and engineering

Authors	Subject	Main objective
Xia et al. (2012)	Power system, electrical Engineering	Development of electric load simulator including effects of superfluous torque
Wei et al. (2012)	Water resource management, civil engineering, management science	Decision tree and neural-network-trained decision tree algorithms were compared in decision making with respect to reservoir release during typhoonlike extreme events
Rajagopalan et al. (2012)	Communication theory, electronic engineering,	Optimization of band use of communication channels
Waszczyszyn and Ziemiański (2001)	structural technology, civil engineering	Study was aimed at estimating duration of structural fatigue
Hussain (1999)	manufacturing process technology, chemical engineering	An overview of neural network applications in predictive control, inverse-model-based control, and adaptive control methods in chemical process technologies was summarized where the satisfactory performance from using a neural network for both simulation and online applications was clearly identified.
Abdullayev and Ismaylova (2011)	Radio medicine	Detection of pathologic changes in electrostimulative electromyograms of patients with normal state of neuromuscular system and for muscular syndromes such as carpal tunnel syndrome
Zeng (2012)	Diagnostic medicine	Study aimed to make an efficient EEG monitoring with neonates possible
Mafakheri et al. (2012)	Metallurgy, nanoscience	Estimation of coercivity of cobalt nanowires
Akbari et al. (2012)	Thermal science, HVAC, electrical appliances	Study tries to predict the effectiveness of latent and sensible heat transfer between exhaust and supply air of a run-around membrane energy exchanger (RAMEE) in a high voltage air-conditioning system
Golmohammadi (2011)	Economics, decision making	Identification of the relationship between criteria and alternatives solutions of a decision-making problem and ranking the alternatives based on the learned knowledge
Kumari and Majhi (2012)	Social science	Determination of an optimal classifier for gender categorization through face recognition

Although GAs have been applied with satisfactory results (Park et al. 2012; Pinthong et al. 2009; Reddy and Kumar 2006) in various problem domains where the optimal solution must be found, but due to the randomized nature of the algorithm and the lack of a predetermined methodology, problems are solved using such metaheuristic algorithms when no other solution is available.

Table 7.2 Applications of neural networks in prediction, classification, and regression or functional approximation problems

Authors	Type of application	Type of neural network	Remarks
Liu et al. (2012)	Prediction	Genetic neural network (GNN)	Evapotranspiration and runoff dynamics of two plantation was predicted with the help of GNN, back-propagation neural network and M-Stat statistical model. The results reveal that GNN has better performance efficiency, robustness, and effectiveness than the other two models
Lohani et al. (2012)	Prediction	Adaptive neuro-fuzzy inference system (ANFIS)	Reservoir inflow was predicted with the help of ANFIS, ANN, and an autoregressive technique. Comparison of the model outputs showed that ANFIS outperformed other two models
Moustra et al. (2011)	Prediction	Feed forward neural network	Magnitude of earthquake was predicted with the help of seismic electric signals, which are known indicators of major upcoming earthquakes
Wu and Chau (2011)	Prediction	ANN coupled with singular spectrum analysis (SSA)	Rainfall-runoff transformation model was developed with the help of modular artificial neural network (MANN) and ANN coupled with SSA. As SSA can remove the lag effect of prediction that generally degrades performance of ANN runoff prediction models, the model performance of the latter was found to be better than MANN

Barkhatov and Revunov (2010)	Classification	Kohonen neural network	Classification of discontinuities in space plasma parameter with respect to solar wind parameter
Yamaguchi et al. (2008)	Classification	N-version programming ensemble of artificial neural networks	Land classification of MODIS satellite imagery by an ensemble fault masking neural network classifier
Aquil et al. (2007)	Prediction	Neuro-fuzzy	Study attempted to model daily and hourly runoff patterns in a continuous-time domain. The result demonstrates satisfactory performance of developed model when compared with Levenberg–Marquardt-feedforward neural network (FFNN) and Bayesian regularization FFNN
Teegavarapu (2007)	Regression	Stochastic neural network	Neural network and Kriging interpolation of rain-gauge data were compared; performance metrics made it clear that the former is more efficient than the latter
Tomandl and Schobe (2001)	Regression	Modified general Regression neural network (MGRNN)	MGRNN was used to generate arbitrary data from a database.
Gupta and McAvoy (2000)	Prediction	Simple recurrent neural network (SRNN)	A multiclass prediction problem was solved successfully by introduction of two different SRNNs

7.2 Methodology

The suitability of crops in vertical irrigation systems was identified using fuzzy logic and neurogenetic models. Fuzzy logic was used to determine the weighting of the input variables, and neurogenetic models were used to predict crop suitability. Crop suitability was estimated based on the characteristics of the input variables represented by different categories, which reflected the different levels of intensity of the input variables.

Table 7.3 presents a step-by-step description of the important phases of the study methodology in identifying the suitability of a species in terms of being cultivated under a vertical irrigation system. Table 7.4 gives the rules that were used to categorize variable data sets and corresponding rankings for encoding the influence of variables in the objective or suitability function, which in turn represents the suitability of a species to be cultured in a vertical irrigation scheme.

Table 7.5 shows the rank and corresponding degree of importance of the same, which were later used to determine the weighting of the variables.

The fuzzy categories of the input variables were established using the rule described in Table 7.5. Inference is performed by comparing each variable with the others and assigning the variable to the given fuzzy category according to Table 7.5.

The rule matrix and corresponding membership function are shown respectively in Tables 7.6 and 7.7. The membership function was determined by dividing the row of the rule matrix by the maximum or worst possible rank assigned for that row.

In the rule matrix, the rank of the importance of the variable with respect to the other variables will be shown in each row. If a variable has a higher importance than the variable with which it is compared, then the cell under the compared variable will have a higher rank (1, 2, …) and vice versa. Thus, when the worst rank received by a row is divided, the lowest value of the operation will be assigned to those variables in comparison to which the present variable has received a high rank and the large value of the result will be for those that are more important than the present variable in the context of the present problem.

Thus, the lowest value of the division will have the highest importance received by the variable and the highest value from the same operation will have the lowest importance assigned to the present variable. The lowest value is inverted to determine the weighting of the given input variable so that the influence due to the importance becomes proportional to the objective of the suitability function.

In the present study, the defuzzification procedure was not required as the authors were interested in predicting a categorized output rather than a numerical one so that the generalization aspect of the modeling platform was not affected.

Table 7.3 Important steps in identification of suitability of a species for cultivation under vertical irrigation systems

Step	Method applied	Purpose	Justification	Tools applied
1	Application of fuzzy logic	To determine the weighting of each variable with respect to its influence on the electability of a species for vertical cultivation	Fuzzy logic is well known for its ability to search for the optimal solution from among the many available. In the present problems also no predetermined weighting was available due to the lack of an adequate number of published studies. As fuzzy logic's theory of maximization has been applied to determine the weighting for similar objectives it was later selected to accomplish the present step	Aggregation
2	Categorization of the variable data set according to Table 7.4	To prepare a combinatorial data matrix and to remove any discrepancy that may arise due to the difference in scale of the variables	Categorization of the data set of a variable converts the variable into a dimensionless value where only the degree of intensity or superficiality of the variable was represented. Such a data set was found to be useful in training neural network models as it does not understand the inherent physical relationship of the variables; instead, the objective of such meta-heuristics was to identify the inherent empirical relationships that exist between variables	IF THEN Rule

(continued)

Table 7.3 (continued)

Step	Method applied	Purpose	Justification	Tools applied
3	Conversion of the categorized variable into its numerical form based on ratings	To determine the value of an objective function, the categorized variable was converted into its numerical counterpart based on the ratings given in Table 7.4	This step was found to be necessary to estimate a value of the suitability function that represents the suitability of the species for cultivation under vertical irrigation system	$S = \text{Suitability function} \dfrac{\sum_{n=i}^{i} n_i \times V_i}{\sum n \times \sum V} \quad (7.1)$ where n_i is the weighting that was determined with the help of fuzzy logic in Step 1, V_i is the numerical value of the variable derived from Table 7.4, and i represents the number of variables considered for the study
4	Conversion of the output into categorized form	As the objective of the model was to predict the suitability instead of predicting the output in numerical terms, which would be highly scale dependent, the suitability was estimated in a categorized form so that the relativity of the suitability could be defined in a deterministic manner	As the objective was to estimate suitability, a categorized form will always be more generalized (Lebowitz 1985)	The rule given in Table 7.4 was followed while categorizing the output

5	Development of neurogenetic model	The model was developed for the prediction of the output variable, i.e., suitability function S. The main purpose of the model development was to introduce a uniform platform of prediction that is free from objective bias that may be introduced by fuzzy logic	Neurogenetic model was found to perform better than the statistical and other nonlinear models in the case of prediction with a categorized data set (Kulkarni et al. 2008; Doğan et al. 2007)	Simple feedforward neural network model trained by conjugate gradient descent algorithm and topology identified by genetic algorithm along with a logistic activation function was applied for predicting the interrelationship between the categorized variables
6	Validation of developed model	The model was validated with the help of precisions Sensitivity, specificity and kappa index of agreement by comparing the actual and predicted category of the output variable	The validation of a model depicts the reliability of its performance capability. The selected performance metrics was found to be a better representative of model accuracy (Midgley et al. 1969; Linder et al. 2008)	Precision-sensitivity-specificity (Tan et al. 1999) Kappa index of agreement (Laurent et al. 2008; Van Den Eeckhaut et al. 2006)

(continued)

Table 7.3 (continued)

Step	Method applied	Purpose	Justification	Tools applied
7	Case study with rice (*Oryza sativa*) and maize (*Zea mays*)	Model was tested for a real-life problem where species like rice and maize were evaluated for use under vertical irrigation systems	The case study can represent the reliability of the developed methodology so that the study can be confidently reapplied to solve similar problems	The developed neurogenetic model, along with the required data describing the input variables for rice and maize crops

Table 7.4 Methods of categorization of variables

Level of intensity	Category	Rating (for variables directly proportional to suitability function)	Rating (for variables partially proportional to suitability function)	Rating (for variables inversely proportional to suitability function)
Extremely intense (values between 86 and 100% of max value)	EH	9	5	1
Very intense (values between 76 and 85% of max value)	VH	8	4	2
Highly intense (values between 66 and 75% of max value)	H	7	3	3
Semi highly intense (values between 56 and 65% of max value)	SH	6	2	4
Neither intense nor superficial (values between 46 and 55% of max value)	N	5	1	5
Semi superficial (values between 36 and 45% of max value)	SL	4	2	6
Highly superficial (values between 26 and 35% of max value)	L	3	3	7
Very superficial (values between 16 and 25% of max value)	VL	2	4	8
Extremely superficial (values less than 15% of max value)	EL	1	5	9

Table 7.5 Degree of importance and corresponding ranks assigned to variables based on their importance compare to other variables (fuzzification)

Rank	Degree of importance
1	Highly important
2	Important
3	Neither important nor unimportant
4	Unimportant
5	Highly unimportant

Table 7.6 Rank of importance assigned to different input variables of proposed model (rule matrix)

	L_R	R_S	N	T	W	Pa	A	P
L_R	0	3	2	1	3	1	3	3
R_S	3	0	2	2	4	3	3	3
N	4	4	0	3	4	3	5	5
T	5	4	3	0	3	3	2	5
W	3	2	2	3	0	2	3	4
Pa	5	3	3	3	4	0	3	4
A	3	3	1	4	3	3	0	3
P	3	3	1	1	2	2	3	0

Table 7.7 Weighting assigned to each variable following application of theory of minimization (membership function)

	L_R	R_S	N	T	W	Pa	A	P	Minimum	Wtg
L_R		1.00	0.67	0.33	1.00	0.33	1.00	1.00	0.33	0.67
R_S	0.75		0.50	0.50	1.00	0.75	0.75	0.75	0.50	0.50
N	0.80	0.80		0.60	0.80	0.60	1.00	1.00	0.60	0.40
T	1.00	0.80	0.60		0.60	0.60	0.40	1.00	0.40	0.60
W	0.75	0.50	0.50	0.75		0.50	0.75	1.00	0.50	0.50
Pa	1.00	0.60	0.60	0.60	0.80		0.60	0.80	0.60	0.40
A	0.75	0.75	0.25	1.00	0.75	0.75		0.75	0.25	0.75
P	1.00	1.00	0.33	0.33	0.67	0.67	1.00		0.33	0.67

7.3 Results and Discussion

The steps described in Table 7.4 were followed to develop a suitability function and a model to predict it with the help of fuzzy logic and a neurogenetic model, respectively. Table 7.6 shows the rank of importance assigned to each of the variables with respect to the others. The importance represented by each rank was already shown in Table 7.5. Table 7.7 presents the value of the weighting assigned to each of the variables according to the theory of maximization rule.

The combinatorial data set was used for training the neurogenetic model so that it could predict any possible unknown combination of the input variables. The parameters of the neurogenetic model and performance as represented by the metrics were shown in Table 7.8.

The values of the performance metrics (Table 7.8) show the level of accuracy of the model. As the precision, sensitivity, specificity, and kappa of the model prediction compared to the actual categories of the output were respectively 93.93, 98.04, 99.62 and 96.78%, it can be concluded that the model is robust and effective enough to be used to predict the suitability function (Eq. 7.1).

Table 7.8 Parameters of neurogenetic models and performance metrics used for validation of simulation platform

Model parameter	Value received
Type of network	Feedforward with logistic activation function
Topology selection algorithm	Sexual genetic algorithm (GA)
GA parameters	
Number of people allowed	60
Number of generations allowed	50
Rate of crossover allowed	0.80
Rate of mutation allowed	0.20
Network topology	8-16-1
Network weight	144
Training algorithm	Conjugate gradient descent (CGD)
CGD parameters	
Generalization loss allowed	±50.00%
Outliers allowed	±70.00%
Training accuracy (A) allowed	98.00%
Number of iterations allowed	1,000,000
Number of retrains allowed	10
Category encoding	9
Testing accuracy	98.15%
Training accuracy	98.69%
Model validation parameters	
Precision	93.93%
Sensitivity	98.04%
Specificity	99.62%
Kappa index of agreement	96.78%

Table 7.9 Categories assigned to variables and prediction results from model

Input variables	Rice	Maize
L_R	VL	N
R_S	VL	N
N	H	L
T	H	H
W	VH	N
Pa	H	N
A	L	L
P	H	VH
Output variable: S	**SH**	**VH**

As discussed in the methodology section, the developed model was applied to predict the suitability of rice and maize for cultivation under a vertical irrigation system. Table 7.9 shows the characteristics of rice (Morita and Nemoto 1995; Agrocommerce can be consulted for a thorough description of the cultivation of *Oryza* sp.) and maize (for an in-depth description of the morphology and cultivation characteristics of maize, FAO manuals can be consulted) represented by the model input. The result of the suitability function is also given in Table 7.9.

For example, in the case of rice, the lowland variety was chosen, and in the case of maize, the yellow variety was selected for the present investigation.

In terms of climatic variables, only conditions required in the growing season were considered.

According to the prediction results, *Oryza* sp. had a suitability score of Semi High, whereas that of *Zea* sp. was predicted to be Very High for vertical irrigation schemes. Although rice has a very short root length and spread compared to maize due to its very high water requirements compare to maize (normal water requirement), the degree of suitability of rice was predicted to be lower than that of maize. Also, maize's profitability score was higher than rice's. Both characteristics of the most important input variables (LR and P were assigned the highest weighting among other variables) was found to favor maize, which explains the prediction result from the neurogenetic model.

7.4 Conclusion

The present investigation proposed a methodology for selecting suitable crop species that could be cultivated under vertical irrigation systems. The features that a crop to be cultivated under such systems should or must have were first identified from various studies and government manuals. Once the features were identified, fuzzy logic was used to determine the weighting of each variable. Once the weighting was determined, a neurogenetic model was prepared to predict suitability through a suitability function. Categorized data considering all possible combinations of the input and output variables were used to train the model, and crop suitability was also predicted in a categorized form so as to maintain the generalized nature of the decision support system. Rice and maize were tested with the modeling platform where the model correctly predicted the lower suitability of rice compared to maize for cultivation under a vertical irrigation scheme. The present study tried to highlight the necessity of evaluating crops in terms of their suitability for vertical farming. The conclusions derived from the model could save both money and energy for a farmer planning to initiate indoor agricultural projects. As a further development of the study, various methods of categorization by objective classification can be experimented.

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