UDC 004.89
Original Scientific Paper

An Artificial Neural Network Modeling for Force Control System of a Robotic Pruning Machine

Ali Hashemi *hashemi@pgu.ac.ir*
Department of Horticulture, Faculty of Agriculture and Natural Resources
Persian Gulf University, Bushehr, Iran

Keyvan Asefpour Vakilian *keyvan.asefpour@ut.ac.ir*
Department of Agrotechnology, College of Abouraihan
University of Tehran, Tehran, Iran

Javad Khazaei *jkhazaei@ut.ac.ir*
Department of Agrotechnology, College of Abouraihan
University of Tehran, Tehran, Iran

Jafar Massah *jmassah@ut.ac.ir*
Department of Agrotechnology, College of Abouraihan
University of Tehran, Tehran, Iran

Abstract

Nowadays, there has been an increasing application of pruning robots for planted forests due to the growing concern on the efficiency and safety issues. Power consumption and working time of agricultural machines have become important issues due to the high value of energy in modern world. In this study, different multi-layer back-propagation networks were utilized for mapping the complex and highly interactive of pruning process parameters and to predict power consumption and cutting time of a force control equipped robotic pruning machine by knowing input parameters such as: rotation speed, stalk diameter, and sensitivity coefficient. Results showed significant effects of all input parameters on output parameters except rotational speed on cutting time. Therefore, for reducing the wear of cutting system, a less rotational speed in every sensitivity coefficient should be selected.
Keywords: power consumption, sensitivity coefficient, back-propagation, rotational speed

1. Introduction

In recent years, the use of robotic systems in agricultural operations has been developed because of advances of robotic and mechatronic technologies. Nowadays, robotic systems are used in many agricultural applications. The most interested application of agricultural robots is harvesting, including strawberry, cucumber, watermelon, tomato, orange, and apple harvesting robots [6].

There are many different manipulator control techniques available for agricultural robots, with the particular application. Position control has been applied in many agricultural applications. However, some tasks such as smooth grinding, cooperative robots, tele-operation and soft-grippers cannot be accomplished by position control. Because of these limitations, force and torque control systems were introduced. The forces being exerted are controlled by the manipulator on its environment with using these methods. Such these systems can automatically align the manipulator holding the connector as it is inserted, increasing the probability of successful completion [3].

Pruning the trees is one of the difficult and tedious operations for human. Moreover, mechanical methods of pruning are expected to be automated due to increasing manpower costs [7]. There has been an increasing application of pruning robots for planted forests due to the growing concern on the efficiency and safety issues. Accurate motion control is important in improving the pruning robot reliability and performance. Reference [9] described a research on intelligent pruning machines. The authors of this research used digital image processing and pattern recognition to establish a dynamic-automatic identification of standing tree limbs. They also extracted the basic growth characteristics of standing trees such as form, size, bending degree and relative space positions.

In a study, main parameters of standing tree pruning robot have been determined: working mode, cutting mechanism and transmission of a standing tree pruning robot [3]. The authors of reference [11] developed a gardening pruning robot which was able to prune trees automatically into varied geometrical shapes by program controlling. According to this research, not only the shape and size of the trimmed trees were accurate and stable, but also the labor efficiency was improved. Reference [14] presented a motion logic control system based on the Complex Programmable Logic Device (CPLD) for remote control pruning robot. They have developed motion control system of remote control pruning robot for standing trees.

Reference [8] reported a robotic pruning machine with force control system. In their research, power consumption and required time for pruning tasks were determined for different sensibility coefficients. They used a force control system to prevent collision damage in pruning machine. This can be achieved by keeping fixed contact force in a definite level. This system decreased the manipulator feed with respect to the set point whenever the contact force increased. In their study, the motion velocity of end effector in horizontal plane was changed by altering the coefficient of sensitivity.

In recent years, Artificial Neural Networks (ANNs) have become useful tools to develop models which express the interrelationship between the input and the output parameters of complicated systems [2]. Many researchers have attempted to use ANN to model various applications in the robotic area. Reference [1] used a system based on ANN to control a robot arm with a highly nonlinear structure. The ANN was used successfully to adjust the parameters of the controllers. ANN controllers have been used by other researchers in order to control the position of the links [4], [5].

Reference [13] proposed a progressive learning method using ANN which can obtain the target impedance parameters by modifying the desired velocity trajectory. Reference [12] developed a control algorithm using ANN for on-line adapting robot parameters to the unknown contact environment.

Reference [10] used ANN to regulate impedance parameters of the manipulator’s end-effector while identifying environmental characteristics through on-line learning. They used four ANNs: three for estimating the position, velocity and force control of the end-effector, and one for the identification of environment conditions. Reference [2] suggested that an ANN with a simple learning rule can be used as a sustainable robot controller for experiments in computational motor control.

The objectives of this study were: (a) to utilize different multi-layer back-propagation networks for mapping the complex and highly interactive of pruning process parameters and to predict power consumption and cutting time of a robotic pruning machine by knowing input parameters such as: rotation speed, stalk diameter, and sensitivity coefficient of the force control system and, (b) to clarify that which input parameter(s) had insignificant effects on the output parameters.

2. Materials and Methods

A pruning robot including a manipulator with three degrees of freedom (PPR), end effector and three actuators was developed (Fig. 1) [8]. End effector included a rotating saw and S-shaped load-cell (DBBP, Bongshin, Korea) (Fig. 2). The current paper reports the capability of different ANN architectures for prediction of power consumption and cutting time in a constructed robotic pruning machine.

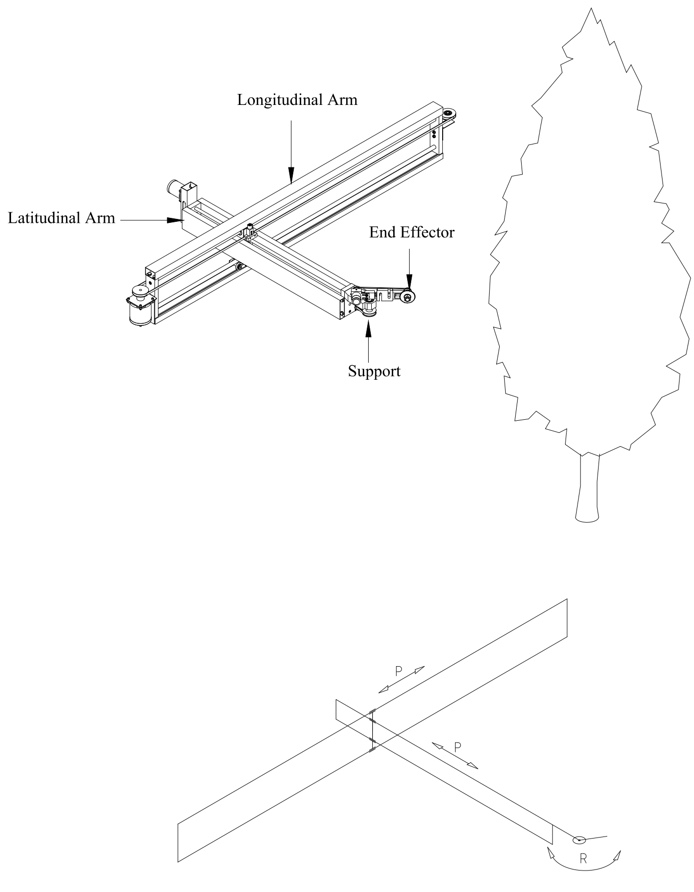

Figure 1. Partial views of the pruning robot [8]

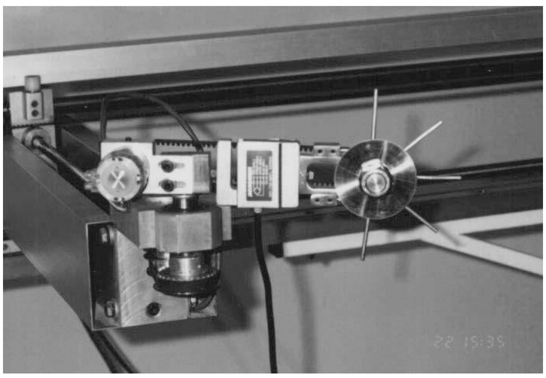

Figure 2. End effector of the pruning robot [8]

The parameters that have effects on the robotic pruning processes are inter-dependent and constantly changing in a complex way. Therefore, a feed-forward structure for the ANN was adopted in this work. There were several factors that influenced the power consumption and cutting time of the force control system in the robotic pruning processes. However, three factors including rotation speed, stalk diameter, and sensibility were coefficient in this research. Four 3-layers feed-forward networks were constructed with one neuron in the output layer. Table 1 shows a schematic representation of a multi-layer ANN configuration employed in this research.

Proper determination of parameters weight and the number of hidden layer neurons is important, because they affect not only the network's convergence, but also the accuracy of the prediction. In order to understand the effect of the ANN parameters on the power consumption and cutting time, the number of hidden-layer neurons was chosen from 2 to 11 for all defined ANNs. The accuracy of each network was evaluated by the Root Mean Square Error (RMSE) between the measured and the predicted values for the training and the testing dataset.

ANN	Network inputs	Network output
ANN_1	Sensitivity coefficient + Stalk diameter	Cutting time
ANN_2	Sensitivity coefficient + Stalk diameter + Rotational speed	Cutting time
ANN_3	Sensitivity coefficient + Stalk diameter	Power consumption
ANN_4	Sensitivity coefficient + Stalk diameter + Rotational speed	Power consumption

Table 1. Hierarchical ANNs for prediction of cutting time and power consumption

The choice of the hidden layer size is one of the most important considerations for the ANN design and it strongly depends on the particular problem under consideration. The exact analysis of this issue was quite difficult due to the complexity of the network mapping and the nondeterministic nature of the many successfully completed training procedures. In this work, the number of neurons in the hidden layer is determined by the trial and error approach. The number of neurons within the hidden layer was selected based on the accuracy of the prediction.

3. Results and Discussion

Table 2 indicates an example of the training data [8]. In order to choose the parameters (weights), the network was trained by training set. Levenberg– Marquardt back-propagation approximation algorithm was employed to train the ANN models. Training of the ANN was performed off-line. Lastly, testing data was used to validate the quality of proposed ANN model.

Inputs			Outputs	
Sensitivity coefficient	Rotational speed (rpm)	Stalk diameter (mm)	Power consumption (KW)	Cutting time (s)
1	2000	12	2.42	21
1	2500	14.5	2.94	22.5
1	3000	19	3.07	29.5
2	3000	12	2.71	23
2	3000	14.5	2.78	23.5
3	2000	12	2.11	25.5
3	2000	19	2.65	27
3	2500	14.5	2.18	23.5
3	3000	12	2.23	23
3	3000	19	2.46	28.5

Table 2. Examples of training data set [8]

Table 3 presents the performance of ANN_1 and ANN_3 with various architectures. According to this table, the lowest RMSE value for ANN_1 was achieved in the 2-7-1 ANN architecture, while the highest RMSE was obtained from the 2-4-1 case. During the training process, it was found that increasing the number of neurons in the hidden layer was not directly related to the decrease of the RMSE.

Results showed that the average RMSE at the training phase was reduced to about 0.13. No further reduction of the RMSE was achieved even if the number of iterations was increased. From the results obtained, it can be observed that the RMSE values from different ANN architectures were able to converge to the final error goal value of 1% within the pre-set maximum training cycle of 8000 epochs. The RMSE at the testing phase was higher than that of the training phase, meaning that the network had good generalization ability.

ANN architecture	Training RMSE ($\times10^{-2}$) for ANN_1	Testing RMSE ($\times10^{-2}$) for ANN_1	Training RMSE ($\times10^{-3}$) for ANN_3	Testing RMSE ($\times10^{-3}$) for ANN_3
2-2-1	3.9	4.1	453.7	533.8
2-3-1	7.5	8.3	299.2	544.0
2-4-1	12.4	15.3	355.3	258.5
2-5-1	9.6	8.7	119.5	398.3
2-6-1	8.3	11.4	966.2	789.4
2-7-1	2.4	3.2	332.8	355.0
2-8-1	5.4	10.7	220.6	443.4
2-9-1	9.9	12.4	455.7	332.4
2-10-1	10.9	9.7	112.6	323.6
2-11-1	6.2	9.2	675.1	766.8

Table 3. Performance of various ANN architectures for ANN_1 and ANN_3

Table 4 presents the performance of ANN_2 and ANN_4 with various architectures. According to this table, the lowest RMSE value for ANN_2 was achieved in the 3-6-1 ANN architecture, while the highest RMSE was obtained from the 3-4-1 architecture. In this case, the RMSE values from different ANN architectures was able to converge to the final error goal value of 1% within the pre-set maximum training cycle of 8000 epochs. Comparison of obtained RMSE values for ANN_1 and ANN_2 showed that ANN_1 had a good performance for prediction of cutting time. Therefore, the effect of rotational speed on cutting time was not significant and cutting time was a function of two parameters: sensitivity coefficient and stalk diameter.

ANN architecture	Training RMSE ($\times10^{-2}$) for ANN_2	Testing RMSE ($\times10^{-2}$) for ANN_2	Training RMSE ($\times10^{-3}$) for ANN_4	Testing RMSE ($\times10^{-3}$) for ANN_4
3-2-1	8.9	11.2	6.7	7.4
3-3-1	11.5	12.8	2.3	4.3
3-4-1	10.1	15.7	3.8	9.7
3-5-1	8.6	6.1	9.5	6.6
3-6-1	3.3	5.9	3.1	5.6
3-7-1	8.9	10.5	4.2	3.4
3-8-1	7.5	13.6	9.3	8.3
3-9-1	6.9	12.0	2.0	2.4
3-10-1	9.9	9.8	5.2	10.5
3-11-1	11.2	13.0	7.5	2.1

Table 4. Performance of various ANN architectures for ANN_2 and ANN_4

According to table 3, the RMSE values from different ANN architectures for ANN_3 was not able to converge to the final error goal value of 1% within the pre-set maximum training cycle of 8000 epochs and prediction error was obtained about 15%. Although, the RMSE values from different ANN architectures for ANN_4 were able to converge to the final error goal value of 1% within the pre-set maximum training cycle of 8000 epochs. The lowest

RMSE value for ANN_4 was achieved in the 3-9-1 ANN architecture, while the highest RMSE was obtained from the 3-5-1 architecture. Comparison of obtained RMSE values for ANN_3 and ANN_4 showed that ANN_3 had not a good performance for prediction of power consumption. Therefore, the effect of rotational speed on power consumption was significant and power consumption was a function of three parameters: sensitivity coefficient, stalk diameter and rotational speed.

Defined ANNs not only indicated the significance of input parameters on output parameters, but also they showed that cutting time and power consumption can be predicted using ANN_1 with 2-7-1 architecture and ANN_4 with 3-9-1 architecture, respectively.

Results of this research were similar to results obtained by reference [8]. They employed a factorial design to identify the input parameters and to compare their influences on the cutting time and power consumption to see which one is most significant. They found significant effects of sensitivity coefficient and stalk diameter on cutting time. By increasing these two input parameters, cutting time was increased. Also, their study showed that rotational speed had not significant effect on cutting time at 1% level. Three input parameters had significant effect on power consumption of pruning machine.

In this study, results showed significant effects of all input parameters on output parameters except rotational speed on cutting time. Therefore, for reducing the wear of cutting system, a less rotational speed in every sensitivity coefficient should be selected.

4. Conclusion

This paper reports the capability of different ANN architectures for prediction of power consumption and cutting time in a constructed robotic pruning machine. Levenberg–Marquardt back-propagation approximation algorithm was employed to train the ANN models. Results showed significant effects of all input parameters on output parameters except rotational speed on cutting time. Therefore, for reducing the wear of cutting system, a less rotational speed in every sensitivity coefficient should be selected. Defined ANNs not only indicated the significance of input parameters on output parameters, but also they showed that cutting time and power consumption can be predicted using ANN_1 with 2-7-1 architecture and ANN_4 with 3-9-1 architecture, respectively. Agricultural Machinery designers would be able to develop a high performance tree pruning machine utilizing the obtained results. Using other artificial intelligence methods such as Fuzzy Logic (FL) and Support Vector Machines (SVMs) for optimizing the values of pruning robot parameters can be useful for further studies.

References

[1] Acosta, L; Marichal, G.N; Moreno, L; Rodrigo, J.J; Hamilton, A; Mendez, J.A. A robotic system based on neural network controllers. *Artificial Intelligence in Engineering*, 13: 393-398, 1999.

[2] Burgsteiner, H. Imitation learning with spiking neural networks and real-world devices. *Engineering Applications of Artificial Intelligence*, 19: 741-752, 2006.

[3] Guang-qing, H; Nai-kang, W; Wen-bin, L. Design method and main parameters of standing tree pruning robot. *Journal of Beijing Forestry University*, 29(4): 27-32, 2007.

[4] Karakasoglu, A; Sundareshan, M.K. Recurrent neural network-based adaptive variable structure model following control of multi-jointed robotic manipulators. *Automatica*, 31(10): 1495-1507, 1995.

[5] Karakasoglu, A; Sudharsanan, S.I; Sundareshan, M.K. Identification and decentralized adaptive control using dynamical neural networks with application to robotic manipulator. *IEEE Transactions on Neural Networks*, 4(6): 919-930, 1993.

[6] Kondo, N; Nishitsuji, Y; Ling, P.P; Ting, K.C. Visual Feedback Guided Robotic Cherry Tomato Harvesting. *Transactions of the ASAE*, 39(6): 2331-2338, 1996.

[7] Liu, W; Kantor, G; Torre, D.L; Zheng, N. Image-based tree pruning. *In Proceedings of the IEEE international Conference on Robotics and Biomimetics*, pages 2072-2077, Guangzhou, China, 2012.

[8] Massah, J; Ghazavi, M.R. Effect of force control system on power and time consumption of tree pruning machine. *Cercetări Agronomice în Moldova*, 42(4): 5-15, 2009.

[9] Renshan, S; Wenbin, L; Yongchen, T; Li, H. Design method and main parameters of standing tree pruning robot. *Frontiers of Forestry in China*, 1(2): 150-153, 2006.

[10] Tsuji, T; Tanaka, Y. On-line learning of robot arm impedance using neural networks. *Robotics and Autonomous Systems*, 52: 257-271, 2005.

[11] Wang, X. Gardening pruning robot, Patent Number: CN2011 07935-Y, Patent Classification: A01G-003/00; A01G-003/04, 2008.

[12] Xiao, N.F; Todo, I. Neural network-based learning impedance control for a robot. *JSME International Journal. Series C, Mechanical Systems, Machine Elements and Manufacturing*, 44(3): 626-633, 2001.

[13] Yang, B.H; Asada, H. Progressive learning and its application to robot impedance learning. *IEEE Transactions on Neural Networks*, 7(4): 941-952, 1996.

[14] Zhang, J; Li, W; Sa, C; Wang, D. CPLD-based optimal control for wireless remote control pruning machine. *In Proceedings of the 13th international Conference on Computer Supported Cooperative Work in Design*, pages 374-377, Santiago, 2009.