International Journal of Electronics Engineering, 1(2), 2009, pp. 145-148

Decision Tree Based Control of Shunt DC Motor

R. S. Bhatia, B. P. Singh & J. S. Lather

Abstract: *A machine learning method called the ID3 (Interactive Dictomiser3) approach is presented for the speed control of shunt dc motor. A generated decision tree which is capable to decide the desire values of developed back emf in the armature, and shunt field current of shunt dc motor is created using the training pattern which is complied from the historical operating records on shunt dc motor. The established decision tree contains the knowledge which is essential for the speed control of shunt dc motor. Thus, it can be applied to speed control of shunt dc motor in an efficient manner. The effectiveness of the ID3 approach on shunt dc motor speed control is demonstrated.*

Keywords: *Average Entropy, Back emf, Iterative Dichotomizer 3 (ID3).*

1. INTRODUCTION

The application of Iterative Dichotomizer 3 (ID3) algorithm is an effective alternative for any problem where decision can be derived on the basis of casual relationships. DTs belong to the machine learning (ML) or artificial intelligence (AI) methods. Together with the group of statistical pattern recognition and that artificial neural network (ANN) they form the general class of supervision learning systems (LS) [1-2].

The speed (N) of a shunt dc motor (SDCM) can be controlled by three methods namely, field controlled (FC), armature controlled (AC), and applied voltage controlled (AVC). In FC method [7], N variation is accomplished by means of variable resistance insert in series with the shunt field. Increases in controlling resistance reduce the field current (I_{sh}) with a consequent reduction in flux (Ø) and an increase in N. Since in this method of SC, Ø can be only reduced (not increase) so the N only above normal can be obtained. In AC method [7], consists simply of a resistance connected in series with armature. With this method, the voltage across the armature drops as the current passes through the series resistance and the remaining voltage applied to the armature is lower than the V_L. Thus, the N is reduced in direct proportion to this voltage drop at the armature terminals. Wide range of N (below normal one) can be obtained by this method. In AVC method, SC requires a variable source of voltage separate from the source applying the I_{sh}. It is more expansive in initial cost and not a practicable method. A comparison of N adjustment of SDCM by means of FC, and AC method shows the superiority of field control for general use [7] [8].

In this paper, a ML method called ID3 approach [1] [2] is employed to SC of SDCM. In ID3 algorithm, a DT, which contains the domain knowledge, is created using the data set for SC of SDCM. To demonstrate the effectiveness of ID3 algorithm, SC of SDCM is formed by considering a motor having an line voltage (V_L) of 500V armature resistance (R_a) of 0.35Ω, a field resistance (R_f) of 80Ω, and a rated (full load) N of 1800 rpm.

This paper has been organized as follows: Section II gives the methodology of DTs. Section III is deals with the ID3 approach. SC of SDCM using DT methodology presents in Section IV. Section V is devoted to conclusion based on result.

2. DECISION TREES

The ordinary tree consists of one root, branches, nodes (place where branches are divided) and leaves. In the same way the DT [3-5] consists of nodes, branches stand for segment connecting the nodes. A DT is usually drawn from left to right or top-down structure, so it is easy to draw it. The first node is the root. The end of the chain from root to node is called leaf. Each internal node (i.e. not a leaf) may grow out two or more branches. Each node corresponds with a certain characteristic and the branches correspond with the range of values. The connection of DT never form closed loops. The general structure of DT is shown in Figure 1.

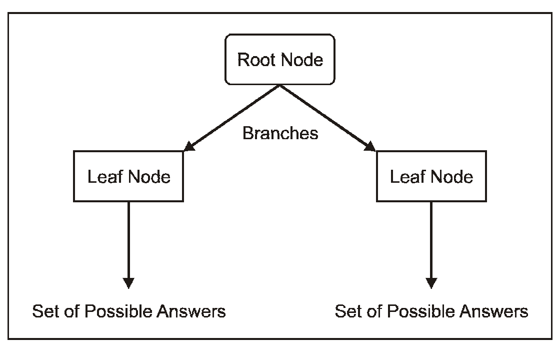

Figure 1: General Structure of Decision Tree

3. ID3 APPROCH

Quinlan [4] originally developed ID3 based on the concept learning system (CLS) algorithm. The actual algorithm is as follows:

Function ID3

Input: (R: a set of non-target attributes, C: the target attribute, S: a training set) returns a DT;

Begin

If S is empty, return a single node with value failure;

If S consists of records all with the same value for the target attribute,

If R is empty, then return a single node with the value of the most frequent of the values of the target attribute that are found in the records of S;

Let A be the attribute with largest gain (A, S) among attribute in R;

Let $\{a_j | j=1, 2, 3 \ldots m\}$ be the values of attribute A;

Let $\{S_j | j=1, 2, 3 \ldots m\}$ be the subsets of S containing respective records of values of a_j for A;

Return a DT with root labeled A and arcs labeled a_1, a_2, $a_3 \ldots a_m$ going respectively to the tree (ID3 (R-{A}, C, S1), ID3 (R- {A}, C, S_2) ….ID3 (R-{A}, C, S_m) ;

Recursively apply ID3 to subsets $\{S_j | j=1, 2, 3 \ldots m\}$ until they are empty

End

The main aspect of building a DT is to choose the 'best' feature at each node in the DT. Once the best feature is chosen at each node, the data is split according to the different values the feature can take. The ID3 algorithm uses a statistical measure called 'Entropy' to determine how effective each feature is in classifying examples. Entropy is a measure of the expected amount of information conveyed by an attribute. Entropy is a measure from information theory, characterized the impurity or homogeneity of an arbitrary collection of examples.

Let–n_b is the number of instance in branch b; n_{bc} be the number of instance in branch b class c. ($n_{bc} \leq n_b$); n_t be the total number of instance in all branches.

Now, the probability an instance on a branch b is positive

P_b = number of positive instance on branch (n_{bc}) / Total number of instance on branch (n_b)

$$\text{Thus, Entropy} = \Sigma - (n_{bc} / n_b) \log_2 (n_{bc} / n_b), \text{ and} \quad (1)$$

$$\text{Average Entropy} = \Sigma (n_b / n_t) \times [\Sigma - (n_{bc} / n_b) \log_2 (n_{bc} / n_b)]$$

4. SPEED CONTROL OF SHUNT DC MOTOR

The word "shunt" means "parallel". These motors are so named because they basically operate with the field coils connected in parallel with the armature. The field winding consists of a large number of turns of comparatively fine wire so as to provide large resistance. The I_{sh} is much less than the I_a, sometimes as low as 5% [6-10]. The current supplied to the motor is divided into two paths, one through the field winding and second through the armature. The fundamental equations governing the operation of the SDCM are as follows:

$$I_L = I_a + I_{sh};\ I_{sh} = V / R_{sh};\ E_b = V - I_a R_a;\ Ø = KI_{sh};$$
$$N = E_b / Ø;\ N = V - I_a R_a / Ø$$

It can be shown that load change is reflected by an I_L and I_a. The information of the V_L, I_a, and Ø are sufficient to calculate the N of SDCM.

The purpose of the DT algorithm ID3 is to maintain a constant N of the motor as load is changed. This SC is accomplished by adjusting the E_b developed in the armature, and I_{sh}. Motor N for various values of I_a, I_{sh}, and E_b are calculated and data set based on calculations are given in Table 1, and range of all attributes in linguistic term are given in Table 2.

Table 1
Data Set for I_a, I_{sh}, E_b, N, and Decision

Condition	*I_a (A)*	*I_{sh} (A)*	*E_b (V)*	*N (Rpm)*	*Decision*
C1	79.6	1.50 (S)	90.23 (S)	1600 (LS)	No Change (Positive)
C2	0.96	2.50 (L)	114.78 (L)	2000 (OS)	No Change (Positive)
C3	40.0	2.00 (L)	100.00 (L)	1800 (OS)	No Change (Positive)
C4	22.3	2.20 (L)	106.23(L)	1865 (OS)	Reduce E_b (Negative)
C5	0.23	2.50 (L)	114.90 (L)	1800 (OS)	No Change (Positive)
C6	33.23	1.80 (S)	102.30 (L)	1865 (OS)	Reduce E_b (Negative)
C7	21.36	2.20 (L)	107.34 (L)	1800 (OS)	No Change (Positive)
C8	66.46	1.50 (S)	97.69 (S)	1735 (LS)	No Change (Positive)
C9	52.30	1.80 (S)	95.50 (S)	1735 (LS)	Reduce I_{sh} (Negative)
C10	67.98	2.20 (L)	93.20 (S)	1600 (LS)	Reduce I_{sh} (Negative)
C11	3.45	2.00 (L)	114.69 (L)	2000 (OS)	Reduce E_b (Negative)
C12	32.35	2.50 (L)	102.34 (L)	1865 (OS)	Reduce E_b (Negative)
C13	24.64	1.50 (S)	107.69 (L)	1735 (LS)	No Change (Positive)
C14	77.89	1.80 (S)	94.69 (S)	1600 (LS)	Reduce I_{sh} (Negative)
C15	31.64	1.50 (S)	101.01(L)	2000 (LS)	No Change (Positive)
C16	76.89	2.50 (L)	94.69 (S)	1735 (OS)	Reduce I_{sh} (Negative)
C17	28.67	2.20 (L)	99.20 (S)	1735 (LS)	Reduce I_{sh} (Negative)
C18	26.35	1.50 (S)	106.78 (S)	1865 (OS)	Reduce E_b (Negative)
C19	23.69	1.80 (S)	101.87 (L)	1800 (OS)	No Change (Positive)
C20	66.54	2.00 (L)	91.58 (S)	1600 (LS)	Reduce I_{sh} (Negative)
C21	6.58	2.20 (L)	114.67 (L)	2000 (OS)	Reduce E_b (Negative)
C22	33.59	2.50 (L)	102.69 (L)	1600 (LS)	Reduce I_{sh} (Negative)
C23	26.67	2.00 (L)	106.89 (L)	1865 (OS)	Reduce E_b (Negative)
C24	58.67	2.00 (L)	97.78 (S)	1735 (LS)	Reduce I_{sh} (Negative)

Table 2
Attributes and Numerical Ranges

Attribute1: N (Rpm)		*Attribute: I_{sh} (A)*		*Attribute: E_b (V)*		*Decision*	
Description	*Range*	*Description*	*Range*	*Description*	*Range*	*Description*	*Range*
LS	< 1800	S	< 2.00	S	< 100.00	Positive	No Change
OS	≥ 1800	L	≥ 2.00	L	≥ 100.00	Negative	Reduce I_{sh}/E_b

Now, DT based on data set (Table 1) is shown in Figure 2;

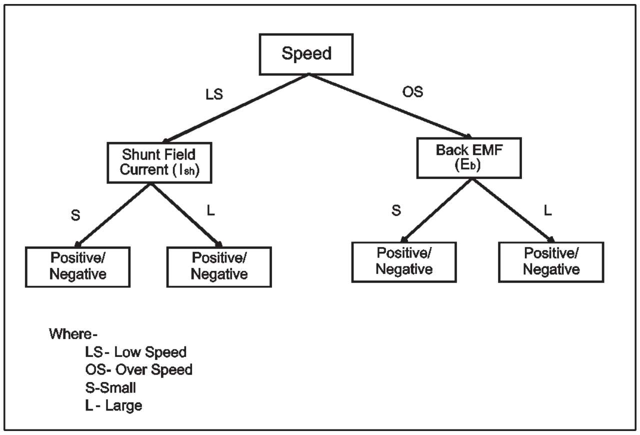

Figure 2: DT for Speed Control of SDCM

Now, calculate average entropy of each three attributes (N, E_b, and I_{sh}) by using equation 1, and results are given in Table 3.

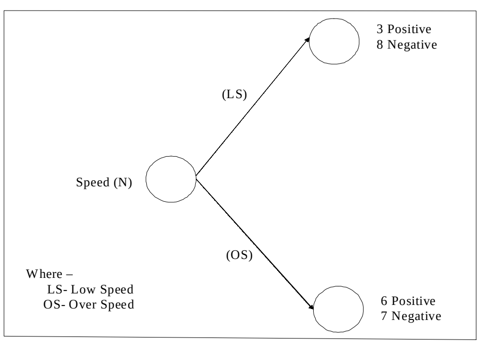

Figure 3: EC for 'N'

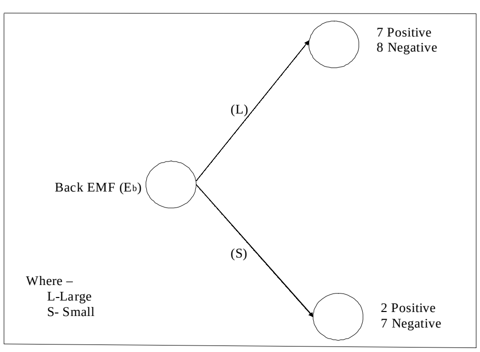

Figure 4: EC for 'E_b'

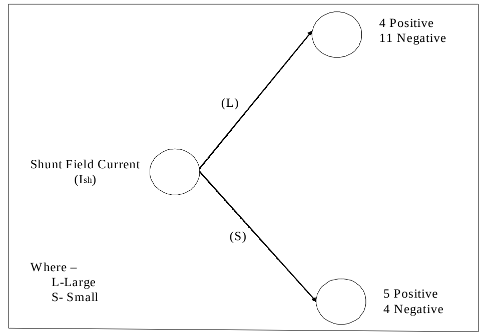

Figure 5: EC for 'I_{sh}'

Table 3
Results of Entropy Calculation of N, E_b, and I_{sh}

Attribute	*Average Entropy*
N	0.925
E_b	0.907
I_{sh}	0.893

Thus, the attribute 'I_{sh}' is selected as the first test node of the DT because it minimizes the entropy and shown in Figure 6.

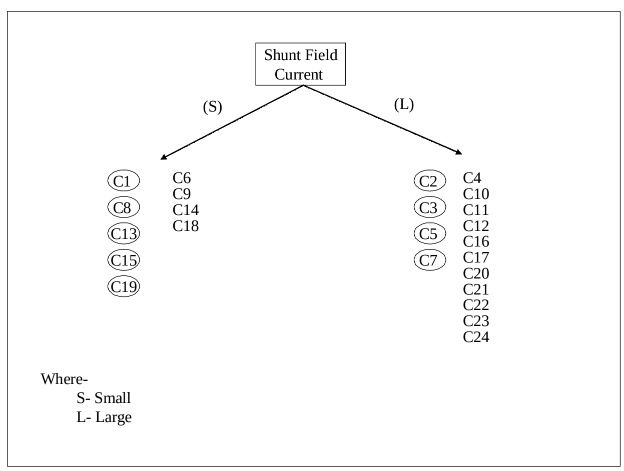

Figure 6: Decision Tree with First Test Node (Root)

Similarly, now choose another test to separate out the 'Positive' and 'Negative' from the 'small' I_{sh} inhomogeneous subset {C1, C6, C8, C9, C13, C14, C15, C18, C19}, and calculate average entropy for remaining two attribute (E_b, and N).

Table 5
Results of Average Entropy Calculation for Remaining Two Attribute (E_b and N)

Attribute	*Average Entropy*
N	0.932
E_b	1.205

Thus, the attribute 'N' is selected as the leaf node as it minimizes the average entropy. Thus, it's resultant DT and shown in Figure 7.

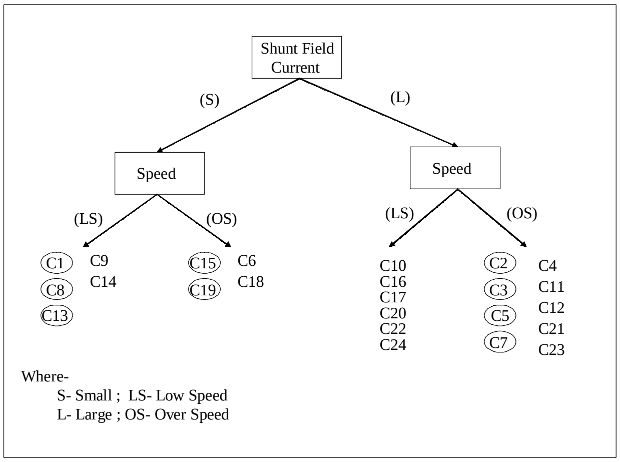

Figure 7: Resultant DT for Speed Control of SDCM

5. CONCLUSION

This paper has demonstrated how the fundamentals of DT can be illustrated through application to the speed control of SDCM. This problem was chosen because it is physically and mathematically straightforward, and because the results are easily understood and easily compared with those of other methods. The development of DT which maintains a fairly constant speed for SDCM has been discussed. An ID3 algorithm was used to demonstrate the speed control of SDCM. The numerical results are seen to be reasonable and illustrate that the DT actually accomplishes its design objectives. We have found that this motor control application provides an ideal introductory illustration of how DT concepts can be successfully applied to a practical engineering problem.

REFERENCES

[1] R. Forsyth and R. Rada, "Machine Learning: Applications in Expert Systems and Information Retrieval," Ellis Horwood Limited, Chichester, England, (1986).

[2] Y. H. Pao, "Adaptive Pattern Recognition and Neural Networks," Addison-Wesley Publishing Company, (1989).

[3] L. Breiman, J. H. Friedman, R. A. Olshen, and C. J. Stone, "Classification and Regression Trees," Belmont, Wadsworth, (1984).

[4] J. R. Quinlan, "Induction of Decision Trees," Machine Learning, **1**, (1986), 81-106.

[5] J. H. Friedmen, "A Recursive Partitioning Decision Rule for Non-Parametric Classification," *IEEE Trans. Computers*, **C-26**, (1977), 404-408.

[6] D. E. Knuth, "Optimal Binary Search Trees," ACTA Inform. **1**, (1971), 14-25.

[7] M. Jevons, "Electrical Machine Theory," American Elsevier Pub. Co., (1966).

[8] G. A. Moberg, "AC and DC Motor Control," Prentice Hall PTR, (1987).

[9] Chiasson, and M. Bodson, "Nonlinear Control of a Shunt DC Motor," *IEEE Trans. on Automatic Control*, **38**, (1993), 1584-1588.

[10] Y. C. Lin, "The Application of Fuzzy Logic Control to Speed Control of a DC Servo Motor System," Proc. of the American Control Con, (1994).