Conjugate gradient with Polak-Ribiere based back-propagation algorithm for the selection of robot in rural agriculture applications

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Abstract - A rapid increase in industrial robots and its utilization by agriculture industries in too many different applications is a critical task for the selection of robots. As a consequence the selection process of the robot becomes very much complex for the potential users as they have a large set of attributes and parameters of the available robots. In this paper, we have proposed Conjugate gradient with Polak-Ribiere based back-propagation algorithm used for the selection of robot manipulators based on the appropriate attributes for the selecting the rank of robots in an optimized way. The ranks with the desired agriculture robots are evaluated with all the best possible robot which specifies the benchmark on the robot for that particular application. At the same time the complete architecture is discussed with different prediction errors such as MSE (Mean Square Error), RMSE (Root Mean Square Error), and R-squared error.

Keywords: Agriculture robot, conjugate gradient, back-propagation, neural network, robot selection index.

I. INTRODUCTION

In engineering and technology robots are the main tool in a variety of advanced manufacturing facilities. The number of robot manufacturers is also increasing with many alternative ranges. The selection of the robot to suit a particular application and production environment from the large number of robots available in the market becomes a difficult task. Various considerations such as availability, production systems and economics need to be considered. Moreover, many of the attributes are conflicting in nature and have different units. But none of these solutions may take care of all the demands and constraints of specific applications. Paul and Nof [1] compared humans to robots. Vukobratovic [6] found that the spherical configuration was superior to other configurations. Khouja [7] presented the application of data envelopment analysis (DEA) in the first phase and a multi attribute decision making model in the second phase. However, DEA requires more computation and if the number of factors that the decision maker wishes to consider is very large and the number of alternative robots small, than DEA may be a poor discriminator. Here the Author's quote example of twenty-seven alternative robots with four attributes robot selection. Again, DEA may be at a disadvantage in terms of the it's rationale if the decision maker is unfamiliar with linear programming concepts. Liang and Wang [5] proposed a robot selection algorithm, which was used to aggregate decision makers' fuzzy assessments about robot selection factor weightings. Chu and Lin [8] pointed out the limitations of Liang and Wang [5] method and proposed a fuzzy TOPSIS method for robot selection. However, the authors had converted the available objective values of the robot selection factors into fuzzy values which violate the basic rule of fuzzy logic. Further, only a 5-point scale was adopted for the rating of robots under subjective factors. Also, the fuzzy method is complicated and requires more computation. Agrawal et al. [2] have presented a multiple attribute decision making (MADM) technique 'TOPSIS' for selection of a robot for an industrial application i.e. considering four attributes and five alternatives robots. Rao et al. [10] have proposed a digraph and matrix methods for robot selection. Four attributes have been identified by Agrawal et al. [2] for the given industrial application and five robots have been shortlisted. In this paper the attributes considered are same as of Agrawal et al. [2] and these are Load capacity, repeatability error, vertical reach, and degree of freedom are beneficial attributes and higher quantitative values are desirable. But

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for qualitative attributes lower values are desirable. This was obtained from the robot selection attributes digraph, which was based on various selection attributes and their relative importance. This method is uncomfortable if the decision maker is unfamiliar with graph theory and matrix method concepts. Babatunji Omoniwa [12] presented a Grey Relational Analysis(GRA) for solving Multi Criteria Robot Selection problems (MCRSPs), and concluded that the distinguishing coefficient has minimal impact on the GRA solution for making this approach appropriate for accurate modeling of MCRSPs. Chatterjee et.al.[13] solved two real time robot selection problems using VICOR (visekriterijumsk kompromisno rangiranje) and ELECTRE (Elimination and Et.choice Translating Reality) methods. Parkan and Wu [9] made particular emphasis on a performance measurement procedure called operational competitiveness rating (OCRA) and a multiple attribute decision making method, TOPSIS. The final selection was made by averaging the results of OCRA, TOPSIS, and a utility model. Suprakash Mondal, S. Chakraborty, presented [11], four models of data envelopment analysis (DEA), i.e. Charnes, Cooper and Rhodes (CCR), Banker, Charnes and Cooper (BCC), additive, and cone-ratio models with respect to cost and process optimization. In addition, multi-attribute decision-making concept has been employed for arriving at the best robot selection. The objective of a robot selection procedure is to identify the robot selection factors and obtain the most appropriate combination. Efforts need to be extended using a logical approach, to eliminate unsuitable robots and selection of a proper robot. This is considered in this paper using the Conjugate gradient with Polak-Ribiére updates back-propagation algorithm for neural network based robot selection methods.

II. MANIPULATOR ATTRIBUTES

According to the growth in robot application, Robots with vastly different capabilities and specifications of manipulator attributes are also available for a wide range of applications. Sometimes in most cases the user needs to be assisted in identifying the robot attributes logically by avoiding the confusion in various techniques. If it is done in a proper way, then the selection of the robot for particular applications will be precise. A robot manipulator can be specified by a number of quantitative attributes such as payload capacity, horizontal reach, repeatability, etc. However, some attributes such as built quality, after sales service etc. cannot be expressed quantitatively. These may be expressed by a rate on the scale say1-5 or 1-10. There are some attributes which are informative significant numbered. There are some attributes which need to be found out by mathematical model and analysis. For instance reliability can be expressed in terms of Mean Time between Failure (MTBF) or Mean Time to Repair (MTTR) methods. While some attributes like life expectancy will be determined by experimentation if not provided by the manufacturer. The various pertinent attributes help the user to create a database. These help the user to select the most suitable robot. The manipulators attribute as found out based on general parameters, physical parameters, and performance is given in table1. The case of operation, termed as manipulability, can be quantified as manipulability measure and can be used as an attribute. The main attributes have been broken down to sub attributes and sub-sub-attributes. So that the robot manipulator can be identified in very precise and detailed manner to select the robot in a quality manner.

Table 1 Major manipulator attributes

Attributes type	Parameter
General	Price ranges, Type of robot and coordinate system
Physical	Type of actuators, weight of the robot, size of the robot, type of grippers supported, number of axes, space requirements of the robot
Performance	Payload of the robot, workspace, stroke, maximum end effector speed, accuracy, repeatability, resolution
Structure/architecture	Degree of freedom, type of joints
Applications	Working environment
Sophistication	Maintainability and safety features
Control/feedback system	Control of robotic joints, gripper control, sensors, programming method, number of input and output channels of the controller
Availability/reliability	Downtime and reliability

III. PROPOSED METHODOLOGY FOR THE SELECTION OF AGRICULTURE ROBOT

In this section we have discussed about the proposed method conjugate gradient with Polak-Ribiere based back-propagation algorithm used for selection of agriculture robots. This section is divided into two parts. In the first part we have discussed the proposed Conjugate gradient with Polak-Ribiere based back-propagation algorithm, in the second part proposed workflow for the selection of the robot rank.

3.1. Proposed Conjugate gradient with Polak-Ribiere based back-propagation algorithm for robot selection

Agriculture robot selection models are complex nonlinear systems which can be solved using powerful estimation methodologies like neural network algorithms. In this work neural network pattern classification technique is proposed for the prediction of manipulator attributes, i.e. quantitative attributes as well as qualitative attributes. A feedforward neural network is trained using different training functions which update weight and bias values. In this work training algorithms such as Conjugate gradient with Polak-Ribiére updates are studied for the implementation of robots selection prediction techniques.

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For all conjugate gradient algorithms, the search direction is periodically reset to the negative of the gradient. The standard reset point occurs when the number of iterations is equal to the number of network parameters (weights and biases), but there are other reset methods that can improve the efficiency of training. One such reset method was proposed by Powell [4], based on an earlier version proposed by Beale [5]. This technique restarts if there is very little orthogonality left between the current gradient and the previous gradient. This is tested with the following inequality as shown in equation 1.

$$|g_{k-1}^T g_k| \geq 0.2\|g \qquad \ldots(1)$$

$$X = X + a * \qquad \ldots(2)$$

$$dX = -gX + dX_{old} \qquad \ldots(3)$$

If this condition is satisfied, the search direction is reset to the negative of the gradient. This algorithm can train any network as long as its weight, net input, and transfer functions have derivative functions. Backpropagation is used to calculate derivatives of performance with respect to the weight and bias variables 'X'. Each variable is adjusted according to equation 2. Where dX is the search direction. The parameter "a" is selected to minimize the performance along the search direction. The line search function is used to locate the minimum point. The first search direction is the negative of the gradient of performance. In succeeding iterations the search direction is computed from the new gradient and the previous search direction according to equation 3. Where gX is the gradient. The parameter "Z" can be computed in several different ways. So, The Powell-Beale variation of conjugate gradient is distinguished by two features. First, the algorithm uses a test to determine when to reset the search direction to the negative of the gradient. Second, the search direction is computed from the negative gradient, the previous search direction, and the last search direction before the previous reset.

3.2. Proposed workflow for selection of robot rank

In general, a realistic robot must have minimum specifications that are equal to or better than equals to the minimal requirements for the desired application. For example, a material handling robot is not feasible unless its specification on payload equals or exceeds the weight of the heaviest part of it. The minimum requirement for this application is tabulated as shown in Table 2. Notice that a robot with specifications all equal to or better than the minimal prerequisites of the application that may nevertheless fail to present the required performance during operation. This failure is because, as discussed in the beginning, the manufacturer's specifications may not hold simultaneously. Table 2 summarizes the principal parameter requirements with its values for the selection of an agriculture robot.

Table 2 Principal parameters required of a robot

Sl	Parameter	Values
1	Working envelop (Manipulator reach)	≤ minimum 500 mm.
2	Payload (Load capacity)	≤ 120 kg.
3	Repeatability	± 0.1 mm
4	Work lot size (Production rate per hour)	≥ 25 tasks
5	Maximum tip speed (Velocity)	at least 255 mm/sec
6	Degrees of freedom	≤ 7
7	Controller type	≤ 4
8	Actuator type	≤ 3
9	Cost	max 400 Lac
10	Arm geometry	≤ 10
11	Programming	≤ 5
12	Functional	depends upon the application

The complete activities for selecting the rank of the robot are presented with a workflow diagram in figure 1.

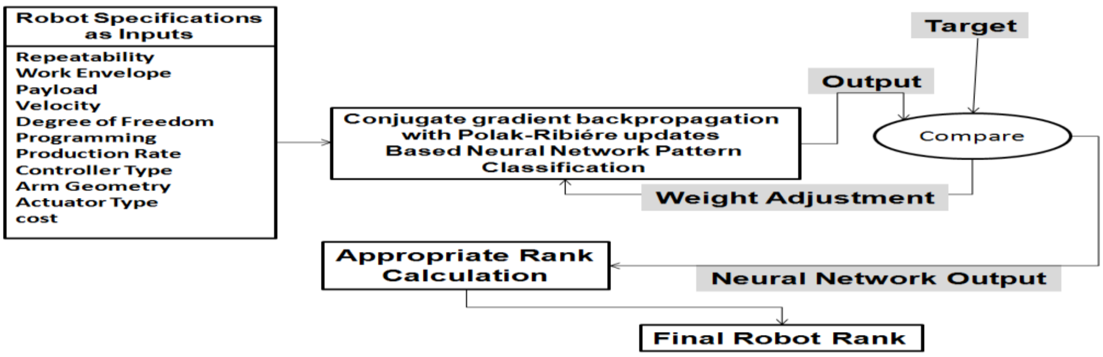

Figure 1. Workflow diagram for selection of the robot rank

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IV. RESULTS AND DISCUSSION

The overall performance of the optimization techniques for the prediction of selection of agriculture robots is examined by considering eleven manipulator attributes. The inputs and output data are listed in table 3. MSE (Mean Square Error), RMSE (Root Mean Square Error), and R-squared error of the prediction are calculated and listed.

Table 3 Inputs and outputs used for prediction of the rank of the robot

Inputs	Output
Working Envelope (WE) Payload (PL) Repeatability (RE) Production rate (PR) Maximum tip speed (MTS) Degree of freedom (DOF) Controller type (CT) Actuator type (AT) Arm geometry (AG) Programming (P)	Ranking and selection of agriculture robot(R)

Conjugate gradient with Polak-Ribiére updates based neural network pattern classification was used to predict the selection of robot from different industrial data. The prediction error with the target value and predicted value are plotted here. It is observed from the 2nd plot of figure 2 that the actual result is matched correctly with the predicted values. Only rank 1, 2, 9, and 10 are having minimum error, but others have 0% error. The ranking prediction response and error curve is shown in

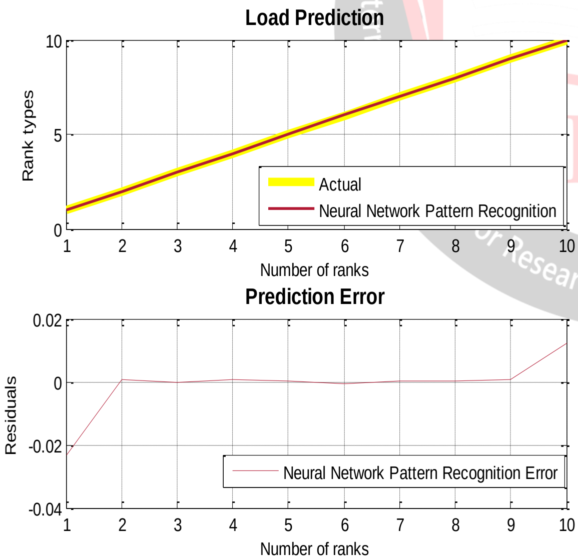

Figure 2. Actual rank type and predicted rank type v/s number of ranks. The error graph plotted between residuals and number of rank [Conjugate gradient with Polak-Ribiére updates based neural network pattern classification]

The Conjugate gradient with Polak-Ribiére updates based neural network pattern classification training performance is shown in figure 3. The best training performance is obtained at 179 epochs.

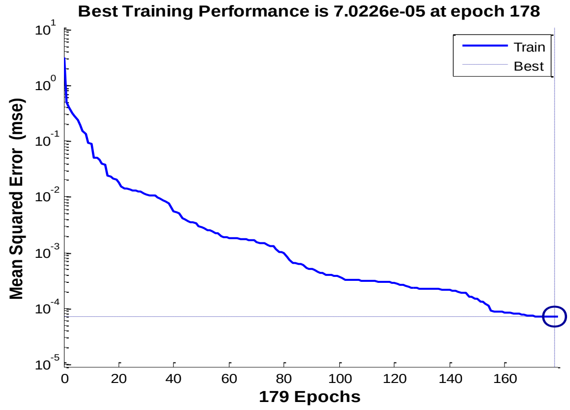

Figure 3. Conjugate gradient with Polak-Ribiére updates based neural network pattern classification training performance.

Training state after neural network training based on the Conjugate gradient with Polak-Ribiére updates technique is shown in below figure 4. The best training performance is obtained at 179 epochs.

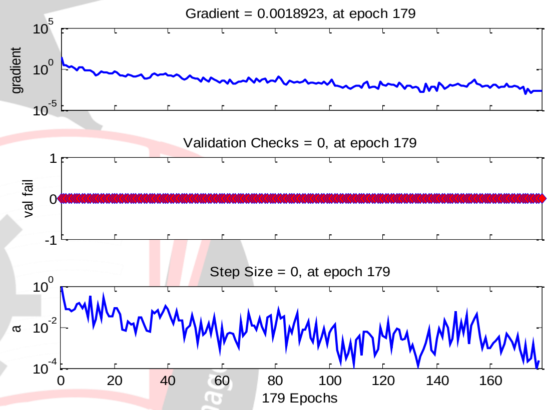

Figure 4. Training state after neural network training [Conjugate gradient with Polak-Ribiére updates based neural network pattern classification]

Error histogram after training performance by Conjugate gradient with Polak-Ribiére updates based neural network pattern classification is shown in below figure 5. "Instances v/s. Error Histogram" is plotted with 20 Bins.

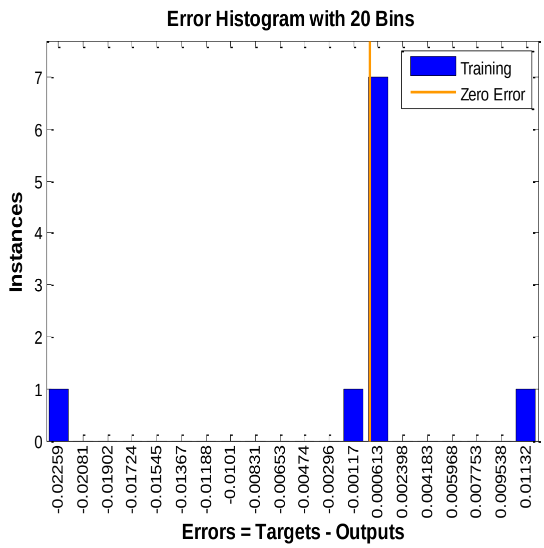

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Figure 5. Error Histogram after training [Conjugate gradient with Polak-Ribiére updates based neural network pattern classification]

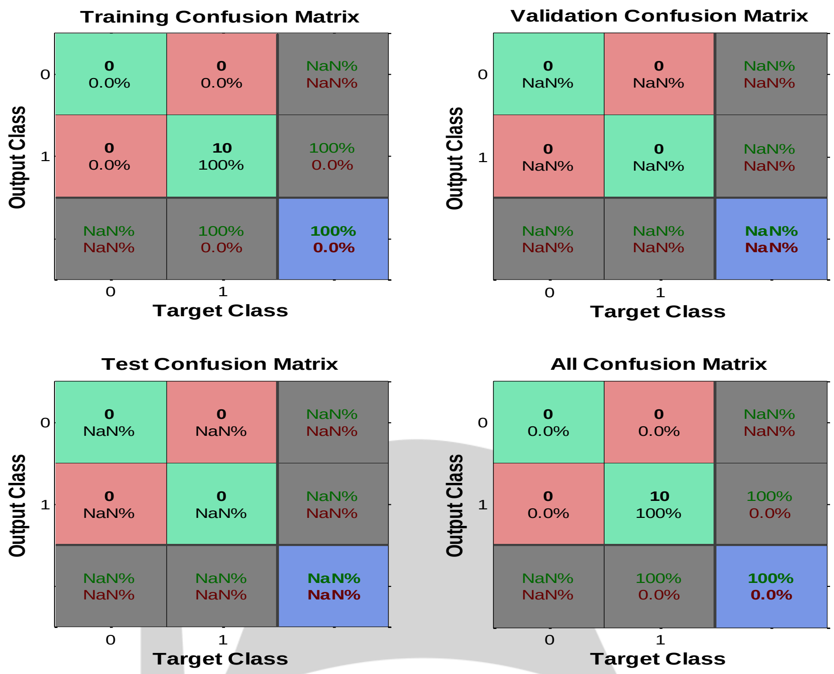

Figure 6. The confusion matrix of Conjugate gradient with Polak-Ribiére updates based neural network pattern classification training.

The confusion matrix of Conjugate gradient with Polak-Ribiére updates based neural network pattern classification is shown in figure 6. The errors obtained from the simulations are RMSE = 0.0059, MSE = 3.4326e-05, R-squared error = 1.0000. It is observed that twenty four data sets are correctly predicted with very efficient performance. The test inputs and outputs of the proposed method are specified in Table 5.

Table 5 Test inputs and outputs of the proposed method

Test Inputs	Desired Rank	Neural Network Pattern Classification output
Repeatability (±mm) = 4 Work envelope (mm) = 2000 Payload (Kg) = 40 Velocity (mm/s) = 2000 Freedom=4 Production rate (Task/hour) =300 Controller=2 Actuator=2 Arm geometry = Cylindrical light Programming = Task-oriented Program	4	Neural Network Training Type: Conjugate gradient with Polak-Ribiére updates Neural network classified rank : 4 Final Robot Rank : 4

V. COMPARISON

The overall comparison of the other published methods with the proposed Conjugate gradient with Polak-Ribiére updates based neural network pattern classification training method for the agriculture robot selection is listed in Table 4.

Table 4 Comparison table with other methodology

Author name, and Reference	Year	Title of the paper	Methodology	No. of major Parameters used	Name of the Parameters used	Range of the parameters	Overall performance
Vijay Manikrao Athawale, Prasenjit Chatterjee,Shankar Chakraborty[13]	2010	Selection of Agriculture robots using compromise Ranking method	VIKOR	7	PL, RE, MTS,WE	Moderate	Good
Babatunji Omoniwa [12]	2014	A solution to Multi Criteria Robot Selection problems using Grey Relational Analysis.	Grey Relational Analysis.	7	PL, RE, MTS, WE, C	Moderate	Very Good

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S. Mondal., S.Chakraborty [11]	2013	A solution to robot selection problems using data envelopment analysis.	Data Envelopment Analysis (DEA)	7	PL, RE, MTS,WE	High	Very Good
Proposed Method	2015	Conjugate gradient with Polak-Ribiére updates	Conjugate gradient with Polak-Ribiére updates based neural network pattern classification	10	PL, RE, MTS,WE, .DOF, PR CT, AT, AG, P	High	Best

It is observed that our proposed method is very much consistent and produces qualitative results in comparison with the published methods. In the published papers the methodology uses the least number of parameters in comparison with the proposed method. In addition to the above facts the proposed method also offers a more objective, easy to use, and simple robot selection approach with maximum numbers of the major parameters of the robot.

VI. Conclusion

The ranking of agriculture robot is efficiently predicted by taking various agriculture robot parameters. The performance analysis of the proposed optimization techniques for neural network pattern classification is done by calculating MSE, RMSE and R-squared error. The MSE and RMSE and R-squared error is obtained by Conjugate gradient with Polak-Ribiére updates based neural network pattern classification are 1.4353e-11, 3.7886e-06 and 1.0000. Hence it is found that Conjugate gradient with Polak-Ribiére updates based neural network pattern classification technique for the selection of agriculture robot will produce better prediction result than any other complicated method. Hence it is found that proposed method Conjugate gradient with Polak-Ribiére updates based on the neural network pattern classification method for the selection of robot produce better results. It has been suggested to all the customers and manufactures to use the proposed method for an efficient way of selecting agriculture robots.

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