



PARAMETRIC SELECTION OF INDUSTRIAL ROBOTS USING REDUCED PCR/PLSR MODELS FOR BETTER ESTIMATES OF EXPECTED COST AND SPECIFICATIONS

Sasmita Nayak

Ph.D Research Scholar, Suresh GyanVihar University, Jaipur,
Rajasthan, India.

Dr. B. B. Choudhury

Department of Mechanical Engineering, IGIT,
Sarang, Odisha, India.

Abstract: Quick advancement of industrial robots along with its usage by the assembling industries for various applications is a basic assignment for the determination of robots. As an outcome, the choice procedure of the robot turns out to be particularly entangled for the potential users since they have a broad arrangement of parameters of the accessible robots. In this paper, Partial Least Square Regression (PLSR) and Principal Component Regression (PCR) algorithm are utilized for the selection of industrial robots. In this proposed technique, eleven different parameters are taken as direct inputs for selecting a robot as compared to those of the existing models, which are limited up to seven parameters. Basing upon the proposed algorithm, the rank of an industrial robot is estimated. Moreover, the best robot that has been selected should satisfy the benchmark genuinity for a targeted application. In addition to this, the robot selection algorithm is measured through Mean Square Error (MSE), and Root Mean Square Error (RMSE), R-squared error (RSE).

Keywords: Industrial Robot, Robot selection, Robot parameters, Partial Least Square Regression (PLSR), Principal Component Regression (PCR), MSE, RSE, RMSE.

INTRODUCTION

Robots have become a very collective entity as far as the modern day industrial production and manufacturing are concerned. This gives rise to a growth in manufacturing of robots as well. As a consequence there is a propagation of evaluation in the manufacturing arena. The challenging job here is to select a specific robot for a desired task at par with the environment, from a pool of available resources of robots [3].

Various thoughtfulnesses for instance accessibility, production, in addition to economic need to be deliberated. Furthermore, many of the properties are inconsistent in nature as well as have a different unit. Additionally, none of the above solutions may not pay attention to all the necessities along with constraints of particular applications [4]. Paul and Nof. [1] have compared robots with human beings. Vukobratovic [6] has confirmed about the betterment of spherical arrangement over others. Khouja [7] has advocated about Data Envelopment Analysis (DEA) and a multi-attribute decision making.

Moreover, DEA needs more calculation assets and the quantity of elements that the chief willing to consider is vast and in addition the quantity of option robots are littler than DEA which might be a poor discriminator. Here the Author's quote case of twenty-seven option robots with four qualities robot choice. Once more, the DEA may has disapproval regarding its method of reasoning, assume the basic leadership is out of line utilizing direct programming procedure. Liang and Wang [5] talked about the robot choice calculation, which was utilized to discover approach producers' fluffly evaluations about robot choice component weightings. The Chu and Lin [8] demonstrated the constraints of the strategy proposed by Liang and Wang [5] and proposed another system fluffly TOPSIS technique for robot choice process [13]. In any case, Liang et al. had altered the destinations DEA for the robot choice

elements into fluffly esteems which really damages the basic administer of fluffly rationale. Further, a 5 point scale was used for the rating of robots under the subjective components. Moreover, the fluffly rationale strategy is truly confounded and needs colossal preparing power. In the comparable setting, Agrawal et al. [2] have proposed a different property basic leadership (MADM) approach with "TOPSIS" for the choice of a mechanical robot i.e. by taking after four characteristics and also five option robots [18]. So also, Rao et al. [10] have proposed a digraph with grid strategy for mechanical robot choice process. Essentially, four qualities have been legitimized by Agrawal et al. [2] for a given modern application and in addition five robots have been shortlisted. In this paper, the required qualities utilized are same as of the technique proposed by Agrawal et al. [2]. Additionally, these parameters are load limit, repeatability mistake, vertical achieve, level of the flexibility and higher quantitative esteems. Be that as it may, for subjective characteristics littler esteems are attractive. This was gotten from the robot determination digraph, which depended on different choice traits and in addition their relative significance. This technique will be awkward if the chief is new to the utilization of chart hypothesis and framework strategies. Parkan and Wu [9] made specific accentuation on an execution investigation method called as Operational Competitiveness RAting (OCRA). A definitive choice was made by averaging the aftereffects of TOPSIS, OCRA, and utility based model. Suprakash Mondal, S. Chakraborty, exhibited [11], four models of information envelopment analysis (DEA), indicated added substance, and cone-proportion models as for cost and process improvement. Additionally, multi-quality basic leadership idea has been utilized in touching base at the best robot determination. The fundamental target of the modern robot determination strategy is to distinguish the robot choice variables and to get the most fitting mix [18]. Endeavors should be augmented utilizing a reasonable legitimate system to dispose of inadmissible sort of

robots and to pick the most suitable robot. In this article, we have proposed the robot determination procedure utilizing halfway minimum square relapse (PLSR) strategy.

PROPOSED METHODOLOGY

In this section, we have discussed two things. In the first part, we have discussed the proposed method partial least square regression (PLSR) used for selection of industrial robots. In the second part proposed workflow for the optimized way of selecting the rank of the robot using the proposed algorithm. In the similar context, Principal Components Regression (PCR) based robot selection mechanism is also studied and compared with PLSR.

A. Partial Least Square Regression (PLSR) Algorithm for Robot Selection

Industrial robot determination models are mind boggling nonlinear frameworks that can be understood utilizing strong estimation strategies like various straight relapse models. In this work, PLSR is proposed for the expectation of controller properties, i.e. quantitative traits and in addition subjective properties. A PLSR model is set up utilizing distinctive info ascribed that creates the coveted robot rank [14].

Fractional minimum squares relapse can be an expansion from the numerous straight relapse models [12]. To utilize most straightforward frame, a direct model indicates the (straight) connection between a reliant (reaction) variable Y, and furthermore a gathering of indicator factors, the X's, all together that

$$Y = b_0 + b_1X_1 + b_2X_2 + \dots + b_pX_p \text{ ----- (1)}$$

With this equation b_0 is the regression coefficient with the intercept as well as the b_i values are classified as the regression coefficients (for variables 1 through p) computed from the data. Multiple rectilinear regression provided by PLSR over rules the limitations of other techniques such as discriminant analysis, principal components regression, and canonical correlation [15]. The representation of PLSR's prediction function are extracted from $Y'XX'Y$ matrix [17].

The count of such functions will over take the superlative variability of Y and X.

To put it briefly, partial method of least squares regression has become the least restrictive of the numerous multivariate extensions from the multiple linear regression models. In case of fewer observations as compared to predictor variables, the traditional multivariate functions are limited to be utilized [14]. The entire flow sheet for robot selection process is shown in figure 1.

B. Principal Components Regression (PCR) Algorithm for Robot Selection

Principal component regression (PCR) is also a regression analysis method which works on principal component analysis (PCA) [15]. Regularly, it considers regressing the result (also called as the response or dependent variable) over a set of covariates (called as independent variables) based on a generic standard linear-regression model, where Principal Component Analysis (PCA) is utilized for estimating the unknown regression coefficients in the above model [16].

Following the usual notation, suppose our regression equation may be written in matrix form as

$$Y = XB + e \text{ ----- (2)}$$

where Y is the dependent variable, X represents the independent variables, B is the regression coefficients to be estimated, and e represents the errors or residuals.

C. Proposed Workflow Design for Selection of Robot Rank

In general, a realistic robot must have minimum specifications which are equal to or better than equals to the minimal requirements for the desired application. The scopes of particulars of robot recorded as appeared in Table 1. It has been observed that a robot with the specifications mentioned in table 1, equal or better than the minimal requisites of the application that may fail during the complete process. This failure occurs due to inappropriate treatment of the manufacturer's specifications. Further, the table 1 summarizes the primary parameter requirements with its values for the better selection of an industrial robot.

Table 1. Principal parameters required for a robot

Sl. No.	Parameter	Maximum Values
1	Working envelope	2600 mm.
2	Payload	≤Maximum 100 kg.
3	Repeatability	± 5.5 mm
4	Work lot size (Production rate per hour)	≥ 600 tasks
5	Maximum tip speed	5000 mm/sec
6	Degrees of freedom	7
7	Controller type	4
8	Actuator type	3
9	Arm Geometry	10
10	Robot Type-Programming	5
11	Cost	604K USD

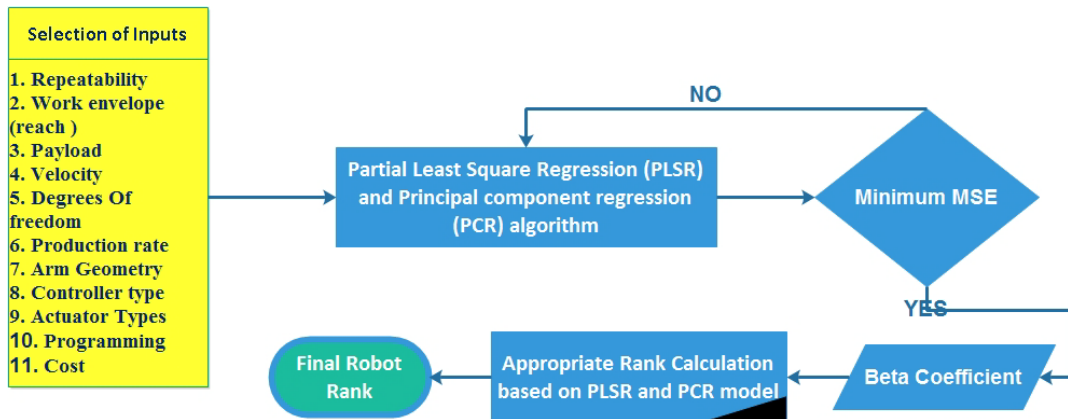


Figure. 1. Proposed architecture of the selection of robot rank methodology

The comprehensive activities for selecting the rank of the robot are presented with a workflow diagram in figure 1. In this article, we have proposed a robot ranking chart by taking into consideration of the standard specifications for every robot ranks. As per the industrial requirements, the eleven

numbers of primary parameters are taken in account as inputs with special values. The outcome provides as the robot rank. The proposed robot classification only for eight categories of robot ranking are listed in Table 2 (A) as well as Table 2 (B).

Table 2.(A) Proposed Industrial Robot Ranking

Sl no	Name of Robot Parameter	Unit	Rank 1	Rank 2	Rank 3	Rank 4	Rank 5	Rank 6	Rank 7	Rank 8	Rank 9	Rank 10
1	Repeatability	±mm	5.5	5	4.5	4	3.5	3	2.5	2	1.5	1
2	Work envelop (reach)	mm	500	1000	1500	2000	2100	2200	2300	2400	2500	2600
3	Payload	Kg	10	20	30	40	50	60	70	80	90	100
4	Velocity	mm/s	500	1000	1500	2000	2500	3000	3500	4000	4500	5000
5	Degrees of freedom	Nos.	1	2	3	4	5	6	7	7	7	7
6	Cost	USD (\$)	7.55K	15.1K	30.2K	45.3K	60.4K	75.5K	151K	302K	453K	604K
7	Production rate	Task/hour	100	200	250	300	350	400	450	500	550	600
8	Arm Geometry	Nos.	1	2	3	4	5	6	7	8	9	10
9	Controller type	Nos.	1	1	1	2	2	3	3	3	4	4
10	Actuator Types	Nos.	1	1	2	2	2	2	3	3	3	3
11	Programming	Nos.	1	1	2	2	3	3	4	4	5	5

TABLE 2 (B). Proposed subcategories of the different attributes of robot

Sl. No.	Attributes of Robot	No. of Subcategories	Different Subcategories with their index specified within bracket
1.	Arm Geometry	10	Spherical light (1), Spherical Medium (2), Articulated light(3), Articulated Medium(4), Rectangular light(5), Cylindrical light (6), Rectangular Medium (7), Cylindrical Medium (8), Rectangular Heavy(9), Cylindrical Heavy (10)
2.	Controller type	4	Non-servo (1), Servo Point-to-Point(2), Servo Continuous Path (3), Combined PTP and CP (4)
3.	Programming	5	Task-oriented Program(1), Off-line Program(2), On-line Program(3), Teach-pendant Program(4), Lead through teach Program(5)
4.	Actuator Types	3	Hydraulic(1), Electric(2), Pneumatic(3)

RESULTS AND DISCUSSIONS

The overall performance of the PLSR model for the prediction of selection of industrial robots is examined by considering eleven manipulator attributes. The name of the inputs and output parameters used are listed in Table 2. Mean Square Error (MSE), Root Mean Square Error (RMSE), and R-squared error

of the prediction are calculated and listed. The partial least square regression technique was used to calculate the selection of robot from different industrial data. The expectation blunder with the objective esteem and anticipated esteem are plotted here. We saw from the figure 2 that the genuine outcome is coordinated accurately with the anticipated esteems. The positioning forecast reaction and blunder bend is in figure 2

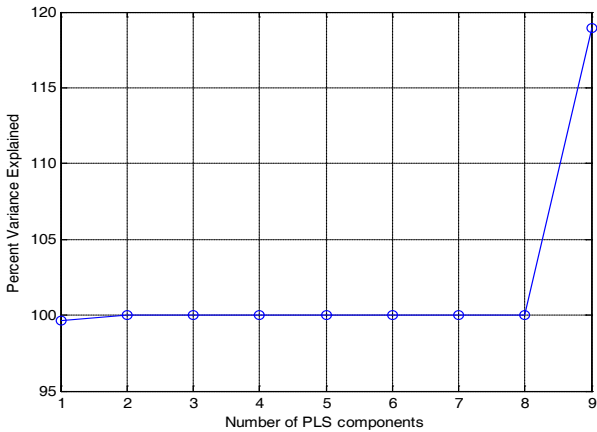


Figure 2. Predicted rank type v/s percentage of variance.

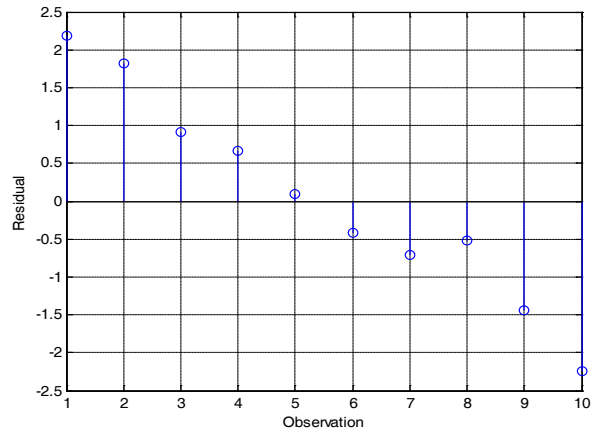


Figure 3. Predicted rank type (Number of observations) v/s Residual.

The partial least square regression (PLSR) performance is shown in figure 3. The residual plot shows that the error obtained during actual robot rank calculation are very less and hence the predicted robot rank appropriately matches the actual rank. The performance of the partial least square regression (PLSR) technique for robot rank calculation is also

found out using MSE (Mean Square Error), RMSE (Root Mean Square Error), and R-squared error. All the above errors are listed in table 2.

The mathematical model obtained during PLSR is defined the equation 3.

$$\begin{aligned}
 \text{Robot Rank} = & (-20341754789398.5) + [(3390292464899.03) \times \text{Repeatability}] \\
 & + [(3.14942297397367e-06) \times \text{Work envelop (reach)}] + [(-67294028522664.6) \times \text{Payload}] \\
 & + [(1362832032777.79) \times \text{Velocity}] \\
 & + [(-0.856955362615008) \times \text{Degrees of freedom}] + [(0.0144793395567071) \times \text{Production rate}] \\
 & + [(-6780584929798.05) \times \text{Index of Arm Geometry}] + [(0.776501617166275) \times \text{Controller type}] \\
 & + [(0.572737461733881) \times \text{Index of Actuator Types}] + [(0.343661894835220) \times \text{Index of Programming}] \\
 & + [(-0.00575152555285495) \times \text{Cost}] \quad \text{----- (3)}
 \end{aligned}$$

In the similar context, the mathematical model obtained during PCR is defined the equation 4.

$$\begin{aligned}
 \text{Robot Rank} = & (-0.0346067647579718) + [(-1.87605259428321e-06) \times \text{Repeatability}] \\
 & + [(0.000122389812435442) \times \text{Work envelop (reach)}] + [3.75210518856741e-05] \times \text{Payload}] \\
 & + [(0.00187605259428371) \times \text{Velocity}] \\
 & + [(1.42634638322808e-06) \times \text{Degrees of freedom}] + [(0.000174122325320102) \times \text{Production rate}] \\
 & + [(3.75210518856741e-06) \times \text{Index of Arm Geometry}] + [(1.49720548322834e-06) \times \text{Controller type}] \\
 & + [(6.39640638600532e-07) \times \text{Index of Actuator Types}] + [(1.87304162794836e-06) \times \text{Index of Programming}] \\
 & + [(0.000431045683160482) \times \text{Cost}] \quad \text{----- (4)}
 \end{aligned}$$

Table 3. Error Calculation during Robot Ranking Prediction

Algorithm type	MSE	RMSE	R-squared
Partial Least Square Regression (PLSR)	9.6706e ⁻¹⁵	9.3521e ⁻²⁹	0.9999998
Principal Component Regression (PCR)	12.5476e ⁻⁹	11.953e ⁻¹²	0.8999977

The number of components should be carefully chosen to make the model better. Cross-validation, for instance, is a widely used method. For now, the plot shown in the figure 3

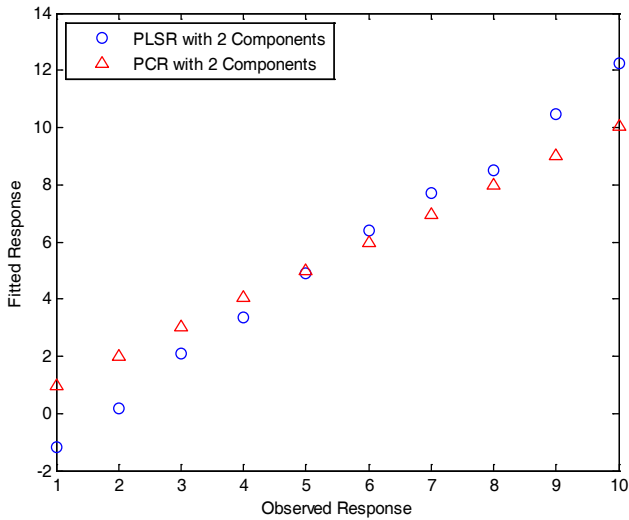


Figure 3. Plot fitted vs. observed response for the PLSR and PCR fits

In the similar context, the comparison in the above plot is performed by considering PLSR and PCR with two components. There is no reason why the PCR model should be restricted in the prediction model. Therefore, with two components, the PLSR performs much better prediction with respect to the fitting targets. In fact, from the horizontal scatter plot as shown in the figure 3, PCR with 2 components is barely predicting better with respect to the PLSR model. The

suggests that PLSR with two components explains most of the variance in the observed target data. Next, a PCR fit model with two principal components is analysed.

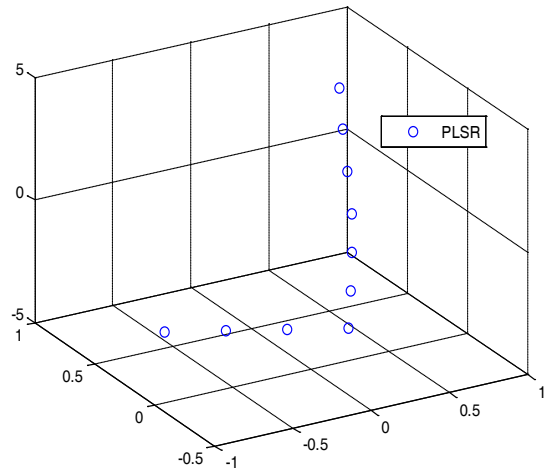


Figure 4. Plot of the response variable against the PLSR

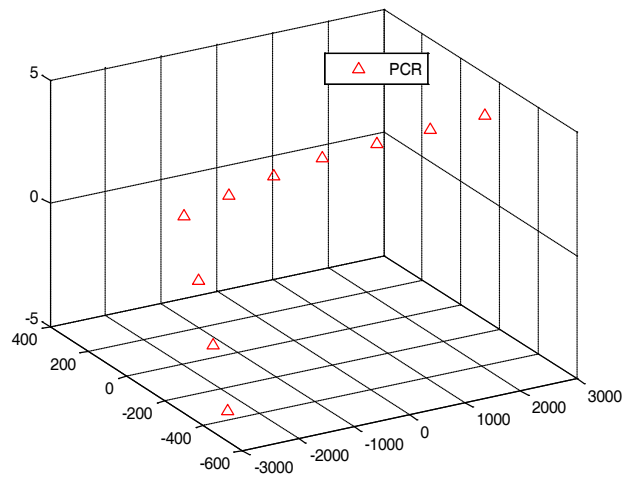


Figure 5. Plot of the response variable against the PCR

It is noticed that while the two PLS components are much better predictors of the observed target data, the figure 6 shows that they explain somewhat less variance in the observed input than the first two principal components used in the PCR.

R-squared values of the two regression models are 1, which concludes that the mean prediction values are same. In a different way, the comparison can be observed from the plotted response against the two predictors such as PLSR and PCR. The plot shown in the figure 4 displays the response variable against the two predictors in PLSR and figure 5 shows the response variable against the two predictors in PCR.

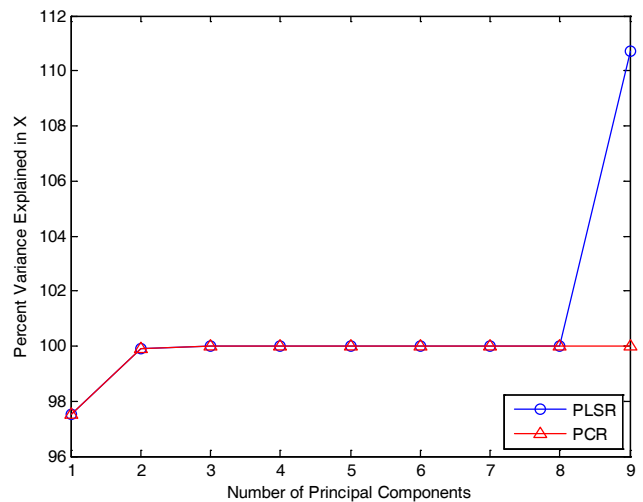


Figure 6. predictors of the observed target data with respect to percent variance experienced in PLSR and PCR

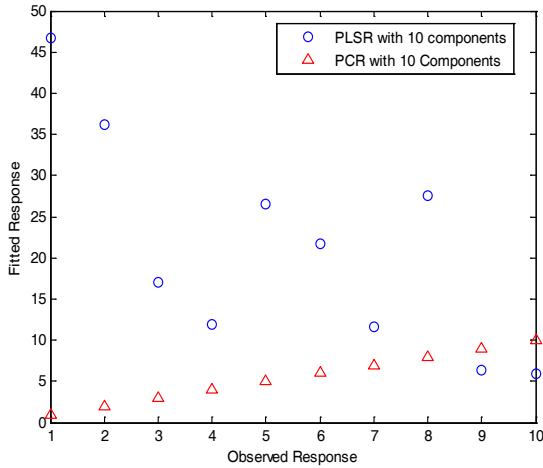


Figure 7. Plot of the difference in residuals for the two methods both in PLSR and PCR

PCR constructs components to best explain inputs, and as a result, those first two components ignore the information in the data that is important in fitting the observed target. As more numbers of components are introduced in the PCR model, it will definitely perform a better prediction over the original target data. This happens because most of the important predictive information in input are there in the principal components. From the figure 7, it is observed that the difference in residuals for the two methods are much less when using ten PLSR and PCR components as compared to the 2 component approach.

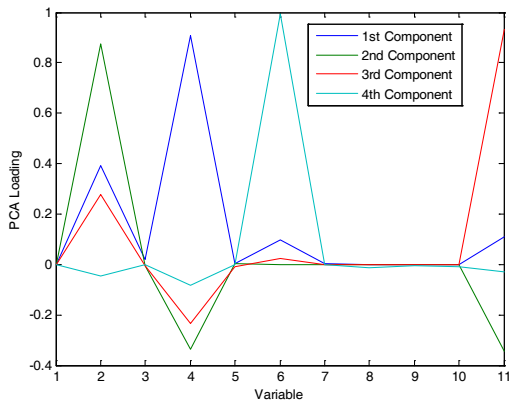


Figure 9. PCA loading for each components

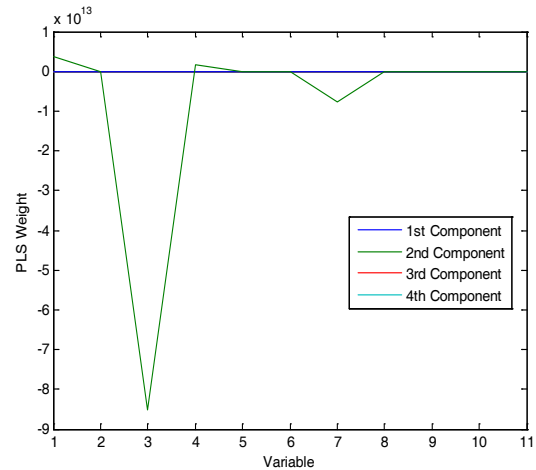


Figure 8. Plot between the input variables and PLS weight components

Similarly, the weights of PLS are linear combinations of the original variables that explains the PLS components. They also portray how strongly every components in the PLSR rely on the original variable along with the direction. The response of the proposed predictive approach is shown in the figure 8 by considering the input variables along with PLS weight parameters.

Similarly, the Principal Component Analysis (PCA) loadings is shown in the figure 9 which describes the strong relationship between each component in the PCR with the original variables.

For either PLSR or PCR, it is observed that each one can be explained in physically meaningful interpretation by inspecting the weights. As demonstrated before, a few parts from a PCR show depicts the variety in the predictive factors, and this may incorporate substantial weights for the factors which are not unequivocally connected with the result. Consequently, PCR may prompt holding factors which sometimes are not generally required for predictive analysis. The test sources of info and response of the proposed technique are given in Table 4.

TABLE 4. TEST INPUTS AND OUTPUTS CONSIDERED FOR THE PROPOSED METHODOLOGY

Test Inputs	Desired Rank (R)	Neural Network Pattern Classification Output
Repeatability (\pm 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: partial least square regression (PLSR) Neural network classified rank : 4 Final Robot Rank : 4

We have observed that our proposed method is greatly reliable and produces qualitative results in comparison with other published methods. In the published articles, the methodology

uses minimum number of parameters as compared to our proposed predictive model. In addition to the above facts, our proposed method also offers more likelihood, practical, as well

as effortless robot selection approach by considering maximum numbers of the major robot selection parameters.

CONCLUSION

The positioning of the modern robot is performed efficiently with the proposed technique by taking different mechanical robot parameters. Through the above-proposed strategy at the maximum eleven parameters are straightforwardly considered as a contribution for the selection procedure of robot. The rank of the favored mechanical robot has been assessed flawlessly and in the meantime the best plausible robot has been gotten that indicates the most bona fide benchmark. The execution examination of proposed method for partial least square regression (PLSR) model is evaluated by ascertaining MSE, RMSE, and R-squared errors. From the blunders acquired amid determination demonstrates that the execution of partial least square regression (PLSR) model gives a better result for the selection of modern robot rank. The MSE and RMSE acquired by these algorithms are $9.6706e-15$, $9.3521e-29$ and 0.9999998 respectively. In the similar sense, PCR model is also used with the same robot specification data and the performance is studied. From the analysis results, it is observed that PCR also provides better prediction results for robot ranks than PLSR. Hence, it is concluded that PCR system for the choice of mechanical robot delivers preferred expectation result over other existing strategies.

REFERENCES

- [1]. R.P. Paul, and Shimon Y. Nof, "Work Methods Measurement: A Comparison Between Robot and Human Task Performance", Taylor&Francis, IFPR, Volume:17, Issue:3, Pages:277-303, 1979.
- [2]. V.P. Agrawal and V.Kohli, S. Gupta, "Computer-Aided Robot Selection: the Multiple-Attribute Decision Making an Approach", International Journal of Production Research, Volume:29, Issue:8, Pages: 1629-1644, 1991.
- [3]. ŞenimÖzgürler, Ali F. Güneri, BahadırGülsün, OnurYılmaz, "Robot Selection for a Flexible Manufacturing System with AHP and TOPSIS Method", 15th International Research Conference on TMT-2011, Prague, Czech-Republic, 2011.
- [4]. M.Z. Rehman, N.M. Nawari, "The Effect of Adaptive Momentum in Improving Accuracy of Gradient Descent Backpropagation Algorithm on Classification Problems", Springer-Verlag, Volume:179, Pages: 380-390, 2011.
- [5]. G.H. Liang, and M.J. Wang, "A Fuzzy Multicriteria Decision-Making Approach for Robot Selection", Robotics, and Computer-Aided Manufacturing, Volume:10, Pages: 267-274, 1993.
- [6]. M. Vukobratovic, "Scientific Fundamentals of Industrial Robots1: Dynamics of Manipulator Robots Theory and Applications", Springer-Verlag Publication, New York, 1982.
- [7]. M. Khouja, "The Use of Data Envelopment Analysis for Technology Selection", Computer Industrial Eng., Volume:28, Pages: 123-132, 1995.
- [8]. T.C. Chu, and Y.C. Lin, "A Fuzzy-TOPSIS Method for Robot Selection", International Journal of Advanced Manufacturing Technology, Volume:21, Pages: 284-290, 2003.
- [9]. C. Parkan, M.L. Wu, "Decision-Making and Performance Measurement Models with Applications to Robot Selection", Computer Industrial. Eng., Volume:36, Issue:3, Pages: 503-523, 1999.
- [10]. R.V. Rao, K.K. Padmanabhan, "Selection, Identification and Comparison of Industrial Robots Using Digraph and Matrix Methods", Elsevier, Robotics, and Computer Integrated Manufacturing, Volume:22, Issue:4, Pages: 373-383, 2006.
- [11]. Suprakash Mondal, S.Chakraborty, "A Solution to Robot Selection Problems Using Data Envelopment Analysis", International Journal of Ind. Eng. Computations, Volume:4, Issue:3, Pages:355-372, 2013.
- [12]. Varun K. Nagaraja, Wael Abd-Elmageed, "Feature Selection using Partial Least Squares regression and optimal experiment design", International Joint Conference on Neural Networks (IJCNN), Pages:1-8, 2015.
- [13]. Chu TC, Lin YC, "A fuzzy TOPSIS method for robot selection", International Journal of Advanced Manufacturing Technology, Volume 21, pages: 284–290, 2003.
- [14]. Nicole Kr'amer, Masashi Sugiyama, The Degrees of Freedom of Partial Least Squares Regression, Journal of the American Statistical Association, Page: 1-23, 2011.
- [15]. B. Efron, The Estimation of Prediction Error: Covariance Penalties and Cross-Validation. Journal of the American Statistical Association, 99(467):619–633, 2004.
- [16]. I. Frank, and J. Friedman, A Statistical View of Some Chemometrics Regression Tools. Technometrics, 35(2):109–135, 1993.
- [17]. Carsten Neumann, Michael Förster, Birgit Kleinschmit, Sibylle Iltzert, Utilizing a PLSR-Based Band-Selection Procedure for Spectral Feature Characterization of Floristic Gradients, IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, Volume: 9, Issue: 9, Pages:3982 - 3996, Sept. 2016.
- [18]. Nayak S., Choudhury B.B., Lenka S.K. Gradient Descent with Momentum Based Backpropagation Neural Network for Selection of Industrial Robot. In: Satapathy S., Das S. (eds) Proceedings of First International Conference on Information and Communication Technology for Intelligent Systems: Volume 1. Smart Innovation, Systems and Technologies, vol 50. Springer, 2016.