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Domestic water demand predicting by factors analysis of planned colony in Ajmer, Rajasthan (India)

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Abstract: In this paper, contribution of variables of domestic urban water demand considered for the purpose of prediction of urban water supply in planned colonies of the City of Ajmer. The data for these 15 variables are entered in the factor analysis under principal component, generalised least square and maximum likelihood method, and five factors/variables are extracted, comprising combinations of these 15 variables. Based on these five principal components (PCs) variables a multi linear regression (PCR) coefficient of 0.76, 0.64 and 0.62 are obtained by the principal component, generalised least square and maximum likelihood model respectively. These five significant principal components are further fed into a multilayer perceptron neural network (NN) model for water demand forecasting. The linear regression coefficient of MLP NN (PCs) is 0.76, very close to the principal component multiple linear regression (stepwise) coefficient of 0.76, and verifying the dependence of water demand on these five principal components. The better result is showing by factor analysis under PCR compare to the factor analysis under Maximum Likelihood and Generalised Least Square methods. The lowest average percentage difference of predicted value is -2.64 PCs MLP (NN) and -2.08 were giving by PCR (PC) respectively. The outcome of the study suggests that the extracted variables are significant for estimation of water demand for planned colonies of Ajmer city.

Key words: Factor analysis, (PCA), generalised least square (GLS), maximum likelihood (MLH), principal component regression (PCR), neural network (NN), domestic water demand

1. INTRODUCTION

Most of the cities of Rajasthan state are also lying under the arid region. For better planning and management of integrated water resources scheme is necessary for such regions. If demand affecting parameters have in controlled for planning and implementation of water resources, scheme/ supply system, it will be helpful in demand management (Choudhary et al. 2012 and Singh et al. 2015). Therefore the accurately domestic water demand forecasting is a crucial way because of it’s depend on personals behavior, climatic factors, socioeconomic and demographic factors of regions.

Water demand management can be carried out in many ways, such as implementation of use of optimization techniques in supply systems, water demand reduction schemes, development of sustainable water sources, and fixing effective water restrictions, as told by Odan and Reisl (2012), Admowski and Karapataki (2010), and Ghiassi *et al*. (2008). Billing and Jones (2008) told that multi linear regression modelling can be applied for urban water demand forecasting which primarily depends on ownership of water appliances, water price, family size , family income, and household density.

Many states in India have problem in supplying enough drinking water in urban areas. Rajasthan state, which lies in arid and semi-arid climatic zones, faces water supply problems in most of its urban cities Singh et al. (2017). Major cities such as Jaipur, Bikaner, and Ajmer in Rajasthan depend on outside sources of water for domestic supply. Analysis of domestic water demand affecting parameters offers a promising solution for reliable urban water supply. To plan an effective demand management, it is necessary to enumerate of the parameters required to estimate the domestic water supply demand accurately.

2. LITERATURE SURVEY

Forecasting of urban water demand (UWD) is crucial in managing water demand and supply, particularly given the changes those will be incurred by the climate change and population growth Adamowski et al. (2013). Understanding associations between UWD and meteorological factors such as precipitation and air temperature can enable both better forecasting and understanding of the natural factors those drive the urban water demand in a big way. It is generally accepted that water demand is affected by various climatic and socio-economic factors, government policies and strategy related factors which differ from place to place, thus necessitating the need to develop city specific models to predict water demand. Most of the climate change studies (Field et al. 2012) had already concluded the greater impacts of climate change on water resources. Climate variability and change affect the availability and quality of water, runoff and temperature extremes. Therefore, how these climatic and socio-economic parameters changes in future will govern the water demand forecasting.

The factor analysis converts the original set of inter correlated independent variables to a new set of uncorrelated variables (i.e. factor/dimension reduction). In the Principal components analysis (PCA) the total variance and attempts to explain the maximum amount of variance by the minimum number of underlying independents variables (Singh et al. 2017 and Hinton et al. 2012). The use of these factors/variables as independent variables in regression method for water demand forecasting to avoid the multicollinearity problems and to identify the most significant variables (Haque et al. 2013 and Singh et al. 2017). Choi et al. (2010) stated that water demand prediction base on factors analysis could be found better when data are considering on a large area that is including more number of cities. They used the factors analysis for determined the water demand considering the social and industrial parameters of various cities in Korea. Haque et al. (2013) found that regression model based on PCA reduced the model complexity by eliminating multicollinearity and improved the model prediction. However, Singh et al. (2017) gave the better result with MLR (stepwise) since it had considered only a few variables in the analysis that was highly correlated with water demand. Literature research showed that the water demand forecasting is depended on many factors (Odan and Reisl 2012, Billing and Jones 2008, Arbues *et al*. 2003, Billing & Jones 2008, Donker *et al*. 2014 and Singh *et al*. 2015). It was found that, principal components based regression (PCR) modelling studies indemand forecasting is very limited in the litrature.

All of these studies found that Step-wise regression method will be most effective analyzed in water demand. Factor analysis can decide the importance of water demand affecting variables through correlation, eigenvector and eigenvalue, transpose matrix and multiple linear regression functions. However, the limitation of PCA is that the naming of new variables or principal components is problematic. Because of factor name was not accurately reflects the original variables Yong and Pearce (2013). However, the MLR (stepwise) gives a better result than PCR (stepwise) because only a few significant variables were considered in the MLR (stepwise), while PCR (stepwise) was based on the comprising of all the variables Singh et al. (2017). The multicollinearity problems were avoiding in the PCR due to the rotation techniques and factor score matrix. So, the PCR (stepwise) model equation could be used to get a better prediction in domestic water demand forecasting.

In this paper, an extracting of principal components (PCs) via factor analysis (FA) under dimension reduction techniques of the PCA, Generalised Least Square (GLS) and Maximum Likelihood (MLH) from independent variables. Further, the MLR (stepwise), based on PCs (i.e. PCR stepwise) analyses for the planned colonies of Ajmer city, identified through the statistics in SPSS software version 23. Authors used the fifteen independent water demand affecting variables for factor analysis (PCA) to obtained principal components (PCs).

3 STUDY AREAS AND SURVEY DESIGN

The historic city of Ajmer is situated in the centre of Rajasthan and lies about 135 km southwest of the state capital, Jaipur. Ajmer is settled in the cradle of the Aravali mountain range at an average elevation of 486 m above MSL. The city has a moderate climate with daily temperature varying from 26.9ºC to 46ºC during summer and 7.6ºC to 22.5ºC during winter. The average yearly rainfall is about 55 cm, and average humidity is 57%. The population of Ajmer is about 800,000 according to the 2011 census. At present, Ajmer is dependent on Bisalpur Dam for its water supply, which is located about 120 km away from the city. However some periphery areas of city are depends on bore well and water tanker supply systems.

A questionnaire was prepared for the household survey and main data was collected from Urban Improvement Trust (UIT) residential planned colonies of Ajmer City. Some other data was also assembled from government offices, such as the Nagar Nigam office, Public Health Engineering Department, census data of Ajmer City. The sample incorporate 112 household carried out from planned colonies of Ajmer, namely, Adarsh Nagar, Ajay Nagar, Panchsheel, HBU Nagar, and Vaishali Nagar. Samples are evenly distributed among seasons and the population. Data descriptions for all these variables are shown in Table 1.

Table 1. Description of study data

Types of Variable	Min.	Max.	Mean	Types of Variable	Min.	Max.	Mean
Monthly Mean Temperature (T)	14.00	36.00	26.95	Number of Rooms (NR)	1.00	5.00	2.88
Rainfall (RF)	0.00	1.00	0.26	Number of Bathrooms (NB)	1.00	4.00	2.11
Age of Respondent	23.00	73.00	41.34	Number of WCs	0.00	6.00	1.97

(AR)							
Family Size (FS)	1.00	8.00	4.15	Number of Showers (NS)	0.00	3.00	1.07
Family Income/ Year (Rs.) (FI)	132.00	2220.00	764.67	Size of Garden (ft.^{2})	0.00	450.00	56.12
Plot Size (yd.^{2}) (PS)	60.00	666.00	241.87	No. of Washing Machines (NW)	0.00	1.00	0.82
House Age (years) (HA)	2.00	50.00	11.02	Number of Coolers (NC)	0.00	6.00	1.63
Water Price per Year (Rs.) (WP)	156.00	1800.0	331.28	Water Demand (per yr.) (*Q*)	111.6	514.80	260.95

4 RESEARCH MATERIALS AND METHODOLOGY

The above primary data was collected via the random sampling method during 2014 and 2015. These data were extracted from the questionnaires. The primary aim of the present study is to analysis a domestic water demand parameters and hence to developed goodness of fit-model. The collected variables are analyzed in SPSS through factor analysis by using Principal components, GLS, and MLH and extracted a new group of variables/principal components (PCs). These significant principal component (PCs) were used in a stepwise multiple linear regression (PCR) and model equations were developed. Lastly, this model is compared with artificial neural network (ANN). Before applying the above methodologies, the null hypothesis was tested to determine whether it should be accepted or rejected.

4.1 Hypothesis test

The hypothesis test of collected data was carried out under nonparametric test under one sample. Domestic water demand and its independent's variables/factors were automatically tested in one sample One-Sample Binomial Test for categorical scale variables such as RF and Owner of household (HH). A One-Sample Chi-Square test is carried out for nominal scale variables such as garden. Similarly, for the remaining variables (i.e. continuous scale variables), a One-Sample Kolmogorov-Smirnov Test was tested at the 95% confidence interval (CI). These variables were significant ($P<0.005$) at 95% CI except age of the house (i.e. significance at 90% CI) and rejected the null hypothesis in all the cases.

4.2 Test of sampling adequacy and sphericity

The sample adequacy and sphericity tests were taken before the performing the principal components analysis. The combined KMO and Bartlett's test gives the sampling adequacy and sphericity in a repeated measure analysis of variance show in table 2. The Kaiser-Meyer-Olkin (KMO) measures the adequacy, and its range is varying from 0 to 1. The rule of thumb of KMO test is that its values greater than 0.5 for satisfied the factors analysis to proceed (Hinton et al. 2012). The result of KMO value of variables is 0.68, which showing that our sample is adequate, and also Bartlett's Test of sphericity gives the significance value ($p<0.05$) indicating that our collected independents variables are better for factor analysis under principal component analysis, GLS and MLH. So we can conclude that the relationship between the predictors' variables is satisfactory.

Table 2. KMO and Bartlett's test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.68
Bartlett's Test of Sphericity	Approx. Chi-Square	586.31
	df	120
	Sig.	0.00

5 RESULTS AND DISCUSSION

5.1 Extracted of principal components (PCs) variables using factor analysis

The impotence of water demand affecting variables can be decided by factor analysis. All these 15 variables were entered in the dimension reduction (factor analysis) under principal component. In our study the first factors analysis is being consider the 'principal components analysis' which was analysed the total independents variables and attempted to explaining the maximum amount of variables through their percentage variance.

Table 3. Total Variance Explained

Component	Initial Eigen values			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
PC_1	3.96	24.76	24.76	3.96	24.76	24.76	2.73	17.06	17.06
PC_2	2.18	13.66	38.43	2.18	13.66	38.43	2.60	16.25	33.31
PC_3	1.55	9.72	48.16	1.55	9.72	48.16	1.77	11.07	44.39
PC_4	1.28	8.01	56.17	1.28	8.01	56.17	1.65	10.33	54.73
PC_5	1.12	7.04	63.21	1.12	7.04	63.21	1.35	8.48	63.21
PC_6	0.97	6.07	69.29	-	-	-	-	-	-
PC_7	0.95	5.98	75.27	-	-	-	-	-	-
PC_8	0.79	4.95	80.23	-	-	-	-	-	-
PC_9	0.73	4.61	84.84	-	-	-	-	-	-
PC_{10}	0.54	3.37	88.22	-	-	-	-	-	-
PC_{11}	0.46	2.91	91.13	-	-	-	-	-	-
PC_{12}	0.41	2.56	93.69	-	-	-	-	-	-
PC_{13}	0.33	2.10	95.79	-	-	-	-	-	-
PC_{14}	0.29	1.84	97.64	-	-	-	-	-	-
PC_{15}	0.22	1.40	99.04	-	-	-	-	-	-

Extraction Method: Principal Component Analysis.

Table 3 is shown the total variance of independents variable with associated of Eigen value with each linear component, which gives the individual % of variance and cumulative %. Generally cumulative % of variation is considered up to Eigen value greater than one or % of variance greater than 3. Total variance of % of our result is showing the 63.21 % variables/components cover the variability and 36.79% of variables variance is showing losses in initial Eigen value, extraction sum of square loading and rotation sums of squared loadings respectively. Five components having Eigen value greater than 1.12 gives the maximum contribution to the water demand.

The rotated components matrix has shown the clear picture that the 15 variables/factors loading into analysis and created the new fifth independents variables (factors). According to table 4 Principal components PC_1 is including the variable like as family size, family income, number of rooms, number of bathrooms, numbers of coolers and numbers of water closet. PC_2 is created by family income, plot size, house age, and number of water closet, garden and numbers of coolers. PC_3 extracted by water price, number of water closet, number of shower, washing machine and AC. PC_4 extracted by rainfall (-ve), age of respondent, family income and number of shower. PC_5 is created by including the temperature (-ve), number of room, and number of shower as shown in table 4. The identity of these new components (PCs) may be decided on the rotated components matrix (table 5) and hence the water demand is dependents on these five new variables/components.

Table 4. Rotated Component Matrixes

Independent variables	Principal component				
	PC_1	PC_2	PC_3	PC_4	PC_5
Monthly Mean Temperature	–	–	–	–	-0.85
Rainfall Occurrence Non-occurrence	–	–	–	-0.75	–
Age of Respondent	–	–	–	0.67	–
Family Size	0.79	–	–	–	–
Income /yrs. (Rupees)	0.48	0.44		0.35	–
Plot Size(sq. yard)	–	0.84	–	–	–
House Age (years)	–	0.67	–	–	–
Water Price per yrs.(Rupees)	–	–	0.65	–	–
Number of Rooms	0.62	–	–	–	0.33
Number of Bathrooms	0.78	–	–	–	–
Number of WC	0.43	0.37	0.39		
Number of Showers	–	–	0.33	-0.42	0.54

Size of Garden (Sqft.)	–	0.86	–	–	–
Washing Machine	–	–	0.78	–	–
Number of Coolers	0.72	–	–	–	–

Extraction Method: Principal Component Analysis.

Table 5. Component Score Coefficient Matrix

Independent variables	Principal Component				
	PC$_1$	***PC$_2$***	***PC$_3$***	***PC$_4$***	***PC$_5$***
Daily Temperature	0.05	0.08	0.09	-0.03	-0.68
Rainfall Occurrence Non-occurrence	-0.01	-0.02	0.19	-0.44	-0.09
Age of Respondent	-0.01	-0.14	0.10	0.43	-0.06
Family Size	0.33	-0.11	-0.11	-0.01	0.08
Income per yrs. (Rupees)	0.13	0.09	0.05	0.17	0.03
Plot Size(sq. yard)	0.03	0.34	-0.08	-0.02	-0.04
House Age (years)	-0.09	0.34	-0.16	-0.09	-0.05
Water Price per yrs.(Rupees)	-0.01	-0.04	0.42	-0.03	-0.19
Number of Rooms	0.21	0.01	-0.04	0.03	0.18
Number of Bathrooms	0.35	-0.07	-0.09	-0.05	-0.16
Number of WC	0.10	0.06	0.15	0.10	0.03
Number of Showers	-0.02	-0.02	0.15	-0.30	0.42
Size of Garden (Sq. feet)	-0.03	0.36	0.003	-0.09	-0.08
Washing Machine	-0.13	-0.12	0.52	-0.01	0.11
Number of Coolers	0.27	0.07	-0.02	-0.05	-0.16

Extraction Method: Principal Component Analysis.

6 PRINCIPAL COMPONENTS REGRESSION (PCR) STEPWISE

Extracted principal components (PCs) were used in PCR (stepwise). In the stepwise regression process, the most significant principal components (PCs) (new extracted independent variable factors) are considering at every step of regression process, and finally those principal components are selected which gives a stronger relationship with water demand modeling. The results of this analysis are summarized in the following sections.

6.1 Correlation of PCs with domestic water demand

The Pearson correlation coefficient between the grouped variables (PCs) and the domestic water demand (WD) was finding out in regression analysis. The result in table 6 show that, the highest relationship of water demand with the PC_1 is 0.83 (i.e. it's dependent on the family size, family income, number of rooms, number of bathrooms, numbers of coolers and numbers of water closet) in the study area. The second and third most were showing with PC_4 and PC_3 is 0.14 and 0.02. Lowest negatives values of correlation coefficient was showing for PC_2 and PC_5 are -0.09 and -0.19 (table 6) respectively and it was not significant to contribution in the developed model.

Table 6. Correlations between water consumption and principal component

Variables	*Q*	**PC$_1$**	**PC$_2$**	**PC$_3$**	**PC$_4$**	**PC$_5$**
Pearson Correlation Coefficient	1.00	0.83	-0.09	0.02	0.14	-0.19
Sig. (1-tailed)	-	0.00	0.15	0.42	0.07	0.02

6.2 Principal Components Regression (stepwise) model summary

This multi-linear regression stepwise (PCR PC) models summary is showing in table 7 in which four models namely *M1* to *M4* were generated base on the importance of PCs (predictors) variables. Model *M1* includes the significant variable PC_1 predictor with lowest R^2 value 0.69, but this shows that water demands highly correlated (R=0.83 Table 6.) with PC_1 and depends on table 6 is considered significant first. Similarly, Model *M4* includes the highest predictors (PCs) such as PC_1, PC_5, PC_4 and $PC_2$with combined R=0.93, highest R square value 0.76 and error 38.30 (Table 6). Hence the model *M4*, the predictors/independents variables included together account for 76.00% of the variance in the domestic water demand with statistically significant (Sig. F value P<0.05 for all models, Table 6). However the principal component PC_3 was excluded from the analysis because it is not significant in stepwise regression process and deleted from the analysis.

Table 7. Multi linear stepwise PCR (PC) models summary

Model	R(Correlation Coefficient)	R Square	Std. Error of the Est.	F Change	Sig. F Change
M1	0.83[a]	0.69	42.66	244.94	0.00
M2	0.85[b]	0.73	40.19	145.43	0.00
M3	0.86[c]	0.75	38.84	106.70	0.00
M4	0.87[d]	0.76	38.30	83.32	0.04

a. Predictors: (Constant), PC_1
b. Predictors: (Constant), $PC_1$and PC_5
c. Predictors: (Constant), PC_1, $PC_5$and PC_4
d. Predictors: (Constant), PC_1, PC_5, PC_4 and PC_2
e. Dependent Variable: Water demand (Q) HH/KL/Yr (m^3)

Analysis of ANOVA and PCR (PC) coefficients

The best goodness of fit statics model was developed namely *M4* in Table 7. For this model the analysis of variance (ANOVA) was satisfactory with statically significant F value is 83.32, P<0.005. As discussed in model summary, the model *M4* was based on significant variables and gives the domestic water demand for a household equation with multiplying constant to PCs and additive constant as shown in equation (1).

$$Q = 63.37 (PC_1) – 7.34 (PC_2) + 10.87 (PC_4) – 14.73 (PC_5) + 260.95 \quad (1)$$

Here result shown that the component PC_1 (family size, family income, number of rooms, number of bathrooms, numbers of coolers and numbers of water closet) is most significant, and highest value of multiple constant B_3 = 63.37 shown in equation (1). The second most significant component is PC_4 (age of respondent, family income and number of shower) Table 8 and multiple coefficient B_1 = 10.87 and shows in equation (1). The PP normal plot is showing good trend (i.e. data shows near by 45^o line) between predicted water demand (WD) verses observed WD as shown in figure 1. Finally the residual statistics were presented in the table 9. The predicted mean value of a household (HH) was 260.95 KL/Yr (m^3) with mean standard error of predicted value = 7.75 were founded.

Table 8. PCR (PC) best model coefficients

Model	Coefficients B	Sig.	95.0% CI	
			Lower Bound	Upper Bound
(Constant)	260.95	0.00	253.77	268.12
PC_1	63.37	0.00	56.16	70.58
PC_5	-14.73	0.00	-21.94	-7.53
PC_4	10.87	0.00	3.66	18.07
PC_2	-7.34	0.04	-14.54	-0.13

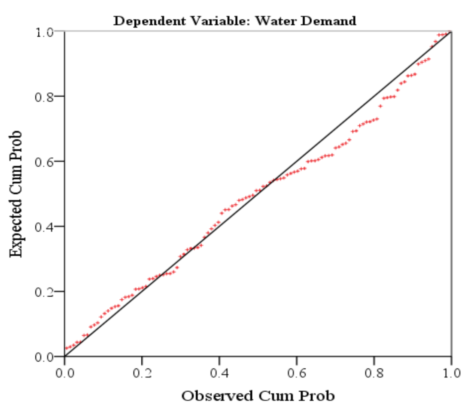

Fig 1: Normal P-P plot for regression standardised residual PCR (PC) output

Table 9. Residual statistics of MLR PCs model

Parameters	Minimum	Maximum	Mean	Std. Deviation	Sample Size
Predicted Value	134.78	466.05	260.95	66.37	112.00
Std. Predicted Value	-1.90	3.09	0.00	1.00	112.00
Std. Error of Predicted Value	4.01	16.92	7.75	2.32	112.00
Adjusted Predicted Value	135.90	470.97	260.68	66.48	112.00
Residual	-106.14	141.02	0.00	37.61	112.00
Std. Residual	-2.77	3.68	0.00	0.98	112.00

Multi-linear equations of PCR (GLS) and PCR (MLH)

Further, these fifteen independent variables were analysed in the factor analysis through generalized least square (GLS) and maximum likelihood (MLH). Five new PCs were generating through the factors analysis. Based on extracted principal components (PCs), the PCR (GLS) and PCR (MLH) model equations (2) & (3) were developed.

$$Q = 48.09\,(PC_2) + 41.35\,(PC_4) + 260.95 \qquad (2)$$

and,

$$Q = 53.52\,(PC_2) + 29.56\,(PC_5) - 10.38\,(PC_1) - 10.92\,(PC_4) + 260.95 \qquad (3)$$

The regression coefficients (R^2) of these models were 0.64 and 0.62, which was goodness-of-fit for statically but represented the quite low values for prediction of water demand as compared to PCR (PC) (R square =0.76). Because of these model equations were considered different combination of PCs in the stepwise MLR analysis as mentioned in equation (2) and (3) respectively. Hence, the better result is showing by PCR of factor analysis under PCA compare to the factor analysis under Maximum Likelihood and Generalised Least Square methods.

7 CORRELATION OF PCR (PCs) WITH MLP (NN)

Multilayer Perceptron neural network model base on (PCs)

Further, these five PCs were used in the generalized regression of Multilayer Perceptron neural network (MLP NN). A neural network can approximate a wide range of statistical models without requiring that you hypothesize in advance certain relationships between the dependent and independent variables IBM (2011). The MLP NN is consisting with the input layer contain PCs, two hidden layer with sigmoid function and one output layer as water demand consumption. In the NN modeling process summary, 82 household data (73.2% of 112 total) were used for training and 30 (26.8%) for testing in the MLP (NN) modeling. For the training data, the sum of square error is 7.93, and the relative error is 0.19 whereas for the testing data, the sum of square error (SE) is 6.33 and the relative error is 0.33 in the NN modeling. The linear R square of MLP (NN) model was 0.76 which was near to the stepwise PCR (PC) model.

The MLP NN gives the direct importance of independent variables/factors as shown in table 10. According to Table 10 normalized importance of PCs, variables resemble the same significance as mentioned in principal rotated component metrics. The PC_1 has highest normalized score i.e. independent variables comes under this component was most significant independent variables in the demand forecasting modelling. The second most significant variable was PC_5. Also figure 2 was showed the clear cut picture for significance of independent variables in the form of graphical normalization.

Table 10. Independent variables (PCs) importance (MLP NN output)

Components	Variables Included	Importance	Normalized Importance
PC_1	FS, FI, WB, NR, NB, WC & NC	0.54	100.0%
PC_2	FI, PS, HA, WC & GS	0.12	21.8%
PC_3	WB, WC, NS & WM	0.05	9.1%
PC_4	RF, AR, FI & NS	0.09	17.6%
PC_5	T, NR & NS	0.20	36.1%

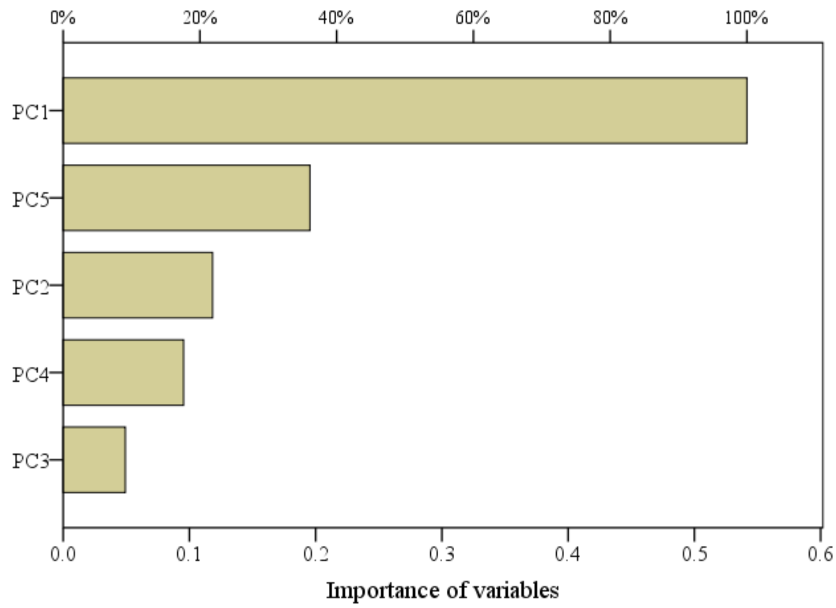

Figure 2: Normalize importance of independent variable (MLP NN PCs output)

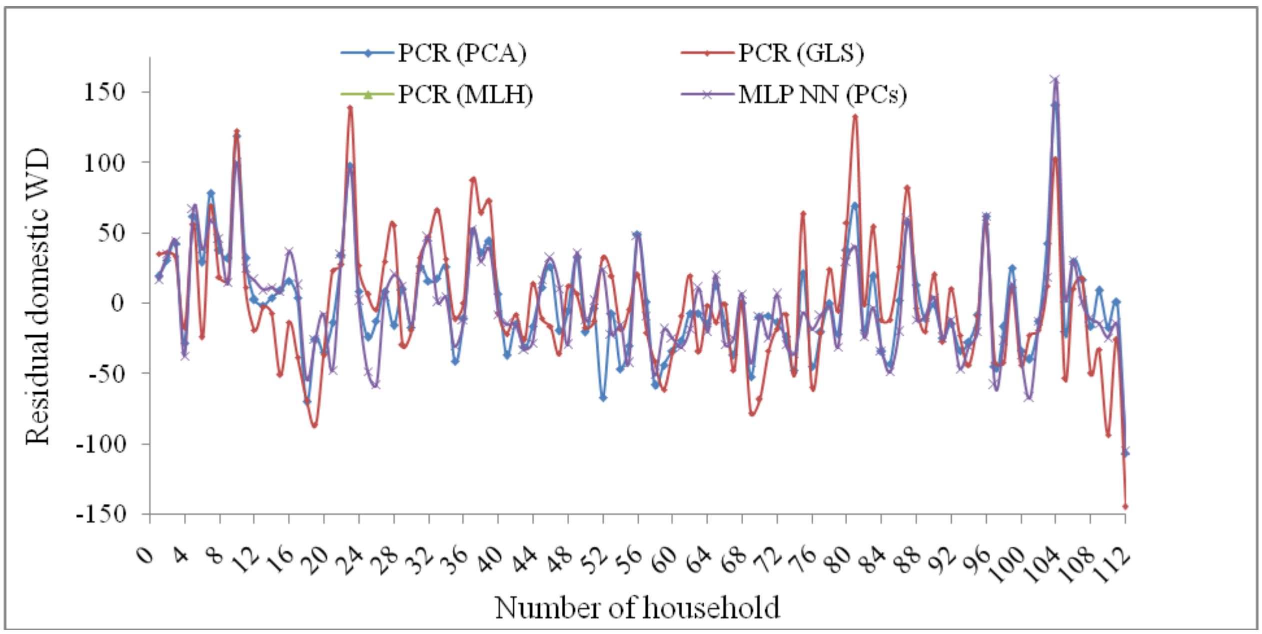

Fig 3 Residual plot of actual domestic WD versus predicted WD of different models

ANN is giving better result rather than other water demand forecasting models (Jain et al. 2001, Donker et al. 2014 and Singh et al. 2015). Also in general, the ANN is used for compare the results with the water demand forecasting methods. Moreover, the lowest average percentage difference of predicted value is -2.64 MLP (NN) and -2.08 were giving by PCR (PC). The residual water demand of all models are plotted and shown in figure 3. Also, figure 3 show that residual water demand consistency data was better for PCR (PC) and MLP (NN) PCs than, the PCR (GLS) and PCR (MLH) models respectively.

8 CONCLUSIONS

The analyses of domestic water demand parameters are essential for proper planning and management of any water resources project. Precise domestic water demand forecasting depends on a number of variables related to socio-economic, climatic and demographic parameters. The data for 15 factors/parameters affecting residential water demand forecasting were collected from urban colonies (112 households) of Ajmer City. By using statistics techniques in SPSS software, various checks of the hypothesis test, adequacy of the data set, and a check for normal distribution are checked. Factors analysis under the PCA, GLH and MLH are carried out on all 15 variables/factors giving five new factors (i.e. principal components PC_1 to PC_5). Out of 15 variables, 5 significant PCs are identified and studied using PCR Stepwise and giving $R^2 = 0.76$, $R^2 = 0.64$ and $R^2 = 0.62$ for PCR (PCA), PCR (GLS) and PCR (MLH) respectively. These results of PCR Stepwise are most suitable and an equation is proposed for prediction of domestic water demand. Also, it was found that principal components PC_1, PC_5, PC_4 and PC_2 were most significant independent variables in the PCR (stepwise) model (Tables 8 &10). Therefore, the independent variables which had a significant score within these PCs could be treated as significant predictor variables for domestic water demand predicting. The same results of PCR Stepwise are also verified by using MLP NN(PCs), which give $R^2 = 0.76$ suggesting that the proposed equation for domestic water demand can be used successfully for these colonies of Ajmer City.

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