

MODELING TOWARDS PENTAVALENT VACCINE COVERAGE IN PAKISTAN

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ABSTRACT

OBJECTIVES: To expose the trend and proposing the forecasting model for monthly pentavalent infant immunization coverage a significant concern in disease management and control.

DESIGN: The reported data of monthly infant pentavalent immunization coverage to National institute of health, Islamabad, Pakistan from January 2009 to October 2014 for the present study has been taken from Pakistan bureau of statistics with total time series entities 70. National institute of health, Islamabad took the record of per month number of doses administered (0-11 months) children by the registered health centre in Pakistan.

PERIOD: January 2009 to October 2014.

SETTING: Pakistan Bureau of Statistics (Statistics House)

METHODS: Two time series techniques namely Box Jenkins and artificial neural network (ANN) has been carried out to develop a forecasting model. Results: ARIMA (1, 1, 1) model with RMSE (56998) and ANN 10-3-1 model with RMSE (34582) are selected after execution of various set of parameters of both techniques. Due to lower RMSE ANN 10-3-1 is an adequate model. The established ANN model revealed that the increment for infant pentavalent coverage is 4.14% expected in next six month.

CONCLUSIONS: ANN 10-3-1 is an efficient model for forecasting the monthly pentavalent infant immunization coverage in Pakistan.

KEYWORDS: Pakistan; Pentavalent infant immunization; time series

INTRODUCTION:

The mandatory dose of DTP (diphtheria-tetanus-pertussis) is vaccinated around 100 million children worldwide¹, while 24 million children are not being reached with vaccines due to several causes like crumble infrastructure of health services, inaccessible domains, military insurgency and refugee children disrupt the vaccine coverage efforts². In 2007, nearly 10% of infants did not receive DTP vaccine dose, as compared with 2% of infants in developed countries². The

immunizations against Haemophilus influenza type B (HIB) in the combined diphtheria, tetanus, pertussis (DTP)-hepatitis B (HBV) are routine vaccination programs for infants recommended by World Health Organization. In fact, the developing countries where, children under 5 years of age are immunized with recommended vaccine dose under National

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immunization program, to protect against tuberculosis, diphtheria, tetanus (including neonatal tetanus through immunization of mothers), pertussis, polio, measles, hepatitis B, Hib; saving approximately 2.5 million children every year². More than 5.8 million infants were vaccinated against preventable disease under the Expanded Programme on Immunization (EPI) in Pakistan annually¹.

Pakistan is a developing as well as 6th most populous county in the globe. More than 70% of the world's unimmunized children live in only 10 developing countries, mainly in Africa and Asia³. Pakistan ranks 26th in the world, where infant mortality rate was 87 per 1000 live births; with more than 50 percent of deaths under 5 years of age⁴. Although, infant mortality rate is decreasing over the past few years, the progress is still unsatisfactory to meet the Millennium Development Goals (MDGs) 2015 target; reducing to 52 deaths per

1000 live births of children under 5 years of age 5.

The immunization status of the children was fairly satisfactory and the rates of immunization are strongly influenced by educational status of parents. Vaccination rate was high in male children and linked with the place of delivery. The reasons of non and partial immunization were inaccessibility, non-availability of vaccine, fear of side effects, inadequate awareness and inconvenience for the parents⁶. The immunization coverage according to EPI is not up to the mark that can be a major contributory factor towards high infant and below five year mortality in Pakistan. More efforts are required to create awareness and availability of vaccination at door step of the people⁷. Vaccination schedule in Pakistan is illustrated in Table 1.

Table 1: Vaccination Schedule in Pakistan

Age	Vaccinations	New schedule (2010 onwards)
At birth	BCG + Polio 0	BCG + Polio 0
6 Weeks	DPT 1 + HBV 1 + Polio 1	Pentavalent + Polio 1
10 Weeks	DPT 2 + HBV 2 + Polio 2	Pentavalent + Polio 2
14 Weeks	DPT 3 + HBV 3 + Polio 3	Pentavalent + Polio 3
9 months	Measles	Measles
12-15 months		Measles 2

This study therefore aimed to better understand the pattern of infant immunization coverage through modelling against these serious diseases (DPT + HBV) that may helpful to improve the vaccination planning and program in Pakistan so that the morbidity and mortality among infant children can be reduced.

Artificial Neural Network in Medical Field:

Artificial neural network approach has been achieved much popularity in last few years. Although the development of ANNs was mainly biologically motivated, but afterwards they have been applied in many different areas,

especially for forecasting and classification purposes⁸⁻¹⁰. The basic objective of ANNs was to construct a model for mimicking the intelligence of human brain into machine. Similar to the work of a human brain, ANNs try to recognize regularities and patterns in the input data learn from experience and then provide generalized results based on their known previous knowledge. From medical perspective the time series models play a significance role in disease prediction. Many researchers applied the ANN algorithm due to its accuracy than other time series models^{11; 12}. Reference¹³ used ANN to predict the diabetes mellitus and found that ANN 8-20-1 as

optimum structure. Reference 14 used the ANN and forecast the diabetes. Artificial neural networks were used for infectious diarrhea prediction and ANN 9-4-1 found to be optimum structure for diarrhea forecast¹⁵.

METHODS AND MATERIAL:

Source of data: A monthly registered data for the infant Pentavalent-1, Pentavalent-2 and Pentavalent-3 immunization coverage from January 2009 to October of 2014 total time series entities 70 was taken from Pakistan Bureau of Statistics (Statistics House) government of Pakistan, Islamabad, Pakistan for the present study. Let X_t be the average number of monthly Pentavalent-1, Pentavalent-2 and Pentavalent-3 doses administered to infant (0-11). artificial neural network⁸⁻¹⁰ is carried out to uncover the infant pentavalent immunization coverage trend and the development of forecasting model by using the statistical software Zaitun time series.

ANN which involves a large number of simple and highly interconnected computing components, called layers or nodes or neurons are a branch of artificial intelligence methods. The formulation of ANNs depends upon a set of layers namely input layer, hidden layers, and output layer. These layers further comprise interconnections between the nodes of successive layers through the weights. The internal weights of the network are adjusted by an iterative process termed training and the algorithm used for this purpose called training algorithm. An appropriate ANN model can be selected by taking into account the various sets of nodes. Among various activation functions like logistic sigmoid function, linear, hyperbolic tangent, Gaussian, etc. can also be used¹⁶. In our study the preferred activation function was

hyperbolic tangent function.

Box-Jenkins methodology was often used in the prediction of infectious diseases¹⁷⁻²². It is a systematic iterative process until an adequate model is achieved. A procedure is enhanced step by step identification, estimation of parameters, diagnostic checks and finally forecast. A model consist the three parameters one autoregressive (p), second differencing order (d) and third moving average order (q)^{23; 24}.

Measures of Forecast Accuracy:

To compare forecasted values with actual values to see how well one model works or to compare models²⁵. Some popular and very useful accuracy measures are (i) Mean Square Error (MSE). Square root of mean square error is termed as root mean square error (RMSE) (ii) mean absolute error (iii) mean absolute percentage error.

Forecast error = Actual value – Forecast value

$$\text{Mean square error} = \frac{\sum(A_t - F_t)^2}{n}(1)$$

where A_t and F_t is actual and forecast value respectively.

RESULTS AND DISCUSSIONS:

Monthly number of pentavalent doses administered (0,1,1 months) children during January 2009 to November 2014 with measure of central tendency, lower quartile (Q1), upper quartile (Q3), absolute measure of dispersion, minimum and maximum immunization coverage are given in Table 2. On the average per month infant immunization coverage is (418993-+79253)

Table 2: Descriptive statistics

Variable	Mean	SE Mean	StDev	Minimum	Q1	Q3	Maximum
C1	418993	9473	79253	124490	419008	461737	515415

A set of ARIAM models were executed by fixing the differencing order $d=1$.i.e. the stationary level achieved after first difference by using the Kwiatkowski-phillips-schmidt-shin test (test statistic $0.046 < \text{critical value } 0.468$). The

detail summary along with accuracy measure root mean square error was illustrated in Table 3, ARIMA (1, 1, 1) considered as efficient forecasting model due to least RMSE (56998.11).

Table 3: A detail summary of models and accuracy measure

ARIMA (p, d, q)	Root mean square error
0,1,1	59969.33
0,1,2	59348.55
1,1,1	56998.11*
1,1,2	57268.53
2,1,0	60523.92
1,1,0	60094.36
2,1,1	60592.5

*lowest value of RMSE

Table 4: ANN model selection using various combinations of input and hidden layers and RMSE

Hidden layer	Input layer											
	1	2	3	4	5	6	7	8	9	10	11	12
	Root mean square error											
1	55108	54921	55312	54654	55466	55484	53240	52290	51766	39940	36014	37624
2	54572	52571	46363	45695	40485	37265	37170	46706	35111	36317	35412	35388
3	54615	52317	44157	45663	37795	36810	35799	34617	35359	34582	35317	34629
4	54505	51543	44178	41995	41266	36087	35179	35870	35578	34740	34716	34551
5	54824	51325	43379	43499	37441	36764	35945	35800	35840	34860	35122	35048
6	54678	52321	44949	44326	38931	37238	36181	36112	36378	35506	35446	32642
7	54741	48031	44618	43202	39290	37848	37386	37449	38786	35918	36188	35625
8	54496	49022	43566	45243	40531	38621	37162	36932	38884	36312	37520	35977
9	54579	51927	44926	43405	40304	40434	38969	37173	40103	38589	39854	36207
10	54662	49190	44719	42958	40430	38090	39337	40654	44939	38370	40118	36793
11	54710	50527	46723	42455	42132	41151	40838	37700	48111	40404	38651	37326
12	54429	48035	45754	44463	43697	43753	41463	44893	49822	42691	41578	37988

Different set of parameters i.e. input and hidden layers (weights) are executed by using the learning rate 0.05 and hyperbolic tangent function as an activation function while the maximum number of iteration used 3000 were executed with the object to establish the efficient ANN model for forecasting the monthly infant immunization coverage. The detail description of various set of nodes and root mean square error are illustrated in Table 4. The established efficient ANN model is 10-3-1 with least root mean square error 34582.

After comparing the RMSE for both the models the ANN 10-3-1 model has least forecast error. The graphical illustration of the final selected model is shown from Figure 1 through Figure 2. The predicted values agree well the actual values are shown in Figure 1 by taking the monthly infant pentavalent immunization coverage along y-axis and time (month) along x-axis. Half year forecast made successfully by using the ANN 10-3-1 (Figure 2) the expected increment 4.14% in next six month (Table 5).

Table 5: Expected per cent change under ANN model

Actual (May 2014 to Oct 2014)	Forecast (Nov 2014 to Apr 2015)	% change
2550749.67	2656242.60	4.14

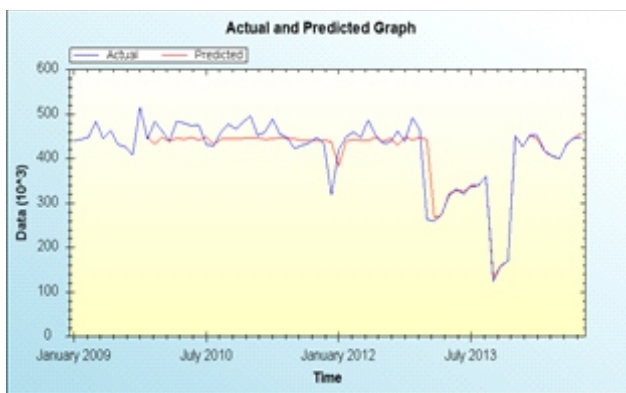


Figure 1: A plot of actual and predicted

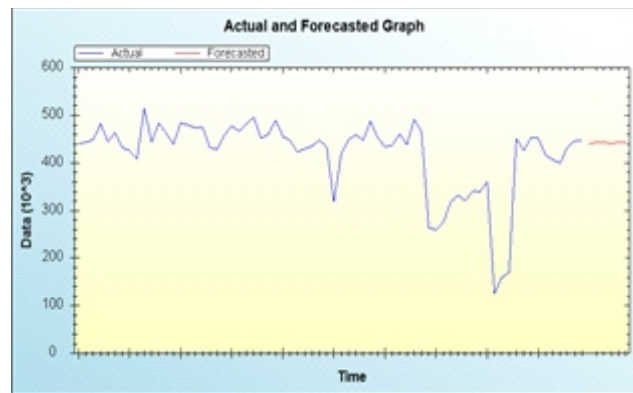


Figure 2: A plot of actual and forecasted

CONCLUSION:

After the implementation of artificial neural network algorithm, ANN 12-9-1 is an optimum forecasting model for monthly pentavalent infant immunization coverage in Pakistan. The availability of these statistical outcomes will serve as a guide to improve measles vaccination and formulate adequate policies and program so that the morbidity and mortality due to diphtheria-tetanus-pertussis can be declined in children.

REFERENCES:

1. Hasan, Q., Bosan, A., and Bile, K. (2010). A review of EPI progress in Pakistan towards achieving coverage targets: present situation and the way forward.

2. Maurice, J.M., and Davey, S. (2009). State of the World's Vaccines and Immunization. (World Health Organization).
3. Burton, A., Monasch, R., Lautenbach, B., Gacic-Dobo, M., Neill, M., Karimov, R., Wolfson, L., Jones, G., and Birmingham, M. (2009). WHO and UNICEF estimates of national infant immunization coverage: methods and processes. Bulletin of the World Health Organization 87, 535-541.
4. UniCEF. (2014). The State of the World's Children 2014 in Numbers: Every child counts—Revealing disparities, advancing children's rights. United Nations Children's Fund, 1-111.
5. UNDP. (2012). Goal 4: Reduce child mortality. Retrieved from: undp.org.pk/goal-4-reduce-child-mortality.html

6. IMRAN, S., RAMZAN, M., and MAQSOOD, I. (2014). STATUS OF IMMUNIZATION OF CHILDREN AND FACTORS RELATED TO PARTIAL AND NON-IMMUNIZATION. *Biomedica* 30, 1.
7. Ikram, M.A., Sajid, A., Irshad, F., and Zafar, S. (2013). Immunization coverage of children according to expanded programme on immunization; where do we stand? *Rawal Medical Journal* 38, 417-421.
8. Vemuri, V.R., and Rogers, R.D. (1993). *Artificial Neural Networks-Forecasting Time Series.*(IEEE Computer Society Press).
9. Azoff, E.M. (1994). *Neural network time series forecasting of financial markets.*(John Wiley & Sons, Inc.).
10. Fausett, L.V., and Hall, P. (1994). *Fundamentals of neural networks: architectures, algorithms, and applications.*(Prentice-Hall Englewood Cliffs).
11. Marquez, L., Hill, T., O'Connor, M., and Remus, W. (1992). Neural network models for forecast: a review. In *System Sciences, 1992 Proceedings of the Twenty-Fifth Hawaii International Conference on.* (IEEE), pp 494-498.
12. Srinivasan, D., Liew, A., and Chang, C. (1994). A neural network short-term load forecaster. *Electric Power Systems Research* 28, 227-234.
13. Acar, E., Özerdem, M., and Akpolat, V. (2001). Diabetes Mellitus Forecast Using Various Types of Artificial Neural Network. In *International Advanced Technologies Symposium (IATS'11).* (
14. Sapon, M.A., Ismail, K., and Zainudin, S. (2011). Prediction of diabetes by using artificial neural network. In *Proceedings of the 2011 International Conference on Circuits, System and Simulation, Singapore.* pp 28-29.
15. Wang, Y., Gu, J., and Zhou, Z. Artificial neural networks for infectious diarrhea prediction using meteorological factors in Shanghai.
16. Karlik, B., and Olgac, A.V. (2011). Performance analysis of various activation functions in generalized MLP architectures of neural networks. *Int J Artificial Intell Expert Syst* 1, 111-122.
17. Imran, M., Nasir, J.A., and Zaidi, S.A.A. (2014). Forecasting of New Cases of T.B, Using Box-Jenkins Approach. *JUMDC* 5, 37-42.
18. Soebiyanto, R., and Kiang, R. (2010). Modeling Influenza Transmission Using Environmental Parameters. *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Science* 38, 330-334.
19. Permanasari, A.E., Rambli, D.R.A., and Dominic, D.D. (2009). Prediction of Zoonosis Incidence in Human using Seasonal Auto Regressive Integrated Moving Average (SARIMA). *arXiv preprint arXiv:09100820.*
20. Gyasi-Agyei, K.A., Gyasi-Agyei, A., and Obeng-Denteh, W. (2014). Mathematical Modeling of the Epidemiology of Tuberculosis in the Ashanti Region of Ghana. *British Journal of Mathematics & Computer Science* 4, 375-393.
21. Moosazadeh, M., Nasehi, M., Bahrampour, A., Khanjani, N., Sharafi, S., and Ahmadi, S. (2014). Forecasting Tuberculosis Incidence in Iran Using Box-Jenkins Models. *Iranian Red Crescent Medical Journal* 16.
22. Moosazadeh, M., Khanjani, N., and Bahrampour, A. (2013). Seasonality and Temporal Variations of Tuberculosis in the North of Iran. *Tanaffos* 12, 35.
23. Box, G., and Jenkins, G. (1976). *Time Series Analysis-forecasting and control*; , San Francisco, Calif.,. In. (Holden-Day. San Francisco.
24. Box, G., Jenkins, G., and Reinsel, G. (1994). *Time Series Analysis- Forecasting and Control*, ; Prentice-Hall: Englewood Cliffs, NJ, 1994.
25. Armstrong, J.S., and Collopy, F. (1992). Error measures for generalizing about forecasting methods: Empirical comparisons. *International journal of forecasting* 8, 69-80.

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