A comparison of prediction models in autocorrelated processes for quality assurance

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Improving Health QUALITY, Increasing Global IMPACT

INTRODUCTION

We expect that the forward direction of quality improvement will enable automatic process control, such as the machine performance check (MPC). The approach used in automatic process control is to predict the next observation, and then use the mechanism to adjust so that the observation will be closer to the desired target of quality assurance (QA). With the growing demand for automatic QA in radiation therapy, process characteristics may present various types of dependencies in time series and data are more likely to be autocorrelated. The autocorrelation can significantly affect the accuracy and overall performance of the predictive QA system. The nature of QA processes might cause difficulties in predicting for the future target because of its complicated structure. We compared the accuracy of predictive models for autocorrelated QA data using the machine learning method, artificial neural networks (ANNs) and the traditional approach, the autoregressive integrated moving average (ARIMA).

METHOD & MATERIALS

Data were obtained from a clinical proton beam (IBA Proton Therapy System-Proteus 235) at the National Cancer Center in Korea In this study, sets of data with different patterns (non-autocorrelation and autocorrelation) were deployed to compare the performance of three popular predictive models, ANNs and ARIMA. This aspect was crucial because it might enhance the predicting capability by utilizing autocorrelation as a basis. ARIMA model essentially consists of three components; an autogressive part, a moving average part, and an integrated component. The correlated data is analytically measured by a simple autocorrelation function:

$$\rho(k) = \frac{Cov\,(x_t, x_{t-k})}{V(x_t)}, \qquad k = 0, 1, \ldots.$$

where $Cov\,(x_t, x_{t-k})$ is the covariance between observations using k time periods apart, and it is assumed that the observations with constant variance given by $V(x_t)$.

METHOD & MATERIALS

Here the value of ρ_k is estimated with the autocovariance function:

$$r(k) = \frac{\sum_{t=1}^{n-k}(x_t - \bar{x})(x_{t-k} - \bar{x})}{\sum_{t=1}^{n}(x_t - \bar{x})^2}, \qquad k = 0, 1, \ldots, K$$

The value of the autocorrelation function at lag 0 is 1.

The artificial neural networks (ANNs) offer an alternative to traditional statistical approaches for predictive modeling when non-linear patterns exist. For the ANNs calculations, approximately 2183 time steps were divided into three sets; 70% in training, 15% in testing, and 15% in the validation.

•A typical ANNs consists of 4 interconnected layers of nodes (neurons), including an input layer containing 1 node per independent variable, the first and second hidden layers, and finally, an output layer with 1 node. Each layer connected to another layer with interconnections and adaptive weight values. The neurons were connected to next layer neurons with adjustable weights. Training the network consisted of using a training data set to adjust the connection weights to minimize the error between observed and predicted values. This training was performed according to a Levenberg-Marquardt and quasi-Newton algorithm.

•We use the mean squared error (MSE) to evaluate the error measurement for the predictive model and to make adjustment based on the results. MSE is the average of the squared errors of the prediction. MSE gives greater weight to the larger errors and can be a good measure if the objective is to minimize the larger errors;

$$\text{MSE} = \text{E}(f)^2 = \frac{\sum_{t=1}^{T}(A_t - F_t)^2}{T}$$

where, A_t is the actual value in period t, Ft is the forecast value for period t.

RESULTS

The results indicated that the ANNs is a more powerful and accurate predictive quality than ARIMA in daily output. The ANNs is effective for detecting autocorrelation and provides a prediction of the QA process average will be taken at the next time. This signified that the autocorrelation structure of QA data has no effect on the performance of the ANNs model. Although the ARIMA model was based on the autocorrelation structure, it still had higher MSE than the ANNs.

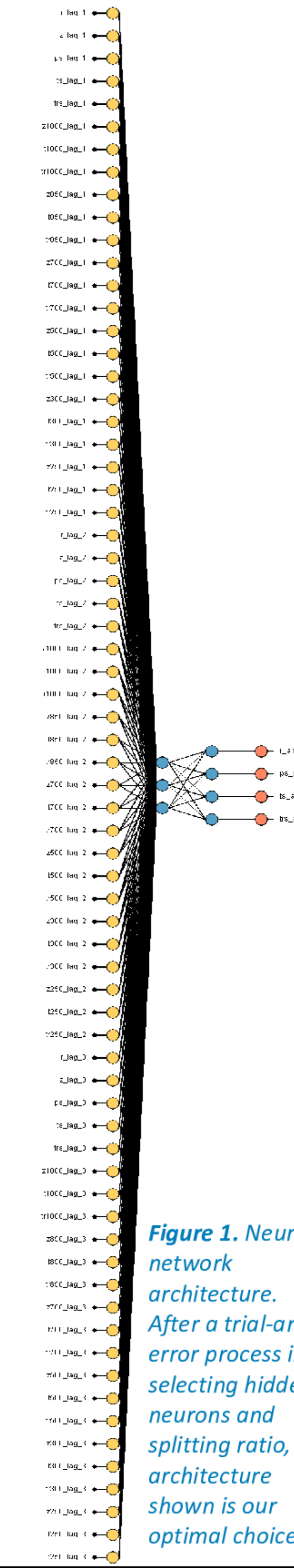


Figure 1. Neural network architecture. After a trial-and-error process in selecting hidden neurons and splitting ratio, the architecture shown is our optimal choice.

Table1. The input values and their corresponding output values; A neural network produces a set of outputs for each set of inputs applied. The outputs depend, in turn, on the values of the parameters.

	Value
r_lag_1	2.56368
z_lag_1	-4.45003
ps_lag_1	925.217
ts_lag_1	12.9486
trs_lag_1	9.57055
z1000_lag_1	147.888
t1000_lag_1	11.4892
tr1000_lag_1	7.07853
z850_lag_1	1402.67
t850_lag_1	6.70606
tr850_lag_1	-2.4578
z700_lag_1	2856
t700_lag_1	-0.493544
tr700_lag_1	13.629
z500_lag_1	5267.57
t500_lag_1	-15.3406
tr500_lag_1	-31.0803
z300_lag_1	8584.82
t300_lag_1	-40.0085
tr300_lag_1	-51.5826
z250_lag_1	9610.05
t250_lag_1	-46.0553
tr250_lag_1	-57.4351
r_lag_2	2.55783
z_lag_2	-4.45831
ps_lag_2	925.216
ts_lag_2	12.9474
trs_lag_2	9.56833
z1000_lag_2	147.073
t1000_lag_2	11.4881
tr1000_lag_2	7.07652
z850_lag_2	1402.65
t850_lag_2	6.70509
tr850_lag_2	2.46242
z700_lag_2	2055.90
t700_lag_2	-0.492935
tr700_lag_2	-13.6311
z500_lag_2	5267.56
t500_lag_2	-15.3473
tr500_lag_2	-31.077
z300_lag_2	8584.84
t300_lag_2	-40.0077
tr300_lag_2	-51.5806
z250_lag_2	9610.06
t250_lag_2	-46.8551
tr250_lag_2	-57.4346
r_lag_3	2.56227
z_lag_3	4.45271
ps_lag_3	925.21
ts_lag_3	12.9476
trs_lag_3	9.56909
z1000_lag_3	147.822
t1000_lag_3	11.4851
tr1000_lag_3	7.0763
z850_lag_3	1402.6
t850_lag_3	6.70472
tr850_lag_3	-2.45901
z700_lag_3	2855.93
t700_lag_3	-0.493362
tr700_lag_3	-13.6284
z500_lag_3	5267.51
t500_lag_3	-15.3470
tr500_lag_3	-31.0769
z300_lag_3	8584.78
t300_lag_3	-40.0062
tr300_lag_3	-51.5864
z250_lag_3	9610.02
t250_lag_3	46.8524
tr250_lag_3	-57.4360
r_ahead_1	3.00315654
ps_ahead_1	1007.69928
ts_ahead_1	13.5275825
trs_ahead_1	9.53001365

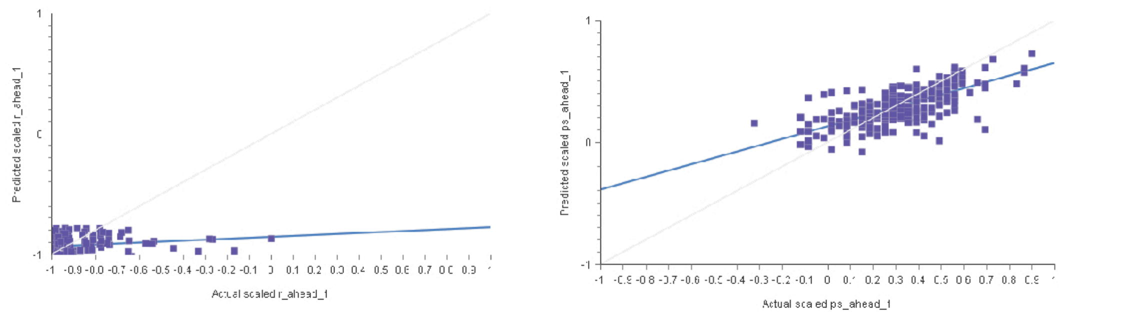
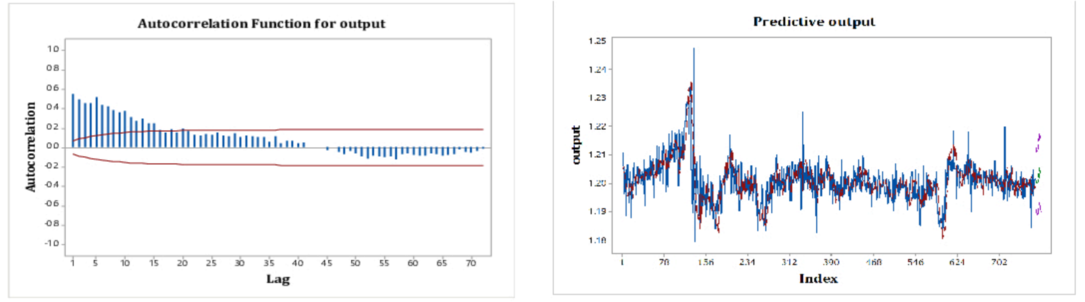


Figure 2. The linear regression for the scaled output r_ahead_1. The predicted values are plotted versus the actual ones as squares. The coloured line indicates the best linear fit. The grey line would indicate a perfect fit..



(a) (b)

Figure 3 (a) Autocorretion function (b) Predictive output using ARIMA model (blue line) and ANNs model (red line)

CONCLUSIONS

Until now, for the QA activities, there are typically two approaches used, being run to corrective and preventive maintenances. The corrective maintenance, known as a run-to failure, starts in the event of a machine failure. The preventive maintenance, including inspections, repairs, replacements, refers to a set of activities to be carried out within a certain period on a set regular frequencies. However, numerous QA activities are running on a daily and monthly basis, but we recognize the fact that it should be simple, rapid, and more efficient. Therefore given (a) these environmental changes and (b) economic feasibility of the most innovative and advanced technologies, the paradigm for the QA activities can be shifted from the corrective or preventive maintenances to the predictive maintenance. The predictive maintenance provides a new perspective and a philosophy on the maintenance strategies to achieve a maximum life expectancy of machines while minimizing the risk of failure. This approach is thus saving a great amount of time and considerable resources.

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