Reliability Analysis and Failure Prediction of Construction Equipment with Time Series Models

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***Abstract*—Reliability and availability of the equipment or plants used in construction and civil engineering field is significant issue for all stakeholders. Unexpected breakdown and repairs could cause serious consequences such as extra cost and project period extension. Therefore, it is necessary to study the reliability of the construction equipment and predict the failures in time with a reasonable degree of accuracy to prevent such losses. This paper adopts time series modelling methods to analyze and forecast the failures and other reliability characteristics such as the expected number of failures per interval and Mean time between failures (MTBF). It is found that time series models is a viable alternative that gives satisfactory results for both point and interval failure predictions in terms of its predictive performance for construction equipment reliability.**

***Index Terms*—construction equipment, failure prediction, reliability, time series, maintenance, ARIMA**

I. Introduction

In construction projects, equipment always plays an important role, especially in the heavy and highways segments of the construction industry [1]. Contractors owning a large equipment fleet or plant owners must take all necessary measures to maximize equipment utilization and minimize equipment failures. Although different maintenance methods such as preventive maintenance and repairs have been adopted for construction equipment, an unexpected breakdown is usually difficult to predict. According to a survey in the US, approximately 46% of major equipment repairs followed an unexpected failure. Repairs are often easy, but the collateral damage caused by the breakdown is more severe. For example, a $500 bearing can ruin a $7,000 transmission; a $100 hose can cause a $2,000 loss in production [2]. Therefore, predicting failures and repairing equipment before break down is essential to the effective cost management of construction equipment utilization or even the whole project.

Collateral costs are extremely difficult to measure because they do not appear in cost reports and they are easily disregarded. Yet the collateral cost of equipment failures in the field cannot be simply afforded if completing construction on time and on budget is required. The impact that breakdowns have on operations and the frequency with which they occur are key factors in managing construction equipment or a fleet as a whole.

Therefore, “prevention is better than cure” is the principle equipment managers should follow in construction equipment management and maintenance. Good managers understand that maintenance actions taken before failure are more cost-effective, less disruptive, and easier to manage than repair actions taken after the machine has broken down and defined both the time and place for the urgently required repair action. Many contractors have taken measures such as monitoring and tracking of the condition of equipment to identify signs of failure or near-failure and conducting repairs or replacements of some components based on the manufacturer’s recommendations or on industrial benchmarks on the expected life of equipment components. However the effectiveness of such strategies is still unsatisfactory as large numbers of unexpected failures still occur.

Predicting equipment failures is necessary to reduce repair cost and manage project and equipment costs [3]. System reliability assessment serves as one of the decisive tools in selecting the right maintenance strategy. It is essential to find more scientific and precise way to analyze and predict construction equipment failures before they happen.

Reliability research on construction equipment is not as developed as it is in other industries. Some researchers have done relevant research on construction equipment maintenance but have not yet developed quantitative measures for predicting failures with reasonable accuracy [4]-[5]. Ref.[6] carried out a comparative study on construction equipment reliability with Power law model and time series model, though it was focused on the comparison of these two research methods. There is more research on the reliability of the plants or equipment in other industries such as mining and aviation industries.

With the development of computer science in the last few decades, more advanced methods such as time series models haven been developed in many other industries [7]-[11].

This research adopts time series techniques to extract rules and patterns from large amounts of data on

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equipment failures collected from the contractors for construction equipment failure analysis and prediction. A time series is a set of observations measured sequentially through time [12]. Time series analysis can be used to describe and model the selected data, and forecast the future values of the series based on the past values. Construction equipment failure follows the time series analysis pattern, and thus time series analysis is adopted and applied in this project. The goal is to bridge the gap between preventive maintenance and repairs, and help to inform managerial decisions on equipment allocation and maintenance.

The aim of this research is to find a way to analyze and predict construction equipment failures to reduce the cost caused by emergency repairs. The main objectives are:

- To investigate the significance of analyzing and predicting construction failures;
- To test time series models on reliability analysis and failure prediction for construction equipment;
- To estimate the reliability and availability characteristics of the selected construction equipment in precise quantitative terms;
- To test and validate the results in real construction cases.

This paper is structured as follows: Section 2 is the literature review of construction equipment maintenance and reliability. Section 3 introduces the basic concepts and a methodology for reliability and availability analysis of construction equipment. Section 4 presents a case study describing the reliability analysis of a piece of construction equipment from industry. Section 5 finally concludes the paper.

II. Construction Equipment Reliability

From the economic consideration, construction equipment should be fully utilized and not left standing idle since plant, whether hired or owned, will have to be paid for even if it is non-productive. Full utilization of a plant is usually considered to be in the region of 85% of on-site time, thus making an allowance for routine, daily and planned maintenance which needs to be carried out to avoid as far as practicable plant breakdowns which could disrupt the construction programme [13].

Construction equipment, like any other machine, can be expected to break down during its working life. This may be due to normal wear and tear, or a sudden failure or a component part. The primary purpose of providing maintenance is to reduce the incidence of failure, by replacement, repair or servicing in order to achieve an economical level of utilization during the working life of the machine.

The factors affecting the productivity of a plant may include task efficiency of the machine, operator's efficiency, and for some special equipment such as excavators may also take type of soil into consideration. Some research articles have pointed out that machines are often traded or replaced at some multiple of the engine life, with transmissions, hydraulic pumps, and undercarriage influencing the decision to various degrees depending on the type of machine and working conditions.

Maintenance costs are a major part of the total operating costs of all manufacturing or production plants. Depending on the specific industry, maintenance costs can represent between 15% and 60% of the cost of goods produced. Recent surveys of maintenance management effectiveness indicate that one-third of all maintenance costs is wasted as the result of unnecessary or improperly carried out maintenance [14]. For example, the U.S. industry spends more than $200 billion each year on maintenance of plant equipment and facilities, so improving the efficiency of maintenance spending.

Traditionally, there are generally three recommended types of maintenance for equipment or plant, which are: maintenance improvement, corrective maintenance, and preventive maintenance. Corrective maintenance deals with the emergency, repair, remedial and unscheduled events. Repairs are always needed. At present, most maintenance activities are corrective. However, better maintenance improvement and preventive maintenance can reduce the need for emergency corrections. Preventive maintenance tasks are intended to prevent unscheduled downtime and premature equipment damage that would result in corrective or repair activities.

Predictive maintenance is not a substitute for the more traditional maintenance management methods. It is, however, a valuable addition to a comprehensive, total-plant maintenance program. Where traditional maintenance management programs rely on routine servicing of all machinery and fast response to unexpected failures, a predictive maintenance program schedules specific maintenance tasks as they are actually required by plant equipment. Predictive maintenance can reduce the number of unexpected failures and provide a more reliable scheduling tool for routine preventive maintenance tasks.

Another aspect of reliability thinking that has developed is the application of statistical methods. Since reliability can be expressed as a probability, and is affected by variation, in principle these methods are applicable. Much research and literature have focused on this subject. However, variation in engineering is usually of such an uncertain nature that refined mathematical and quantitative techniques can be inappropriate and misleading. Therefore, our research will investigate new mathematical techniques on reliability analysis.

Since failure cannot be prevented entirely, it is important to minimize both its probability of occurrence and the impact of failures when they do occur [15]. Reliability is the ability of an item to perform a required function understated conditions for a stated period of time. One of the purposes of system reliability analysis is to identify the weakness in a system and to quantify the impact of component failures. The so-called "reliability importance" is used for this purpose. These importance measures provide a numerical rank to determine which components are more important to system reliability improvement or more critical to system failure.

There has been some research carried on the topic of reliability analysis of mining equipment such as load-haul-dump (LHD) machines [1, 16, 17]. In these studies, graphical and analytical techniques have been used to fit probability distributions for the characterization of failure data, and reliability assessments of repairable mining machines have been reported in these papers. Other mining equipment such as longwall face equipment and crushing plant have also been studied for reliability analysis. Reliability characteristics Time between Failures (TBF) and Time to Repair (TTR) were analyzed for a complicated crushing plant. The parameters of some probability distributions, such as Weibull, Exponential, and Lognormal distributions were estimated with aid of computer software.

There are books and papers researching reliability analysis for building components and civil engineering areas such as bridges and substructures [15]. However, there is not much research investigating the reliability analysis for construction equipment or plant. Ref. [5] used an impending failure matrix to demonstrate the strategies to bridge the gap between preventive maintenance and repair. Ref. [4] performed lifecycle research on several types of construction equipment (excavator, wheel-loader life, crawler-dozer, backhoe-loader, and articulated-dump-truck) by dividing the equipment life into B20, B50 and B80. Ref. [6] did a comparative analysis of construction equipment (D11 dozer system) failures using the classical power law models and the new time series models; the researcher found out that the power law models are easy to apply and are capable of predicting reliability metrics at both the system and subsystem levels with fair results, while time series models based on predictive data mining algorithms are more flexible, comprehensive, and accurate by taking various influencing factors into account.

The highly popularized ARIMA model has been successfully applied in not only economic time series forecasting, but also as a promising tool for modelling the empirical dependencies between successive times between failures. It also results in satisfactory predictive performances [18].

III. Basic Approach for Reliability Analysis

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The ability to predict the time or a range of time within a specific confidence level, of the next impending failure is important as it provides a better case from which effective planning on maintenance, decision making on spares provisioning and replacement policies can be carried out.

A time series is a set of attribute values over a period of time. The mathematical equation of a time series could be:

$$Yt = f\,(Yt\text{-}1, Yt\text{-}2, Yt\text{-}3, \dots, Yt\text{-}n) + \varepsilon t \tag{1}$$

where *Yt* is the value of *Y* at the corresponding time *t*, *Yt-1* to *Yt-n* represent the previous value of *Y*, and *εt* stands for noise that does not obey the predictable pattern.

Time series analysis may be viewed as a method for finding patterns in the data and predicting future values. The values usually are obtained as evenly spaced time points (daily, weekly, hourly, etc.). There are three basic functions performed in time series analysis: distance measures are used to determine the similarity between different time series; the structure of the line is examined to determine (and perhaps classify) its behavior; the historical time series plot used to predict future values. Detected patterns may include [19]:

- Trends: a trend can be viewed as systematic nonrepetitive changes (linear or nonlinear) to the attribute values over time.
- Cycles: here the observed behavior is cyclic.
- Seasonal: here the detected patterns may be based on time of year or month or day.
- Outliers: to assist in pattern detection, techniques may be needed to remove or reduce the impact of outliers.

For decades, researchers have used different statistical methods for modelling and forecasting time series, which vary from a moving average (MA) and exponential smoothing to linear and non-linear regressions. ARIMA models developed by Box and Jenkins (1976) are a classical time series model. But it operates under the presupposition of linearity that the future value of a variable is assumed to be a linear function of several past observations and random errors. A number of alternative methods were developed instead. Some researchers, however, suggested that the ARIMA model is better suited for short-term forecasts while models like neural networks are better suited for longer-term forecast [7].

The model is generally referred to as an ARIMA (p, d, q) model where parameters p, d, and q are non-negative integers that refer to the order of the autoregressive, integrated, and moving average parts of the model respectively. ARIMA models form an important part of the Box-Jenkins approach to time-series modelling.

In practice most time series are non-stationary and so we cannot apply stationary AR, MA or ARMA processes directly. One possible way of handling non-stationary series is to apply differencing so as to make them stationary. If the original data series is differenced d times before fitting an ARMA (p, q) process, then the model for the original undifferenced series is said to be an ARIMA (p,d,q) process where the letter “I”in the acronym stands for integrated and d denotes the number of differences taken. Mathematically,

$$X_t = \emptyset_1 X_{t-1} + \emptyset_2 X_{t-2} + \cdots + \emptyset_p X_{t-p} + e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \cdots - \theta_q e_{t-q} \tag{2}$$

where $\{\emptyset_t\}$ and $\{\theta_t\}$ are are the coefficients, p and q are the orders of autoregressive and moving average polynomials, respectively. The original model uses an iterative three-stage modeling approach: Model identification and model selection, parameter estimation, and model checking [20].

A. Trend Removal and Stationary

A time series is said to be stationary if both its mean (the value about which it is oscillating), and its variance (amplitude) remain constant through time. Classical Box-Jenkins ARMA models only work satisfactorily with stationary time series, so for those types of models it is essential to perform transformations on the series to make it stationary. Many time series do not exhibit a fixed mean, therefore, removing trends from time series and adjusting the amplitude are usually required before modeling the data. The software DTREG can automatically remove the trend and it uses regression to fit either a linear or exponential function to the data. However, not all software has this function, and manual operations are always necessary.

There are several ways to remove the trend, a process called "detrending". Differencing and log transformation are two common ways, and in the case study of this thesis, log transformation is used to stabilize the mean and variance. "Differencing" means calculate the difference between pairs of observations at some time interval. A difference of one time interval apart is calculated by subtracting value #1 from value #2, then #2 from #3, and on, and plotting that data to determine if mean of 0 and a constant variance are present. If differencing of one does not detrend the data, calculate the differences if necessary to stabilize the mean and variance. Differencing has the advantages of ease of use and simplicity, but also has disadvantages including over-correcting for trends, which skews the correlations in a negative direction. Another method can be used to remove trends is ordinary least squares analysis.

Trend removal is almost always beneficial; however, variance stabilization (amplitude adjustment) is beneficial about 20% of the time and harmful about 80% of the time based on experiments [21].

B. Model Evaluation

There are several different metrics for evaluating the fitness of a model. By comparing the values of these metrics, the best fit model can be found. A thorough comparison of model selection tools is given elsewhere for various classes of time-series model [12].

It is not sensible to simply choose a model to give the best fit by minimizing the residual sum of squares or equivalently by maximizing the coefficient of determination, R2. The latter measures the proportion of the total variation explained by the model and will generally increase as the number of parameters is increased regardless of whether additional complexity is really worthwhile. There is an alternative fit statistic, called adjusted-R2, which makes some attempt to take account of the number of parameters fitted, but more sophisticated model-selection statistics are generally preferred. Akaike's Information Criterion (AIC) is the most commonly used. AIC essentially chooses the model with the best fit, as measured by the likelihood function, subject to a penalty term that increases with the number of parameters fitted in the model. This should prevent overfitting.

An alternative widely used criterion is the Bayesian Information Criterion (BIC). The BIC, like the AIC, penalizes the addition of extra parameters more severely than the AIC, and should be preferred to the ordinary AIC in time-series analysis, especially when the number of model parameters is high compared with the number of observations.

Other metrics include DF which stands for degree of freedom, sum of squared errors, variance, standard deviation, MAPE, MAE, -2LogLikelihood, etc. MAPE is the mean absolute percentage error and MAE is the mean absolute error. -2LogLikelihood is minus two times the natural log of the likelihood function evaluated at the best-fit parameter estimates. Usually smaller values are better fits.

IV. Case Study

Several papers have emphasized that equipment mangers should focus on repair before failure and bridges the gap between preventive maintenance and repair [2]. To achieve this goal, reliable machine information such as component lifespan and machine history is needed.

The data used in this research comes from a contractor's equipment fleet which works on 3-shift schedule around the clock in Canada. Among the equipment fleet there are dozers, graders, trucks, backhoes, etc. The contractor has a team of operators, superintendents, project managers working on the jobsite and keeping full working records of downtime, uptime, failure events, and repair details on each unit. Apart from the preventive maintenance and scheduled overhauls, there are unscheduled random failures on each equipment unit. The contractor is keen to predict the reliability of each unit so that better decisions on allocations of equipment and maintenance resources can be made for scheduling purpose.

The maintenance and repair details were written down in the records and the useful information has been reorganized for reliability analysis and failure prediction. Construction equipment is complex system comprising of various subsystems: engine, braking system, hydraulic system, undercarriage, etc., these subsystems and components have different economic lifespans and different reliability metrics. They are not completely independent and must be kept in working conditions and work in coordination for the equipment to function properly.

For each equipment unit, the contractor is interested in predicting the equipment reliability metrics for the planning period, such as rate of failures, reliability level for the scheduled mission, availability, time between failures (TBF), time to repair (TTR), and length of uninterrupted working hours without failure given a minimum reliability level.

A. Data Preparation

Three basic steps were taken at the beginning for determining reliability characteristics, which are: data collection, data sorting and data classification (i.e., TBF, TTR, frequency, total breakdown hours, total working hours, total maintenance hours, etc.). There are many sources of data in a piece of construction equipment that are relevant to reliability modeling such as maintenance reports, operational and maintenance information, data from sensors on equipment, etc. Table I presents the TBF and TTR data of one piece of construction equipment in chronological order.

TABLE I. SAMPLE OF TBF AND TTR DATA SET OF A PIECE OF CONSTRUCTION EQUIPMENT

Index	Cumulative TBF	TBF	Cumulative TTR	TTR
1	142.00	142.00	3.20	3.20
2	194.03	52.03	14.78	11.58
3	471.00	276.97	53.15	38.37
4	621.00	150.00	54.98	1.83
5	766.00	145.00	61.50	6.52
6	993.00	227.00	88.93	27.43
7	1151.00	158.00	104.87	15.93
8	1190.00	39.00	105.88	1.02
9	1436.50	246.50	106.38	0.50
10	1525.28	88.78	113.63	7.25
11	1829.00	303.72	114.80	1.17
12	1910.00	81.00	142.20	27.40
13	2040.50	130.50	235.10	92.90
14	2285.50	245.00	297.87	62.77
15	2459.50	174.00	298.20	0.33
16	2664.00	204.50	298.53	0.33
17	2799.50	135.50	299.48	0.95
18	2948.33	148.83	308.07	8.58
19	3141.00	192.67	309.07	1.00
20	3141.00	0.00	309.07	0.00
21	3359.42	218.42	309.57	0.50
22	3536.02	176.60	323.40	13.83
23	3751.75	215.73	325.12	1.72
24	3958.02	206.27	335.37	10.25
25	4082.00	123.98	340.62	5.25
26	4315.50	233.50	380.63	40.02
27	4521.58	206.08	412.57	31.93
28	4688.02	166.43	500.83	88.27
29	4824.00	135.98	501.33	0.50
30	4974.37	150.37	505.68	4.35

The data collection, analysis and action process continues through the production and in-use phases. Throughout the product lifecycle, the reliability is assessed, first by initial predictions based upon past experience in order to determine feasibility and to set objectives, then by refining the predictions as detail design proceeds and subsequently by recording performance during the test, production and in-use phases. This performance is fed back to generate corrective action, and to provide data and guidelines for future products.

B. Data Modelling and Validation

After data are reorganized and cleaned, the next step is to choose the suitable modeling method for reliability analysis.

As been discussed earlier, when using the ARIMA model for reliability analysis and prediction, an important step is to trend removal and stationary. Some software (i.e., DTREG) can perform this function automatically by simply selecting the choice in the platform; however, in some case there is need to remove trend and make the series stationary manually through the method we presented earlier. The trend-free data are further analyzed to determine the accurate characteristics of the failure pattern of the construction equipment for estimating reliability and failure prediction.

Several types of software have been considered for time series modeling in this project, which include JMP, DTREG, and Eview. The example showed in this paper is the time series modeling process in DTREG and JMP. As can be seen from the software platform, two options can be selected which are: generate a normal predictive model and generate a time series forecasting model. What we chose is the latter option. Again there are many types of model can be built in DTREG, and here we use “linear regression” as the simplest method. It is because of the concept of “parsimony” [12]. We have seen that the mathematical models we need to employ contain certain constants or parameters whose values must be estimated from the data. It is important, in practice, that we employ the smallest possible number of parameters for adequate representations. The central role played by this principle of parsimony in the use of parameters will become clearer as we proceed.

V. RESULTS & DISCUSSIONS

For system reliability analysis, what are expected from the modelling may include: expected number of failures, conditional reliability and unreliability, MTBF or failure intensity, optimum overhaul and system operation plot.

By adopting time series models, we are able to deliver several reliability characteristics of construction equipment. Table II is an example which presents the result of the predictions of the number failures per interval (weekly). It is more useful when the actual failure time is not available which more frequently happens in a field. A summary of the predictive errors noted as absolute error is also presented in the table. By comparing the forecast with the actual numbers of failures (“Absolute error”), it can be noticed that time series models can give satisfactory predictions in the case.

More common reliability metrics which are often predicted are time between failures (TBF) and time to repair (TTR). TTR measures the time needed to fix a failure. In this case, we not only predicted the number of failures of a piece of construction equipment, but also performed forecast on the MTBF with TTR contributed as a predictor (Table III a and b).

TABLE II. PREDICTIONS OF NUMBERS OF FAILURES PER INTERVAL BY TIME SERIES MODELS

Failure Interval	Actual Failures	Predicted Failures	Absolute Error
25	1	1.62	-0.62
26	2	1.61	0.39
27	5	1.60	3.40
28	4	1.58	2.40
29	1	1.57	0.57
30	2	1.55	0.45

The utilization of the equipment is directly related to the average value of two parameters, namely MTBF and MTTR, for all the subsystems and delays. MTTR, is a crucial parameter, indicating that equipment parts will soon return to normal and have a great impact on the overall stability of the system. Table III b presents the prediction of the Cumulative TBF based two parameters: TBF as well as TTR. It is explored that adding TTR as a parameter in time series forecast gives different result than the one using TBF as the only parameter. From the experiment results we noticed that the time spend on repairing the equipment (i.e., TTR) has impact on the occurrence of next failure (TBF). Therefore, TTR should be taken in consideration when operating reliability analysis and failure forecast of construction equipment. As some researcher summarized, generally the following factors affect MTTR: the competence of the tunneling crew, inventory system of spare parts, production of lining material, the level of the ongoing geotechnical investigation and monitoring during excavation, the response speed of the crew to changing ground conditions, and level of preparation of the on-site management for contingencies (such as high water inflow).

TABLE III. (A) TIME SERIES PREDICTION USING TBF AS THE ONLY PARAMETER (B) TIME SERIES PREDICTION USING BOTH TBF AND TTR AS PARAMETERS

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--- Validation Time Series Values ---

Row     Actual    Predicted     Error      Error %
-----  ---------  ---------  ----------  --------
   31   30.33000  195.42110  -165.09110   544.316
   32  424.42000  291.43612   132.98388    31.333
   33  247.60000  243.31995     4.28005     1.729
   34  234.48000  245.41212   -10.93212     4.662
   35  270.52000  270.65061    -0.13061     0.048
   36  204.00000  247.10309   -43.10309    21.129

--- Forecast Time Series Values ---

Row    Predicted
-----  ---------
   37  300.30521
   38  237.40540
   39  232.99696
   40  293.33548
   41  238.90645
   42  260.42574
```

```
--- Validation Time Series Values ---

Row     Actual    Predicted     Error      Error %
-----  ---------  ---------  ----------  --------
   31   30.33000  196.45928  -166.12928   547.739
   32  424.42000  267.49719   156.92281    36.973
   33  247.60000  260.94599   -13.34599     5.390
   34  234.48000  249.07135   -14.59135     6.223
   35  270.52000  245.85686    24.66314     9.117
   36  204.00000  259.71238   -55.71238    27.310

--- Forecast Time Series Values ---

Row    Predicted
-----  ---------
   37  370.79594
   38  237.45276
   39  271.81419
   40  293.55519
   41  276.96399
   42  277.00491
```

Apart from the point forecast of the reliability attributes (TBF, TTR and numbers of failures), interval forecast were also carried out in the experiment. Interval-valued data arises quite naturally in many situations in which such data represent uncertainty (i.e., confidence intervals), variability, etc. The forecasting of the lower and upper bounds of the interval value of the time series is accomplished through a combination of forecasts from the mid-point and range of the interval values. Table IV presents the ARIMA time series prediction of TBF with upper and lower confidence levels.

TABLE IV. TIME SERIES PREDICTIONS OF TBF WITH UPPER AND LOWER CONFIDENCE LEVELS

Row	**Actual TBF**	**Predicted TBF**	**Upper CL (0.95) TBF**	**Lower CL (0.95) TBF**	**Residual TBF**
25	356.50	338.38	473.02	203.74	18.12
26	226.00	226.04	360.68	91.40	-0.04
27	315.50	243.51	378.15	108.87	71.99
28	160.90	174.04	308.68	39.40	-13.14
29	297.10	256.16	390.80	121.51	40.94
30	287.17	203.89	338.53	69.24	83.28
31	30.33	162.87	297.51	28.23	-132.54
32	424.42	371.86	506.50	237.22	52.56
33	247.60	192.50	327.14	57.86	55.10
34	234.48	189.98	324.63	55.34	44.50
35	270.52	200.24	334.88	65.60	70.28
36	204.00	175.14	309.78	40.50	28.86

Model validation: the proposed approach was validated by comparing the predicted failure data to the actual system failure. The result shown in Table IV shows the predicted failure time based on mean time between failures (MTBF) compared with the actual occurrence of failure. In the JMP software, several validation options are provide for model selection, which include AIC, SBC, RSquare, -2LogLH. By comparison, it was found the ARIMA model is the most suitable one in this case.

Fig. 1 shows the time series values and forecast for TBF while the blue points are the validation data and the red line represents the forecast values.

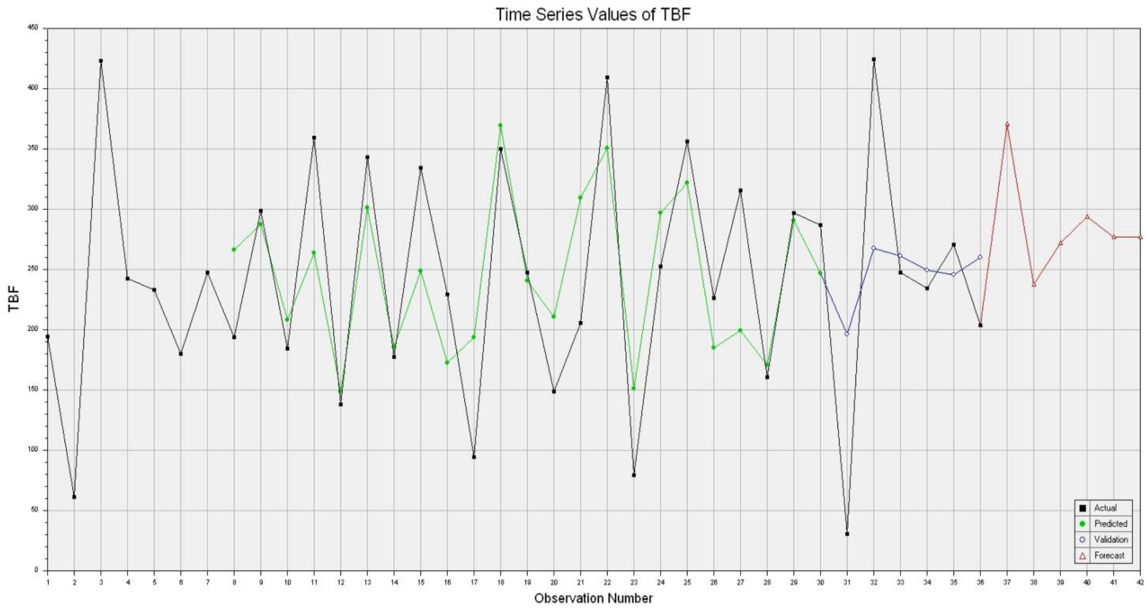

Figure 1. Time series values and prediction of TBF.

A. *Impact on Management Decisions*

The reliability assessment of construction equipment can affect the decision in selecting the right maintenance strategy in civil engineering project. Use of old and unreliable equipment should be avoided because of its low working efficiency and the reality that spare parts are often not easily available in local markets. Managers should replace this kind of equipment with the ones having higher availability and assign the older machines to operations where they can work alone [22]. In our research, by analyzing the reliability of particular equipment, trend can be detected; furthermore, numbers of failures and MTBF for a fixed interval can be predicted, as shown in tables and figures illustrated. Based on this information, the equipment manager can recognize the status of the equipment and make adequate maintenance service accordingly.

Apart from the contribution on construction equipment maintenance and management decisions, this paper also demonstrates that the ARIMA model is a viable alternative that gives satisfactory results in terms of its predictive performance. By iteratively adjusting the weights it this time series model, autocorrelation between the failure data can be explored and better estimates can be obtained. The result is valuable in planning a system shutdown depending on the organization's reliability target.

VI. Conclusion

In this research, time series models for construction equipment reliability analysis and forecasting failures have been examined and the results has been discussed, with emphasis on its delivery of the reliability characteristics such as expected numbers of failures per interval and MTBF. It can be noticed from the experiments and results that time series forecast techniques is a suitable alternative in modeling the failure pattern of construction equipment. In selecting the right maintenance strategy, system reliability asassment serves as one of the very important decision tools available for decision makers. The significance of the analyzing and predicting construction equipment failures has been studied in this paper and verified through literature review. Time series models were adopted to estimate the reliability and availability characteristics of the selected construction equipment in precise quantitative terms. Real data from the field was obtained and analyzed in the case study to test and validate the results. As the research results show, time series models can be used for forecasting of reliability metrics of construction equipment. It makes little assumption and is very flexible. It is theoretically and statistically sound in its foundation and no a priori postulation of models is required when analyzing failure data.

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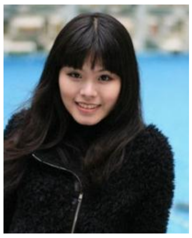

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