Research Article
Short-term Performance Prediction Model for Aviation Job-shop

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Abstract: This study proposes a method to evaluate and diagnose the performance of a job-shop that considers production planning and control aspects, such as throughput, delivery reliability and turnaround time. The short-term performance prediction can be used for weekly performance evaluation. The model considers the actual achieved performance instead of average values. The prediction of the throughput and component completion time in the maintenance repair and overhaul MRO job-shop are considered to be the primary performance indicators, from which other measures can be easily derived, such as job-shop efficiency, capacity utilization, delivery reliability, effectiveness and productivity. The model was tested on a case study, an aircraft component MRO job-shop and the results showed a low prediction error and low standard deviation error compared with those of long-term planned performance.

Keywords: Component completion time, maintenance job-shop, MRO, performance indicators, throughput

INTRODUCTION

Entrepreneurs will never stop searching for tools that will help drive their companies towards their intended goals. A tool that can likely measure the objectives for all business shareholders must be able to determine performance and business success. Previously, performance measurements were restrained to financial measures only (Kaplan, 1984; Andersson *et al.*, 1989). Currently, non-financial performance indicators are included with the existing measures to evaluate other performance features, such as quality, timeliness, flexibility and process (Maskell, 1991). Brignall and Ballantine (1996) and Brignall and Modell (2000) applied non-financial measurements to the service industry and suggested dividing performance into determinants and results. At the operational level (shop floor level), non-financial indicators excel over financial indicators (Muchiri *et al.*, 2011). Examples of relevant performance indicators at the shop floor level are the mean order flow time, order delivery reliability and capacity utilization (Weston and Brothers, 1984). Thus, we can see that the actual performance in organizations as described by most performance indicators oscillate over time. Periodically, for example, at the beginning of each week, the performance of the previous period is evaluated and discussed. The evaluation of performance is performed by comparing the latest reported performance on each performance indicator against the performance norm. Typically, the performance norm is set based on either the past average performance achieved or a stated managerial goal. The variation between the actual performance and the performance norm may influence actions for improvement.

Operation managers have commented that performance variations from the performance norm can be explained by modern production systems, such unexpected worker absenteeism, unexpected tool breakdowns and complex tasks that disturb the process of other tasks. In certain cases, these explanations sound plausible. However, these explanations have not been examined explicitly to question their validity. Detecting the actual causes behind performance variations is the process of diagnosis. These causes can then be eliminated or mitigated to improve performance. In this study, we develop an approach that can be used to predict the operational short-term performance of a shop floor to explain the achieved performance. The explanations behind performance variations can be used to either to take action for performance improvement or to make more accurate performance predictions.

The important reason to measure and monitor the performance is to improve performance. Another reason for performance measurement, particularly in a job shop, is to evaluate how well a staff can control the tasks they are responsible for. In this study, we consider short-term performance as periodically (weekly) reported that is evaluated and compared with performance norms. Then, if deviations do appear, diagnosis begins to determine the causes behind the

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deviations. However, the dynamic nature of a shop job due to processes, capacity and workload may cause performance variance. Therefore, focusing on short-term performance predictions will help operation managers understand the short-term performance that can be achieved and these performance predictions will answer the ambiguous question of why there are deviations from the performance norm. Thus, a long discussion regarding the performance deviation can be avoided.

It is important to manage all activities of maintenance operations, where activities can be managed by evaluating the performance of the process and efficiency of the maintenance crew involved. According to Neely *et al.* (2005) performance measurement is a process of quantifying the efficiency and effectiveness of an action. A framework was proposed by Aditya and Uday (2006) to measure the maintenance performance for internal and external effectiveness. However, Ivaturi *et al.* (1995) focused on evaluating and identifying strategies to improve crew maintenance team effectiveness in aviation maintenance operations. Zisis *et al.* (2009) showed the effect of measuring performance in service quality. Dietz and Rosenshine (1997) studied the structure of a maintenance workforce and optimized staff performance and cost. Oyetunji (2009) proposed a job-shop scheduling model to determine the number of maintenance technicians that need to be assigned to each center (Singh *et al.*, 2010) measured the performance of different types of maintenance, preventive, proactive and aggressive and its effect on cost saving. More recently, Duer (2010) integrated an Artificial Neural Network (ANN) and expert knowledge-based systems to improve the efficiency of an aircraft maintenance crew. Aviation maintenance is unlike other types of maintenance due to its severity and strictness requirements.

Even with the best located equipment, infrastructure tools, manpower and qualified maintenance crew to ensure that maintenance tasks are performed on time, there can still be deviations between the planned and actual achievement. Quan *et al.* (2007) studied the important schedules and the correlation between workforce and optimized maintenance time for preventive maintenance. However, for an aviation maintenance company to achieve world-class performance, much effort to improve quality and productivity is required and reduced costs. Short-term performance measures can be used as a control and diagnostic tool to provide direction and motivation toward achieving goals. This type of control tool is a form of single-loop feedback that is used to calculate the deviation from the standard performance norm and the ability to be corrected (Otley, 1999; Burney and Widener, 2007).

DEFINITIONS

Capacity: Typically, an MRO job-shop consists of several workstations, where each workstation consists of several machines and laborers. There are multiple aircraft components being processed in an MRO job-shop, which have different processing routes. The processing of different operations can be processed at different workstations. However, sometimes, the component or task can be processed by more than one laborer or machine. Therefore, the task must be assigned to an appropriate worker and machine to complete the task, which is called a production task assignment. The determination of labor (workforce) and machines in a workstation is called the production capacity. In fact, there are three scenarios of job-shop capacity, which are as follows:

- **Under capacity:** Airline cannot satisfy its own demands of workforce and machines to perform MRO maintenance activity.
- **Optimum capacity:** In this scenario, the airline has a sufficient resource of workforce and machines to support its demand of MRO.
- **Over capacity:** There sources of the MRO are greater than what the airline requires due to reduction of flying hours, which will lower the number of maintenance activities. In this case, the airline offers their MRO capacity to the open market, which is a make and sell. Therefore, to improve the productivity and profitability of MRO job-shops, the available workforce must be used.

Assumptions: The following are factors that influence a job-shop's short-term performance measurements:

Symbols	Description
m	: The number of workstations in the job-shop
$I_i(n)$	: The actual work in process at workstation i at measurement period n
$C_i(n)$	: The available capacity at workstation i during measurement period n
$W_i(n)$	: The work assignment to workstation i during measurement period n
$S_i(n)$	: The amount of component scrap at workstation i during measurement period n
$V_{i,j}$	: The collection of components at workstation j with a higher priority than component i
$Z_{i,j}$	: The collection of components with a higher priority than component i that is expected to arrive at workstation j within the next measurement period
$F_{i,j}$	: The expected flow time of component i at workstation j

$MW_{i,j}$: The minimal waiting time of component i at workstation j

$EW_{i,j}$: The expected extra waiting time of component i at workstation j

$P_{i,j}$: The processing time of component i at workstation j

The planned net available capacity of workstation i at the job-shop during measurement period n, measured in hours, is denoted $\dot{C}_i(n)$. The planned net available capacity at workstation i is a function of both the net available operators capacity $\dot{O}_i(n)$ that is planned to be allocated and the planned net available tools capacity, denoted by $\dot{T}_i(n)$, both at workstation i during measurement period n and is measured in hours:

$$\dot{C}_i(n) = f(\dot{O}_i(n), \dot{T}_i(n)) \quad (1)$$

The planned amount of work assignment during measurement period n at workstation i of the job-shop is measured in hours and denoted as $\dot{W}_i(n)$. The plan for the work assignment of workstation i during measurement period n consists of new components that are expected to arrive for repair (external work assignment), $\dot{W}_{i,\text{ext}}(n)$ and components expected to come from other workstations within the production path (the expected internal work assignment), $\dot{W}_{i,\text{int}}(n)$. Therefore, the expected work assignment can be estimated using the list of all work in the process and the list of all components to be released next, where:

$$\dot{W}_i(n) = \dot{W}_{i,\text{ext}}(n) + \dot{W}_{i,\text{int}}(n) \quad (2)$$

The aforementioned factors refer to the workstation level. An aggregation of influencing factors for the total job-shop can be obtained through the summations of the values of all workstations and is as follows:
The total work in process:

$$\dot{I}_s(n) = \sum_{i=1}^{m} \dot{I}_i(n) \quad (3)$$

The total capacity:

$$\dot{C}_s(n) = \sum_{i=1}^{m} \dot{C}_i(n) \quad (4)$$

The total work assignment:

$$\dot{W}_s(n) = \sum_{i=1}^{m} \dot{W}_i(n) \quad (5)$$

The total component scrap:

$$\dot{S}_s(n) = \sum_{i=1}^{m} \dot{S}_i(n) \quad (6)$$

The estimated available capacity $\dot{C}_i(n)$, work assignment $\dot{W}_i(n)$, component scrap $\dot{S}_i(n)$ and estimated work in process $\dot{I}_i(n)$ are used, where m is the total number of workstations in a job-shop and i denotes the workstation number.

SHORT-TERM PREDICTION PERFORMANCE INDICATORS

Prediction output: The expected work in process at a workstation for the next measurement period $\dot{I}_i(n+1)$ is calculated by the level of work in process $I_i(n)$, the expected work assignment and the expected capacity when the next period begins, as described in (4):

$$\dot{I}_i(n+1) = \max\left(0, I_i(n) + \dot{W}_i(t) - \dot{C}_i(n)\right) \quad (7)$$

The prediction output $\dot{O}_i(n)$ for measurement period n at workstation i measured in hours is determined by the actual work in process, $\dot{I}_i(n)$, the expected available capacity $\dot{C}_i(n)$ and expected work assignment $\dot{W}_i(n)$, Analogous to the aggregation of the work in process, the available capacity and work assignment from workstation level to production path level (job-shop level), the prediction output (hours) $\dot{O}_i(n)$ of the job-shop are considered as one of the main performance indicators, where the prediction output for a certain measurement period can be calculated by (5):

$$\dot{O}_i(n) = \min\left(\dot{W}_i(n), +I_i(n), \dot{C}_i(n) - \dot{S}_i(n)\right) \quad (8)$$

The job-shop expected output $\dot{O}_i(n)$ can be obtained by totalling the expected output of the m individual workstations in the production path by:

$$\dot{O}_i(n) = \sum_{i=1}^{m} \dot{O}_i(n) \quad (9)$$

Completion time: The estimation of the component completion time Turnaround Time (TAT) will be directed at individual components. To determine the components completion time, the processing time of the component at the current workstation and the expected flow time at the remaining workstations in the routing of the component are considered.

The processing time of the component at the current workstation can be described by Eq. (10):

$$F_{i,j} = MW_{i,j} + EW_{i,j} + P_{i,j} \quad (10)$$

For,

$$MW_{i,j} = \sum_{x \in V_{ij}} P_{x,j}; \ and EW_{i,j} = \sum_{x \in Z_{ij}} P_{y,j} \quad (11)$$

$Z_{i,j}$ is determined by considering each workstation except workstation j; the estimation is performed by considering which component will be processed at the workstation and is based on a study by Rupp *et al.* (2000).

An MRO job-shop should first repair the components that have a high probability of being in immediate demand. The number of failures of a component can be described by a Poisson distribution. The quantity of spare parts of a component c is denoted by SPQc. These spare components are owned by the

MRO job shop and can be exchanged during repair or overhauling. All variables are assumed to refer to a specific component if not stated otherwise.

If a component is faulty in a Bernoulli experiment with a very small probability of failure ($p \to 0$), then it is well known that if such an experiment is conducted repeatedly ($n \to \infty$), then the sum of the Bernoulli-distributed stochastic variables converges to a Poisson distribution with parameter $\lambda = n.p$, or as stated by (Bartoszynski and Niewiadomska-Bugaj, 2007):

$$\lim_{n \to \infty} \binom{n}{k} p^k (1-p)^{n-k} = \frac{\lambda^k}{k!} e^{-\lambda} \qquad (12)$$

where, the left-hand side is the binomial probability of k successes in n trials (Bartoszynski and Niewiadomska-Bugaj, 2007). Note that the probability follows that the time between two failures is independently and exponentially distributed (Bartoszynski and Niewiadomska-Bugaj, 2007). As a consequence of the number of failures, the number of demands within the Turnaround Time (TAT) is Poisson distributed, where the turnaround time is the repair time of a component at the job-shop. The parameter λ of the Poisson distribution is its mean and also its variance. Hence, if we know the demand per day d_c of a component c and the length t_c of the TAT interval, we can calculate the probability $P(\lambda, n)$ that n demands occur during the TAT interval in the following way:

$$P(\lambda, n) = \sum_{i=0}^{n} \frac{(d_c.t_c)^i}{i!} \exp^{-d_c.t_c}$$
$$= \sum_{i=0}^{n} \frac{\lambda^i}{i!} \exp^{-\lambda} \qquad (13)$$

Eventually, it can be determined which selected component has the higher priority than component i. Thus, by calculating the expected flow time at the first workstation in the remaining workstation routing, we can now predict the expected flow time of the remaining workstations to which the component will be routed.

However, the expected waiting time at other workstations can be approximated by the amount of work still in the process at these workstations at the time when this component arrives. By doing so, the flow time of the second workstation k can be expected for the routing of component i by (14):

$$F_{i,k} = \dot{I}_k(F_{i,j}) + P_{i,k} \qquad (14)$$

Thus, from the above two indicators, the predicted output (hours) and the predicted component completion time of the job-shop, which considers other main performance indicators, such as capacity utilization, delivery reliability, job-shop efficiency, effectiveness and productivity, can be easily derived from these two measures.

Case study: The organization considered in the case study is one of the largest MRO service providers in the

Table 1: Example of data obtained from 9 production units in the MRO job-shop

Work station no.	Work in process	Expected capacity	Actual capacity	Planned throughput	Actual throughput
1	490	549	544	517	451
2	639	653	710	697	537
3	167	172	186	186	212
4	294	368	327	326	326
5	185	204	205	205	161
6	431	510	479	479	437
7	306	360	351	351	351
8	144	168	160	158	148
9	156	177	173	178	140
Total				3097	2763

Table 2: Examples of the prediction quality of the predicted throughput

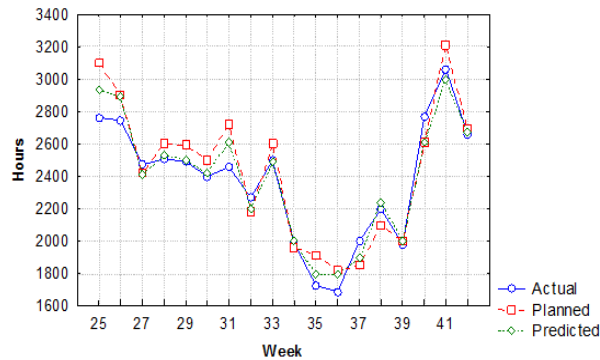| Weeks	Actual throughput	Planned throughput	Std.	Predicted throughput	Std.
25	2763	3097	236.1730	2931	118.793
26	2746	2900	108.8940	2892	103.237
27	2473	2423	35.3553	2411	43.840
28	2509	2600	64.3467	2530	14.849
29	2492	2592	70.7107	2500	5.656
30	2400	2500	70.7107	2420	14.142
31	2460	2722	185.2620	2610	106.066
32	2269	2188	57.2756	2198	50.204
33	2500	2600	70.7107	2489	7.778
34	1989	1960	20.5061	2000	7.778
35	1729	1920	135.0570	1800	50.204
36	1690	1820	91.9239	1800	77.781
37	2000	1850	106.0660	1900	70.710
38	2200	2100	70.7107	2240	28.284
39	1980	2005	17.6777	2001	14.849
40	2770	2611	112.4300	2612	111.722
41	3060	3211	106.7730	3000	42.426
42	2662	2700	26.8701	2672	7.071
Total			1587.4550		875.398

Fig. 1: Actual, planned and predicted throughput for 18 weeks

Asia-Pacific region. The organization, which was established in 1972, has over 36 years of experience in the MRO business, delivering a comprehensive range of services for aircrafts, such as the F50, B737 Classic and B747 series, the A330 and A320 families and the B777 and is currently supporting MRO services for more than 100 airlines. The data were taken form 9 random workstations. Each production unit works 8-h shifts, five days a week, where Table 1 shows the data for 18 weeks. Occasionally, overtime is required to reduce production order backlogs.

To show the quality of the predictions of throughput, the prediction errors for all production orders that were completed in the production units were determined by taking the difference between the predicted throughput and the actual throughput. For each production unit, the averages and standard deviations of the prediction errors over 18 weeks are shown in Table 2.

It can be observed that the predicted throughput in production units on average is more accurate than the planned performance, with only a small error between the actual performances. As can also be observed from Fig. 1, the prediction model follows, on average, the fluctuations with the actual performance extremely well.

CONCLUSION

In this study, a method to evaluate and predict short-term performance for an MRO job-shop is described. This model is used to predict the accuracy of the planned performance of the job-shop and also to predict what performance can be achieved.

The purpose of the performance prediction model is to provide realistic information of the state of a production unit. The model helps management of the shop floor to improve their performance by taking into account the actual state of the job-shop and the expected input. The prediction model provides the basis for discussions between the people involved to determine how work should be organized to realize the performance targets. This model was implemented and tested on an actual job-shop and the results were

impressive, showing a small range in standard deviation and error rate between the predicted result and the actual achievement compared with the planned performance.

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