A SCHEDULER BASED ON OPTIMIZATION OF RESOURCE CAPACITY FOR THE MAINTENANCE OF AIRCRAFT ENGINES AND A METHOD THEREOF

TECHNICAL FIELD OF THE INVENTION

[001] The present invention relates to the Maintenance, Repair and Overhaul (MRO) of aircraft engines

[002] Particularly, the present invention relates to the optimization of resources and capacity planning.

[003] More particularly, the present invention relates to the prediction and scheduling of routine and non-routine maintenance of aircraft engines.

BACKGROUND OF THE INVENTION

[004] Aircraft maintenance is a sequence of activities, including overhaul, repair, inspection, or modification of an aircraft or aircraft systems, components, and structures to ensure an aircraft retains an airworthy condition. An MRO is an aircraft maintenance facility capable of performing required maintenance/ inspection. An MRO is one of the certified entities that qualify to perform maintenance, repair and overhaul on an aircraft, engine, or accessory. Maintenance is a specifically preventative maintenance which should be an ongoing aspect of any flight department's day-to-day operations as they keep their jet in optimal condition. Repair is necessary when parts break or malfunction, thus help returning an accessory/ component or aircraft to serviceable condition. Overhaul is repairing/ replacing parts on an aircraft accessory/ component, engine or an item on an aircraft that come due after a specific number of operating hours are completed.

[005] In the aviation industry, a commercial aircraft must undergo regular maintenance to prevent component and system failures during operations. Many of the aircraft maintenance

activities take place after an aircraft has been operating certain flight hours, flight cycles, or calendar days.

[006] Many a times an aircraft component such as engine, landing gear or any other less complex part needs to be sent to an overhaul shop for the kind of maintenance. After such maintenance, the component is released back to service. So multiple shop visits can be required for an engine in the process of MRO.

[007] Engine MROs receive demands from both contracted (Engine OEMs, Lessors, Airlines) and sporadic clients. Engine MROs have seen fluctuation in demand since the onset of the pandemic with build goals and work scope level is very different to the trends pre-pandemic. Uncertainly, post the pandemic compelled Airlines and Lessors to send engines in for lower build goals in order to conserve cash. The trend is slowly changing with market recovery but the demand and profile of Engines coming to have variations to pre-pandemic patterns.

[008] The majority of shop visits consist replacement of LLPs and/ or overhauls or restorations depending on build goals set and/ or leases committed to. Cash conservation can alternatively compel airlines to send Engines for lower build goals which may have long term cost impacts.

[009] Slot sales are done well in advance by MROs. Demand fluctuations impact the profitability that an MRO is able to extract out of a slot sale. By utilizing data models that accurately predict routine and non routine demand, scrap rates using operational, technical and environmental data, contracts can be tuned with fixed price elements with the certainty of cost optimization and profitability maximization.

OBJECTS OF THE INVENTION

[0010] It is an object of the present invention to provide a Scheduler for capacity planning for an engine maintenance based on resource availability prior to arrival of engine, thereby optimizing the cost and maximizing the profitability.

[0011] It is another object of the present invention to provide a solution for creating an online real time augmentable running simulation of engine shop visits from multiple asset owners and vendors over any period of time.

[0012] It is yet another object of the present invention to provide a Scheduler for forecasting and simulating the Shop Visits for MROs prior to the arrival of an engine based on contracts and committed slots so as to ensure delivery of an engine within predetermined TATs.

[0013] It is still another object of the present invention to provide a method of forecasting the non-routine maintenance scrap rates, and deciding the impact of such non-routine maintenance on the management of resources.

[0014] It is still another object of an invention to provide a method of simulating shop visits to ensure delivery of an engine within predetermined TAT by dynamically altering loads and feeds so as to complete maximum visits within TAT and at the same time minimizing the penalties where they are unavoidable.

SUMMARY OF THE INVENTION

[0015] The present invention discloses a Scheduler for an engine based on an optimization of resources required for routine as well as non-routine maintenance demands at the task and subtask level, even before arrival of engine at the shop. The Scheduler of the present invention assists in forecasting and simulating the Shop Visits for MROs prior to the arrival of an engine based on contracts and committed slots so as to ensure delivery of an engine within predetermined TATs. It further aids in optimization of the associated risks based on the real-time updates of the engine and allocation of resources to each phases of the visit. It checks various loads and feeds so as to complete maximum visits within TAT and at the same time minimizes the penalties where they are unavoidable.

[0016] The method for an engine maintenance scheduling based on an optimization of a resource capacity comprising: selling maintenance slot by a sales department to the asset owners or airlines;

receiving the maintenance information from the sales department; making a contract with confident NTEP elements for maximizing conversion and profitability per slot with the asset owners or airlines based on the required repair information; estimating a routine and a non-routine maintenance based on a stochastic model and a machine-learning model; forecasting total resource demands for the visit based on the estimated routine and non-routine maintenance; scheduling a slot by a Master Scheduler and a Slave Scheduler; determining the standard/ baseline schedule for and finalizing the visit; updating the standard/ baseline schedule of a visit and recalculating the associated risk based on a real-time update of an engine; training and retraining the machine learning model based on the operational parameters and maintenance/ capacity requirements of an engine as an input using a Bayesian update mechanism.

BRIEF DESCRIPTION OF THE DRAWINGS

[0017] Further features and advantages of the present invention will become apparent from the following detailed description, taken in combination with the appended drawings, in which:

[0018] Fig. 1 is a flowchart of exemplary method for an engine maintenance scheduling based on an optimization of a resource capacity.

[0019] Fig. 2 depicts a plurality of phases of a visit.

[0020] Fig. 3 depicts the process of scheduling of the Master and the Slave Scheduler based on the phase capacity.

[0021] Fig. 4 depicts process flow of training and retraining of the Machine Learning model.

[0022] Fig. 5 depicts the System Dynamics of the Scheduler.

[0023] It will be noted that throughout the appended drawings, like features are identified by like reference numerals.

DETAILED DESCRIPTION

[0024] The present invention discloses a scheduler based on an optimization of a resource capacity for the maintenance of an engine and a method thereof.

[0025] The scheduler of the present invention helps in forecasting and simulating the Shop Visits for MROs, prior to the arrival of an engine based on contracts and committed slots so as to ensure delivery of an engine within predetermined TATs. And these contracts are negotiated with customers which are intended by TAT (Turn Around Time). Every engine that is brought in for service has a promised delivery date set, and if that date is not met, penalties are assessed based on the number of days the engine is late. In addition, time on wing guarantees and EGT Margin guarantees are inherent factors that drive the success of a contract against the carried out maintenance. The scheduler of the present invention aids delivery of an engine within predetermined TAT by dynamically altering loads and feeds so as to complete maximum visits within TAT and at the same time minimizing the penalties where they are unavoidable. The Scheduler communicates across Supply Chain, Labor and Tools / GSE management teams to ensure seamless completion of visits through decision making.

[0026] Fig. 5 explains exemplary system dynamics for the Scheduler of the present invention. It depicts the working of the Scheduler based on the simulations and analytics. This schedule has two important parts i.e. Master Schedule Analytics and Phase Schedule Analytics.

[0027] The process of an engine maintenance scheduling is depicted in fig. 1. At first, the sales department of the MRO sells the maintenance slot to the asset owners or airlines. Once the slot is sold, the engine planning team and finance team receive the maintenance information from the sales team. The engine planning team schedules the visit slot during existing maintenance windows with the help of the Master and Slave Scheduler. As multiple sales and customer facing professionals negotiate slots with Airlines, Lessors and OEMs, it is important that the demand is forecasted as accurately as possible so as to ensure that TATs are not exceeded. Large Engine MROs can prospect over 1000 airlines, contract with 500 and eventually sign up close to 300 slots a year depending on their capacity and size.

[0028] Contracts agreed with customers have many fixed price elements to increase the chances of conversion. These elements, referred to usually as NTEP (Not To Exceed Price), require MROs to have strong conviction over incoming demand based on the Engine profile. Based on a stochastic model and a machine learning model, the Scheduler estimates a routine and a non-routine maintenance which further forms a basis for forecasting total resource demands for the visit. These demands are made for the resources such as manpower, material and equipment required for the maintenance of an engine. The routine maintenance demand is the resource required to perform the contractual maintenance, which remains the same through all the phases. The non-routine demand is the resource required for the maintenance which is not mentioned in the contract. Non-routine maintenance occurs due to wear & tear of the smaller components which cannot be detected unless the engine is stripped. It is not so easy to estimate the non-routines before arrival of an engine to the shop. Inputs given by the past performance of the engine of a similar type are very useful in determining potential non-routines.

[0029] While estimating the routine and the non-routine maintenance, a stochastic model is used to measure the amount of statistical randomness in the demand. Estimation of the non-routine maintenance demand is carried out by using the operational parameters and maintenance requirements of the engine as an input in the machine learning model by determining probability of these parameters associated with the required demands. These input values are taken from the history of these parameters across the maintenance visits. This way, machine learns the relationship between parameters and non-routines thereby making it data-driven model for the predictions (fig. 4). The operational parameters used in the machine learning model include but not limited to - Time Since New (TSN), Cycles Since New (CSN), Time Since Repair (TSR), and Cycles Since Repair (CSR), Exhaust Gas Temperature Margin (EGTM), Specific Fuel Consumption (SFC), Average Thrust Derate and Operating Environment (Hot / Dry, Temperate, Corrosive).

[0030] As shown in fig. 1, the resource demand information, estimated by the machine learning model is further transferred to the Master Scheduler. The Master Scheduler and the Slave Scheduler schedule a slot and determine the standard/ baseline schedule and finalize the visit. The Master Scheduler utilizes the existing schedule of visits and automatically adjust the overall schedule to drive the resource to the visit based on the priority. The priority is decided by various

criteria like visits from regular customers, high demand engines etc. The Master Scheduler sends the instructions to the Slave Scheduler to modify the visit in order to assign a resource with less risk. The major risk associated with the maintenance visits is the time taken for the visit to complete which is called as Turn Around Time (TAT). TAT is the critical criteria in any contract. MROs must return the engine on time; if it is not returned on time, MROs have to pay penalties to the customers. Thus, any delay in operating the engine on time causes financial loss to the asset owners/ airlines. Therefore, TAT is one of the crucial parameters which has to be optimized by the schedulers. In the cases where an engine goes on hold or the maintenance process does not start until MROs get response from asset owners/ airlines on some critical queries, it causes delay in the process and in TAT, for which MROs are not liable to pay royalties to the asset owners/ airlines. However, the resource was allocated for the engine, the Master Scheduler is meant for deciding to free up the resource for that particular engine till the MROs receive the response from the customer based on the current capacity load. The Master Scheduler is meant for optimizing the potential risks of freeing up the resources. This resource can be utilized for some other priority visits and can immediately be resumed on the earlier work upon customers response. It is a very crucial role of the Scheduler.

[0031] In one of the embodiment, the visit demand details are transferred from the Master Scheduler to the Slave Scheduler which aids in scheduling a plurality of phases of the visit. The instructions are sent by the Master Scheduler to the Slave Scheduler to modify the visit in order to assign a resource with less risk. As shown in fig. 2, a shop visit consists of a plurality of phases, each phase of the visit contains a set of tasks and sub-tasks and each of the task and sub-task has different resource requirement.

[0032] As shown in fig. 3, the Master Scheduler and the Slave Scheduler schedules the phases based on each phase capacity. There is a daily limit of capacity per phase, in any MRO, due to which the engine planning team has to be careful while scheduling any slot to the existing visit schedule. The Slave Scheduler aids to determine the risks associated with the scheduling any visit. A plurality of phases of a visit can overlap with the same phases of other visits which may cause high demand on capacity. The Slave Scheduler optimizes on the minimum TAT and minimum resource usage thereby avoiding the huge load on the capacity.

[0033] As depicted in fig. 1, upon allocation of a resource to the respective task and sub-task, the Slave Scheduler creates a tentative schedule for the maintenance by optimizing the analytical parameters and minimizing capacity and TAT risks associated with the visit. Based on this analytics, the engine planning team decides whether to proceed with the visit or to simulate other plan for the visit. The standard/ baseline schedule is finalized upon approval by the engine planning team.

[0034] The slot for the maintenance of an engine is sold by the sales team of the MRO at least 4-6 months before or in many cases, much earlier the arrival of an engine. By the time the engine arrives at the maintenance department, the operational parameters of the engine which were provided 4-6 months ago may get changed. In such cases, the Master Scheduler aids in changing the standard/ baseline schedule at any time in order to incorporate these changes in the operational parameters of the engine. This change in the standard/ baseline schedule is done by the Master Scheduler by notifying to all of the slave schedulers to make changes as per the visit requirements. Whenever the engine gets started, the real-time updates of an operational parameters are being sent to the standard/ baseline schedules and the optimization of the Scheduler is done along with the recalculation of the associated risks automatically on a daily basis based on these real-time updates. If given the input of an actual capacity update to the machine learning models, these models are retrained in order to improve demand estimations.

[0035] Fig. 4 depicts the process flow of training and retraining of the machine learning model. The operational parameters of an engine are used as an input for training of the machine learning model. The model is learned by using prior information retrieved from the previous visits and maintenance records of the engine. The machine learning model is continuously updated based on the recent incoming data using the Bayesian mechanism, thereby assisting to understand the most recent demand patterns of the engine.

[0036] As depicted in all of the figures and embodiments of the disclosure, the Scheduler of the present invention is meant for creating an efficient visit plan by providing accurate demand estimations for both, routine and non-routine maintenance requirements at the task and sub-task

level, even before the arrival of an engine at the shop. At the same time, it aids in optimization of the associated risks based on the real-time updates of the engine and allocation of resources to each phases of the visit. The Scheduler is learned from the recent demand patterns in order to improve the accuracy of demand estimation. Based on the computed risks and resource usage as an output of the Scheduler, the Finance team of the MRO is able to plan a visit in a cost-effective budget and more profitability.

CLAIMS

I/ We claim,

1) A method for an engine maintenance scheduling based on an optimization of the resource capacity, the method comprising:
selling maintenance slot by a sales department to the asset owners or airlines;
receiving the maintenance information from the sales department;
making a contract with confident NTEP elements for maximizing conversion and profitability per slot, with the asset owners or airlines based on the required repair information;
estimating a routine and a non-routine maintenance based on a stochastic model and a machine-learning model;
forecasting total resource demands for the visit based on the estimated routine and non-routine maintenance;
scheduling a slot by a Master Scheduler and a Slave Scheduler;
determining the standard/ baseline schedule for and finalizing the visit;
updating the standard/ baseline schedule of a visit and recalculating the associated risk based on a real-time update of an engine;
training and retraining the machine learning model based on the operational parameters and maintenance/ capacity requirements of an engine as an input using a Bayesian update mechanism.

2) The method of claim 1, wherein the scheduling of the slot by the Master Scheduler and the Slave Scheduler comprising:
transferring the forecasted resource demand information to the Master Scheduler;
utilizing the existing schedule of visits by the Master Scheduler;
sending the instructions to the Slave Scheduler by the Master Scheduler to modify the visit in order to assign a resource with less risk;

scheduling and rescheduling the visits based on the real-time capacity update by the Master Scheduler;

Optimizing and deciding on the potential risks of freeing up the resource and utilizing for other phases of visits by the Master Scheduler when not getting response from customers;

scheduling a plurality of phases of the visit by the Slave Scheduler;

determining a set of tasks and sub-tasks for the plurality of phases of the visit;

allocating a resource to the respective task and sub-task;

creating a tentative schedule for the maintenance by optimizing the analytical parameters and minimizing resource usage and TAT risks associated with the visit;

deciding whether to proceed with the visit or to simulate other plan for the visit.

3) The method of claim 1, wherein the demands are made for the resources including but not limited to manpower, material and equipment required for the maintenance of an engine.

4) The method of claim 1, wherein the operational parameters for training and retraining the machine learning model include but not limited to - Time Since New (TSN), Cycles Since New (CSN), Time Since Repair (TSR), and Cycles Since Repair (CSR), Exhaust Gas Temperature Margin (EGTM), Specific Fuel Consumption (SFC), Average Thrust Derate and Operating Environment (Hot / Dry, Temperate, Corrosive).

5) A scheduler based on an optimization of a resource capacity for the maintenance of an engine, the scheduler comprising:

a processor coupled to the memory; and

at least one application stored in the memory and executable by the processor for:

selling maintenance slot by a sales department to the asset owners or airlines;

receiving the maintenance information from the sales department;

making a contract with confident NTEP elements for maximizing conversion and profitability per slot, with the asset owners or airlines based on the required repair information;

estimating a routine and a non-routine maintenance based on a stochastic model and a machine-learning model;

forecasting total resource demands for the visit based on the estimated routine and non-routine maintenance;

scheduling a slot by a Master Scheduler and a Slave Scheduler;

determining the standard/ baseline schedule for and finalizing the visit;

updating the standard/ baseline schedule of a visit and recalculating the associated risk based on a real-time update of an engine;

training and retraining the machine learning model based on the operational parameters and maintenance/ capacity requirements of an engine as an input using a Bayesian update mechanism.

6) The scheduler of claim 5, wherein the scheduling of the slot by the Master Scheduler and the Slave Scheduler comprising:

transferring the forecasted resource demand information to the Master Scheduler;

utilizing the existing schedule of visits by the Master Scheduler;

sending the instructions to the Slave Scheduler by the Master Scheduler to modify the visit in order to assign a resource with less risk;

scheduling and rescheduling the visits based on the real-time capacity update by the Master Scheduler;

optimizing and deciding on the potential risks of freeing up the resource and utilizing for other phases of visits by the Master Scheduler when not getting response from customers;

scheduling a plurality of phases of the visit by the Slave Scheduler;

determining a set of tasks and sub-tasks for the plurality of phases of the visit;

allocating a resource to the respective task and sub-task;

creating a tentative schedule for the maintenance by optimizing the analytical parameters and minimizing resource usage and TAT risks associated with the visit;

deciding whether to proceed with the visit or to simulate other plan for the visit.

7) The scheduler of claim 5, wherein the demands are made for the resources including but not limited to manpower, material and equipment required for the maintenance of an engine.

8) The scheduler of claim 5, wherein the operational parameters for training and retraining the machine learning model include but not limited to - Time Since New (TSN), Cycles Since New (CSN), Time Since Repair (TSR), and Cycles Since Repair (CSR), Exhaust Gas Temperature Margin (EGTM), Specific Fuel Consumption (SFC), Average Thrust Derate and Operating Environment (Hot / Dry, Temperate, Corrosive).