Introduction to PAM

Business Need for PAM

The business need for **PAM** is that asset-rich organisations require much greater insight and understanding than is currently available into how the performance of individual assets is influenced by a range of factors, for example their maintenance and failure histories, design specifications and operating environments. Using an asset management policy based on this knowledge will result in improved operational and financial performance.

The solution to this need is to use predictive analytics and discrete event simulation (** see below) to model, simulate and optimise asset performance. Business intelligence cannot achieve these goals because it looks *backwards* to report what has happened whereas predictive analytics looks *forward* to predict what might happen under a range of different scenarios by modelling historical data and then projecting the models forward.

PAM uses survival analysis (Kaplan Meier analysis and Cox regression) to model the risk of asset failure as a dynamic phenomenon and change the asset management policy from reactive fail-and-fix to proactive predict-and-prevent. The models are then applied with discrete event simulation to optimise future asset management subject to constraints, for example the organisation's maintenance capacity and attitude to the risk of asset failure. (The appendix has a brief description of survival analysis.)

Key Features of PAM

System and Model

PAM:

- ♦ is a complete ready-to-use system rather than a set of generic modelling procedures from which users must build their own models and system
- ♦ models the risk of asset failure as a dynamic phenomenon so that changes in the risk of asset failure can be monitored
- ♦ models each asset as a unique and distinct entity with its own risk of failure profile rather than as a member of a group that share the same risk of failure profile

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** Discrete event simulation is a form of simulation in which events are simulated as pulses at defined times rather than as continuous events. With respect to **PAM**, the events are the maintenance interventions on defined assets at defined (discrete) times.

- calculates three measures of the risk of asset failure: the likelihood of failure; the likelihood of failure adjusted by asset criticality; and the likelihood of failure adjusted by asset cost
- models the failure of repairable assets and non-repairable assets
- models the effects of duty and standby assets on the risk of asset group failure.

Assets and Asset Management Policy

PAM:

- can be applied to a wide range of asset-rich industries
- changes the asset management policy from reactive fail-and-fix to proactive predict-and-prevent
- optimises asset management at individual asset level and at the operational, tactical and strategic levels with respect to the assets' maintenance and replacement costs, and the consequence costs of asset failure.

The Structure of PAM

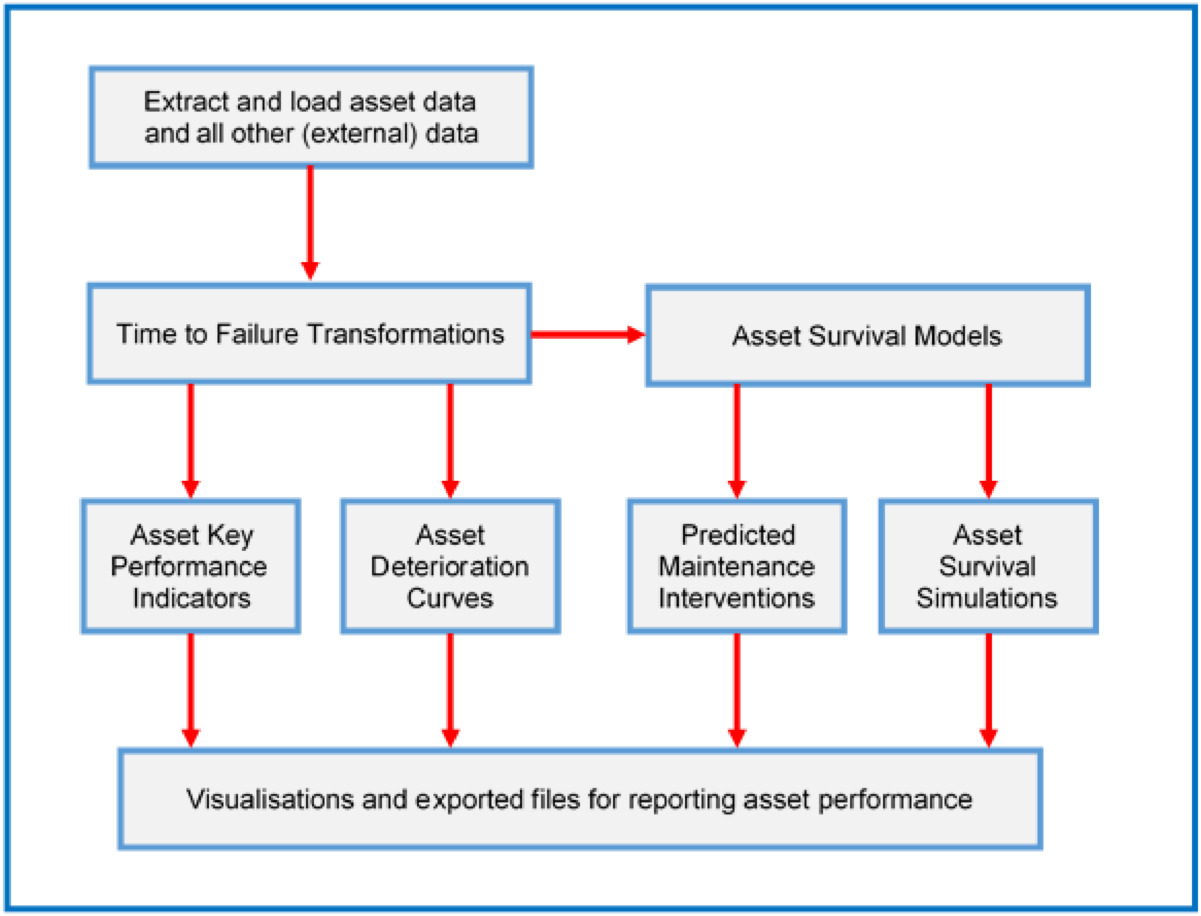

Table 1 summarises the role of each module.

Table 1

Module	Modelling Stage	Why Used
Load Data	***Input***. Load and merge all the input data	Map the input data to the **PAM** data repository
Time to Failure Transformations	Data preparation	Calculate the assets' failure signatures
Asset Key Performance Indicators	***Output***. Empirical analysis	Calculate key performance indicators
Asset Deterioration Curves	***Output***. Produce risk deterioration curves	*Tactical* asset management optimisation
Asset Survival Models	Develop the failure model for each functional class	Failure models (the heart of **PAM**)
Predicted Maintenance Interventions	***Output***. Calculate each asset's current risk of failure	*Operational* asset management optimisation
Asset Survival Simulations	***Output***. Simulate a range of asset management policies	*Strategic* asset management optimisation
Asset Reporting Visualisations	***Output***. Each output module has its own visualisation component	Enterprise-wide reporting of asset performance

Asset Management Optimisation

PAM optimises asset management at the operational, tactical and strategic levels.

Operational level asset management optimisation (Predicted Maintenance Interventions module)
Operational level asset management optimisation identifies assets at greatest risk of imminent failure so that they can have proactive maintenance to reduce their risks of failure rather than repaired or replaced after they fail, and also rather than on assets that are scheduled for maintenance then as specified by the manufacturers but whose risks of failure then are smaller. This allows a virtuous proactive maintenance feedback policy to be created.

Tactical level asset management optimisation (Asset Deterioration Curves module)
Tactical level asset management optimisation involves producing a series of deterioration (risk) curves that show how the risk of asset failure changes for different values of a factor, for example manufacturer, as assets are used. The curves identify the asset type with the highest survival probabilities or lowest cumulative hazards (see the appendix for explanations of these terms).

Strategic level asset management optimisation (Asset Survival Simulations module)
Strategic level asset management optimisation involves simulating the financial implications each month of a range of asset maintenance and replacement policies to determine the optimal, i.e. most cost-effective, policy subject to a range of constraints, for example the organisation's maintenance capacity and attitude to the risk of asset failure.

Detailed information on each module can be downloaded from PAM Modules.

Module Run Frequencies

PAM must be run regularly to ensure that the most recent maintenance and failure data are used in the models and therefore reflected in the outputs. Table 2 shows the suggested run frequency for each module. The actual run frequencies depend on the industry, asset type and any special conditions, and are discussed and agreed with the client.

Table 2

Module	Suggested Run Frequency
Time to Failure Transformations	Monthly
Asset Key Performance Indicators	Quarterly
Asset Deterioration Curves	Quarterly
Asset Survival Models	Monthly
Predicted Maintenance Interventions	Monthly
Asset Survival Simulations	Biannual

Model Refresh Frequencies

After the models have been used for some time, they are refreshed by using the most recent intervention data (and older data and other data) as new input data. Before the refreshed models are developed, the

Time to Failure Transformations module must be run on all the data to ensure that they have the correct structure.

Repairable Assets and Non-Repairable Assets

Assets can be classified as repairable or non-repairable. Repairable assets can be restored to a state in which they function satisfactorily, if not to their original states. Non-repairable assets are replaced at first failure, tend to be cheaper than repairable assets and are not critical.

PAM models the failure of repairable assets and non-repairable assets. Table 3 shows how **PAM** models both types of asset.

Table 3

Output Module	Non-Repairable Assets	Repairable Assets
Asset Key Performance Indicators	First failure only	All failures
Asset Deterioration Curves	First failure only	All failures
Predicted Maintenance Interventions	Proactive maintenance only	All maintenance interventions
Asset Survival Simulations	Proactive maintenance only	All maintenance interventions

Table 3 shows that the models for non-repairable assets are simpler than the models for repairable assets because they only have proactive maintenance and are replaced after their first failures whereas repairable assets have proactive maintenance and reactive maintenance.

Asset Criticality and Redundancy

Asset Criticality, Redundancy and Risk of Failure Scores in PAM Introduction shows how **PAM** uses asset criticality to develop a risk score for asset failure and models asset redundancy in groups of assets to develop a group risk of failure score.

Asset Management Planning Levels

Since **PAM** optimises asset management at the operational, tactical and strategic levels, it is important to define these terms. This can be done in two alternative ways. The first is based on the time horizon as shown in Table 4. The horizons shown are only guides and depend on the asset.

Table 4

Planning Level	Horizon	PAM Module
Operational	<2 years	Predicted Maintenance Interventions
Tactical (planning)	2-5 years	Asset Deterioration Curves
Strategic	>5 years	Asset Survival Simulations

An alternative approach to defining planning levels is by their objectives:

- Strategic plans are high level plans for achieving the projects' objectives. They usually involve most or all of the organisation's procedures and operations.
- Tactical plans describe the actions (tactics) required to achieve the objectives of the strategic plans. They are at lower levels and more specific than strategic plans.
- Operational plans describe how the strategic and tactical plans will be implemented.

Using these definitions, the implementation order is top-down, i.e. from strategic through tactical to operational. The three plans are not carried out as discrete pieces of work but as a continuous process with feedback to adapt and enhance them as they are implemented.

PAM's Asset Survival Simulations module helps define the strategic benefits of the project by simulating a range of scenarios subject to operational constraints. After the strategic analysis has been carried out, the Asset Deterioration Curves module (the tactical level) allows users to compare the effects of different values of a factor on the assets' failure rates. The performance of each asset is then optimised at the operational level in the Predicted Maintenance Interventions module by identifying assets with high risks of failure and which therefore are in greatest need of imminent maintenance.

Appendix – Survival Analysis

The survival model in **PAM**, the proportional hazards model, was first proposed by Sir David Cox in his seminal paper 'Regression Models and Life Tables' published in the *Journal of the Royal Statistical Society, Series B* (1972). This appendix provides an introduction to some of the key concepts of survival analysis. More information on survival analysis is available in the literature.

Introduction

Survival analysis is a class of statistical method for analysing and modelling the occurrence and timing of events, for example deaths and the onset of disease. It is known by a variety of different names depending on the application. For example, in medical statistics and more generally it is called survival analysis, in engineering it is called reliability analysis, in economics it is called duration analysis and in sociology it is called event history analysis. Typical questions that survival analysis can answer include what proportion of the population will survive beyond a certain time, and of those who do survive what are their rates of dying. With respect to asset management, survival analysis answers questions such as what is the probability of an asset surviving beyond a particular time and how do different factors influence asset failure rates.

Survival Analysis Applied to Asset Management

Survival analysis has three key concepts: risk sets and censored observations; the survival (survivor) function; and the hazard rate. They are described below with particular reference to asset management.

Risk Sets and Censored Observations

In studies of asset failure it is common for only a proportion, usually a small proportion, of the assets to fail – most assets will still be working or in working order at the end of the study. This raises a very important feature of survival analysis. Observations (assets) are retained in the risk set, i.e. the observations at risk of suffering the event, until they suffer the event, if they do. When an observation suffers the event, it is removed from the risk set, so reducing the size of the risk set, and the observation's survival probability calculated. Observations that did not suffer the event during the study are 'alive' at the end of the study and are called censored observations.

With respect to asset failure, an asset that did not fail during the study is a censored asset. This does not mean that censored assets will never fail, only that they did not fail during the study. Survival times for censored observations are as least as long as the duration of the study. Censored observations can be regarded as a type of missing observation but with a very different meaning to that encountered in other areas of statistical analysis.

Survival Function

The survival function is the probability distribution of survival times. It is used to calculate the probability of an asset surviving to at least time *t*.

Hazard Rate and Cumulative Hazard

The hazard rate of an asset at time *t*, also known as the instantaneous failure rate, hazard function or conditional failure rate, is the probability of the asset failing at time *t* given that it survived to just before time *t*. It is not actually a probability in the strict sense because it can be greater than 1 – it is a rate because its dimensions are $time^{-1}$. More accurately, the hazard rate of an asset at time *t* is the potential for it to fail at time *t* adjusted for the number of assets in the risk set just before time *t* and so ‘available for failure’.

In practice, the cumulative hazard, i.e. the integral of the hazard rate, is used for assessing asset reliability because it can be calculated directly from the survival function. The cumulative hazard at time *t* is the accumulated risk of failure at time *t*. With respect to asset management, the cumulative hazard at time *t* can also be defined as the expected number of failures up to time *t* if failures were repeatable. Cumulative hazard, $H(t)$, and survival probability, $S(t)$, are related by

$$H(t) = -\ln S(t) \tag{1}$$

Since the range of $S(t)$ is (0,1), the range of $H(t)$ is (0,∞).

With respect to asset management, the relative values of the cumulative hazard before and after a maintenance intervention can be used to assess the effectiveness of the intervention.

- If the cumulative hazard of an asset after a maintenance intervention is unchanged from before the intervention, the asset is in an ‘as bad as old’ condition after the intervention.
- If the cumulative hazard of an asset after a maintenance intervention is the same as it was when the asset was new, the asset is in an ‘as good as new’ condition after the intervention.

Hazard rate and therefore cumulative hazard are very important concepts in survival analysis and the following example shows why.

As an asset gets older, the probability of it failing calculated from its failure probability distribution becomes smaller because it is given by the tail area of the distribution. This result is counter-intuitive and occurs because it assumes that the size of the risk set just before time *t* is the same as it was at the start of the study whereas it is smaller because some assets had failed by then. The hazard rate as a measure of the failure probability at time *t* corrects this probability by considering the decreasing size of the risk set as assets fail. Thus, hazard rate is a more accurate measure of the potential for failure than the unadjusted failure probability.

As an example, consider assets that are 30 years old and assume that few assets survive this long. Of the few assets still in use then, a large proportion would be expected to fail in the following year. As explained above, the probability of failure in the 31st year calculated from the failure distribution is small because the relevant area in the probability distribution is very small. As time goes by, assets fail and the risk set becomes smaller. For a 30 year old asset to fail in the following year, it had to survive 30 years. The small risk set after 30 years leads to a larger probability of failure in the following year than the probability calculated from the failure distribution when the initial (larger) risk set is used. The large probability is more realistic than the small probability calculated using the risk set at the start of the study.

For an asset to fail at time t^*, it had to be in use just before t^*. The risk set just before t^* is all the assets that were in use then. The risk set just before t^* rather than the risk set at an earlier time must be used to calculate the probability of an asset failing at t^*. The probability of failure at time t^* conditional on the risk set just before t^* is called the hazard rate and is given by

$$h(t) = \frac{f(t)}{1-F(t)}$$

where $f(t)$ is the probability density function of the failure distribution and $F(t)$ is the probability distribution function of the failure distribution. The hazard rate is the potential for an asset to fail in the time interval $(t, t+\Delta t)$ given that it survived to time t. As it increases, the potential for failure increases.

Survival analysis has two main parts: Kaplan Meier analysis and Cox regression.

Kaplan Meier Analysis

The Kaplan Meier estimator, also known as the product limit estimator, is a non-parametric statistic for estimating the survival function and cumulative hazard. (A non-parametric statistic is a statistic that does not assume a probability distribution for the data – failure data in this case.) With respect to asset management, Kaplan Meier analysis is used to produce asset deterioration (risk) curves.

Kaplan Meier analysis uses the decreasing size of the risk set (see above) as assets fail to calculate the survival probability and cumulative hazard of the remaining assets at each time. The curves show how the risk of failure profile changes as assets are used. They allow the effects of different values of a factor, for example manufacturer, on the risk profiles to be studied. The factor value with the highest survival probabilities or lowest cumulative hazards is the value with the lowest risk of failure (cumulative hazard and survival probability have an inverse relationship – see (1)). The curves consist of a series of steps rather than smooth curves (the steps are the censored assets).

Cox Proportional Hazards Model

The Cox proportional hazards model is a regression model for calculating the hazard rate from a set of predictor variables. It is given by

$$h_j(t) = h_0(t)\exp\left(\sum_{i=1}^{n} a_i x_{ij}\right) \tag{2}$$

where $h_j(t)$ is the hazard rate of asset j at time t, $h_o(t)$ is the baseline hazard at time t for all the assets, x_{ij} is the value of covariate i for asset j and a_i is the coefficient of x_{ij}. If a_i is positive, $h_j(t)$ increases as x_i increases, and if a_i is negative it decreases as x_i increases. The profile of the hazard rate over time is defined by the baseline hazard, and the covariates determine the overall magnitude of the hazard rate.

The hazard rate is the product of two terms. The first term in (2), the baseline hazard at time t, $h_o(t)$, varies with time but is independent of the covariates, and the second term (containing the exponential term) depends only on the covariates but not on t. If all the x_i are 0, the hazard rate at time t is the baseline hazard at time t.

The Cox proportional hazards model, (2), is a semi-parametric model because it has parametric and non-parametric components. The baseline hazard, $h_o(t)$, is the non-parametric component and the exponential term is the parametric component. The Cox model is a popular survival model because it is not necessary to specify a probability distribution for the survival times, for example Weibull (in many cases the distribution is not known).

The proportional hazards assumption states that at any time the ratio of the hazard rates of two assets depends only on the values of the predictor variables and not on the baseline hazard, i.e. the time.

In common with other types of regression model, the Cox proportional hazards model establishes the predictor variables that determine the target variable (the hazard rate). By studying the effects of changes in the values of the predictor variables on the hazard rate, the model provides insight and understanding into the causes of asset failure.

Since the Cox proportional hazards model can handle censored observations, it cannot be estimated using ordinary least squares. An alternative estimation method that considers both censored observations and observations that suffered the event is required and it is for this reason that the maximum partial likelihood method was developed.

Table 5 has a brief comparison of the Kaplan Meier model and Cox regression models.

Table 5

Model	Advantages	Disadvantages
Kaplan Meier (non-parametric)	♦ does not make assumptions about the distribution of the data	♦ results are descriptive, not predictive ♦ can only include one covariate (by stratifying)
Cox regression (semi-parametric)	♦ makes no assumptions about the shape of the hazard function ♦ covariates can be included ♦ model is at individual asset level ♦ can gain insight and understanding into the causes of asset failure ♦ can make predictions and run simulations	♦ difficult to incorporate time-dependent covariates ♦ strong assumption about how covariates affect the hazard function (proportional hazards assumption)

