

# VIRTUAL IRON BIRD – A MULTIDISCIPLINARY MODELLING AND SIMULATION PLATFORM FOR NEW AIRCRAFT SYSTEM ARCHITECTURES

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## 1. ABSTRACT

The concept of a Virtual Iron Bird for the modelling of aircraft system architectures is presented. This platform can be used to evaluate and assess more-electric aircraft system configurations by simulations. For these purposes an object-oriented model library is set up by use of the modern multi-physical modelling language Modelica. Besides the design of the library, an inverse modelling approach is shown allowing to analyse the behaviour and power consumption of aircraft systems. In order to determine accuracy estimates of the overall results, Monte Carlo simulations of uncertainty models are performed, which identify the statistical distributions of the results and assessment criteria.

## 2. INTRODUCTION

Multidisciplinary modelling is gaining a more and more important role within areas such as robotics, the automotive or aircraft industry. Particularly with respect to the complexity of aircraft systems, such as air conditioning, electric power generation, avionics, flight controls, hydraulics, landing gears etc., the method of multidisciplinary modelling allows to simulate all aircraft systems, which use different forms of power, in one integrated model. Different physical domains have to be considered in the simulation of complex aircraft systems. An example is presented in FIG 1, which shows a diagram of the conventional power generation, distribution and use on a civil aircraft.

Fuel is being converted into power by the engines of the aircraft. Most of it is expended as propulsive power in order to propel the aircraft. The remainder is the non-propulsive power off-take from the engines: Mechanical power is taken from the engine shafts to drive generators (electrical power) and pumps (hydraulic power). Pneumatic power is taken from the engine compressor as bleed air. These different forms of power are necessary to operate the aircraft systems [1]. On a conventional aircraft, a considerable amount of the non-propulsive power extracted from the engines is lost, due to the specif-

ics of power conversion, transmission and consumption by today's aircraft systems.

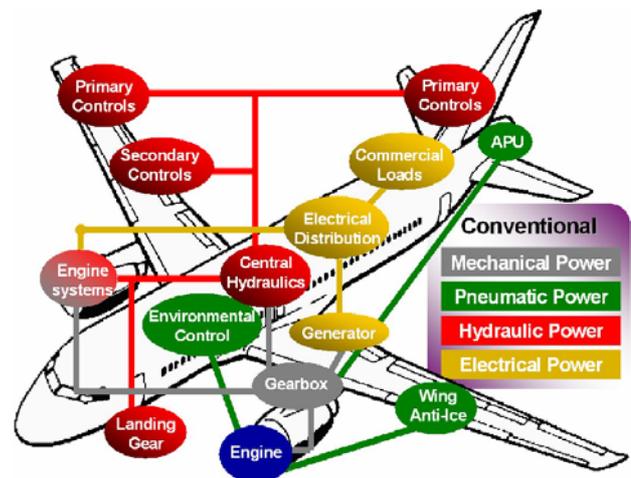


FIG 1. Power distribution network on a large civil aircraft [1]

The European aircraft industry is targeting at improving their products by advancing the development of aircraft systems of greater efficiency. A reduction of the system power demands of the next generation – power optimised – aircraft shall contribute to savings in fuel consumption and eventually reduce aircraft operating cost. To promote the development of new technology and more power efficient aircraft systems, the EC has founded the Power Optimised Aircraft (POA) project [2], involving European aircraft, equipment and engine manufacturers as well as research institutes. The concept of a more-electric aircraft is investigated within POA, focusing on the technology's impact on weight, fuel consumption, maintenance and operating cost.

A Virtual Iron Bird (VIB) is developed in order to assess the impact of new technology aircraft systems on non-propulsive power and fuel consumption at aircraft level. The VIB is a multidisciplinary modelling and simulation platform which offers the capability to analyse entire aircraft architectures including all systems. On the VIB, the aircraft systems are represented by simulation models which are used to predict and compare the power consumption and

behaviour of various aircraft system architecture candidates.

This article describes the concept of the Virtual Iron Bird and is structured as follows: Following this introduction, the modern multidisciplinary modelling language Modelica and the configuration of the object-oriented VIB model library are presented. In Section 4 an inverse modelling approach is shown which is commensurate with the goals of the VIB. Next, to analyse the power consumption of the aircraft systems and architectures, appropriate assessment criteria are described in detail. In Section 6 an uncertainty modelling approach is presented, which is a statistical method to identify the accuracy of the simulation results and assessment criteria by means of Monte Carlo simulations. A conclusion completes the paper.

### 3. OBJECT-ORIENTED MULTIDOMAIN MODELLING

The modelling and simulation environment enabling to assess the various aircraft system architectures is realised by means of the modelling language Modelica [3]. Modelica is a free object-oriented modelling language with a textual definition to describe physical systems in a convenient way by differential, algebraic and discrete equations. It is designed to allow component-oriented modelling of complex physical systems, e.g. systems containing mechanical, electrical, electronic, hydraulic, thermal, control or process-oriented subcomponents.

For the simulation of the Modelica models the commercial tool Dymola is used, which is a simulation environment with a graphical modelling editor and offering a Modelica translator [4]. The graphical model editor allows to define a model by drawing an object diagram as shown in FIG 3 for instance. The diagram is set up by positioning icons that represent the component models and by drawing connections. Connections specify the physical interactions between the components and are represented graphically as lines between the different physical connectors. Connectors contain all quantities (potential and flow variables) needed to describe the physical interactions. For example, voltage (potential) and current (flow) are needed for electrical components, angle and torque are needed for rotational mechanical elements, see [5] for more details.

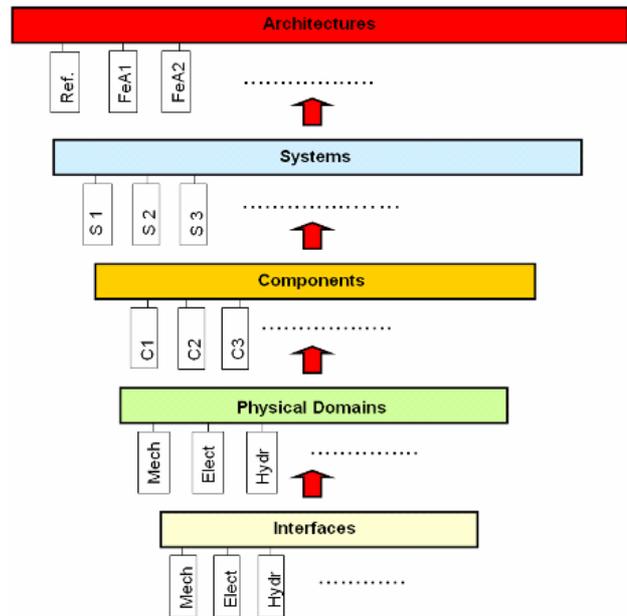


FIG 2. Hierarchical model library structure

The modelling and simulation platform Virtual Iron Bird (VIB) is set up as a Modelica library whose object-oriented structure consists of several levels, see FIG 2. The hierarchy of the library can be summarised as follows: Physical *Interface* definitions are the basic modules for generic physical models on the level *Physical Domains*, such as electrical resistors, mechanical inertias or hydraulic valves. Aircraft *Components* like motors, mechanical gearboxes or hydraulic pumps are implemented by using basic physical models. On the next level aircraft *Systems* (e.g. electrical power generation, flight control actuation, landing gears) are built so that each level is based on the underlying levels of the entire library.

The hierarchy ends on the aircraft *Architecture* level (the top level) that comprises the new (more-electric) aircraft configurations. The creation of different aircraft level models can be realised in a very flexible and easy way by exchanging the accordant model classes. This can be done automatically if it becomes necessary due to the number of diverse aircraft architectures. An example for an aircraft architecture model with its systems and components is shown in FIG 3. The electrical power generation system (EPGS) is extracted from the aircraft architecture model and indicates one of the generators on component level. In FIG 4 the flight control system model with its surface actuation components illustrates the complexity of the diverse aircraft system models.

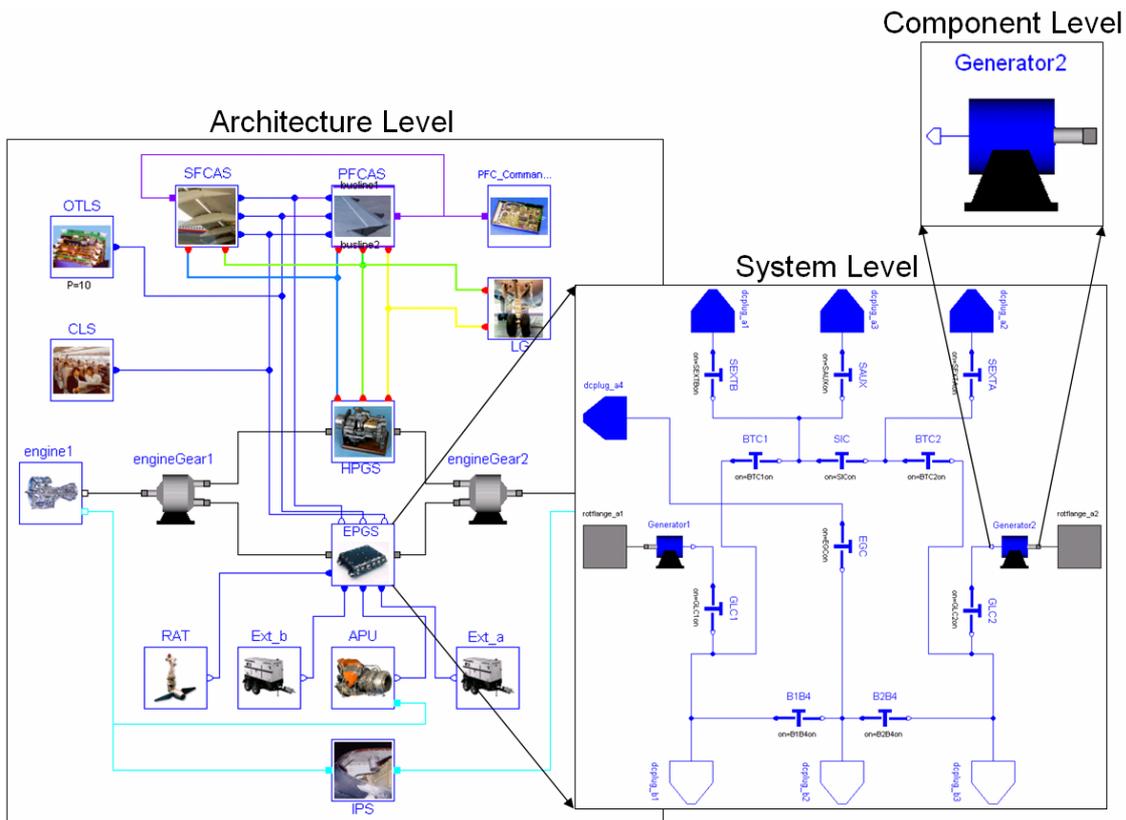


FIG 3. Modelica diagrams of hierarchical aircraft system models

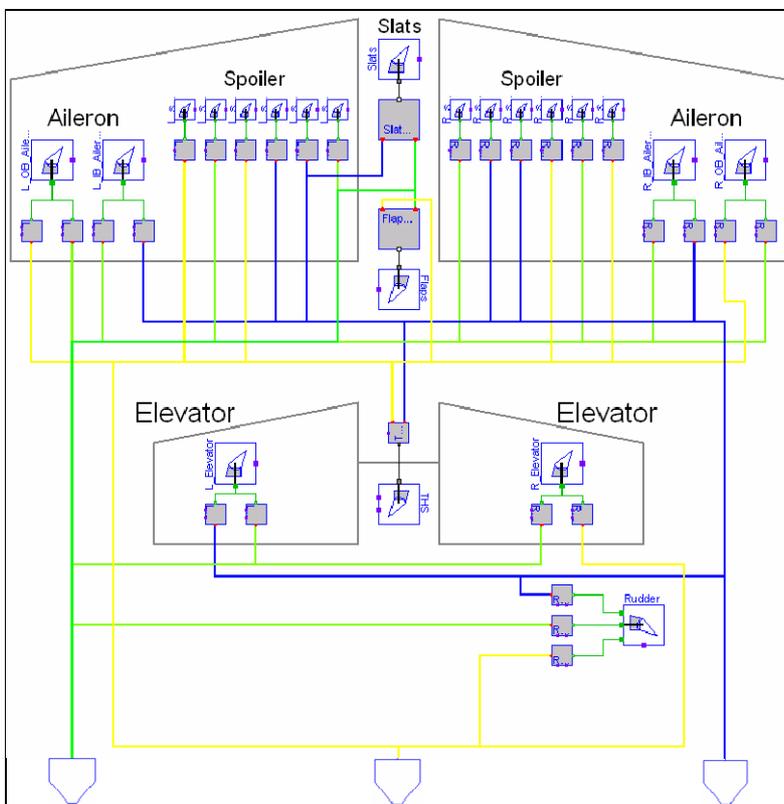


FIG 4. Modelica diagram of the flight control system

#### 4. INVERSE MODELS

For the VIB aircraft system simulations an inverse rather than a direct modelling approach is used. The origin of inverse models can be found in the field of controller design [6] where the automatic inversion of nonlinear plant dynamics is an important feature. An inverse model can be interpreted such that the meaning of the input and output functions is exchanged.

A Modelica model is primarily represented by DAEs (Differential Algebraic Equations) of the form:

$$f(\dot{x}, x, y, u, t) = 0.$$

The variables  $x$  may appear differentiated in the model, but parts of  $x$  can be algebraic,  $y$  are output variables and  $u$  are input variables; time  $t$  is the independent variable of the system.

For a direct model the DAE will be solved for  $x(t)$  and  $y(t)$  for a given  $u(t)$ . In this case,  $u(t)$  are the input variables and  $y(t)$  are the output variables, whereas the inverse model DAE is solved for  $x(t)$  and  $u(t)$  by a given  $y(t)$  under the condition  $\dim(u) = \dim(y)$ . The unknown variables of a direct model are treated as the known input functions of the inverse model and vice versa.

Both modelling methods are discussed in the following using an aircraft-like example with a power source (engine and electrical generator) and a control surface driven by an electro-mechanical actuator. For a given control surface profile (time dependent load torque and angular position) the basic VIB simulation task is to compute the necessary electrical power at the generator and the resulting change in fuel consumption at the engine.

FIG 5 shows the direct model for the above example. The generator, driven by the engine, supplies the electro-mechanical actuator with electrical DC power. The voltage level of the generator is determined by the generator control unit, which is integrated into the generator model. The motor is steered by the motor power electronic and the actuator motor control unit and changes, via a gear-box, the position of the control surface according to the demanded values.

For the comparison between the direct and the inverse modelling approach, only the part of the electro-mechanical actuator and the control surface model in FIG 5 are considered. The engine and generator simulation models are still the same for both applications to calculate the necessary electrical power and the resulting change in the fuel consumption.

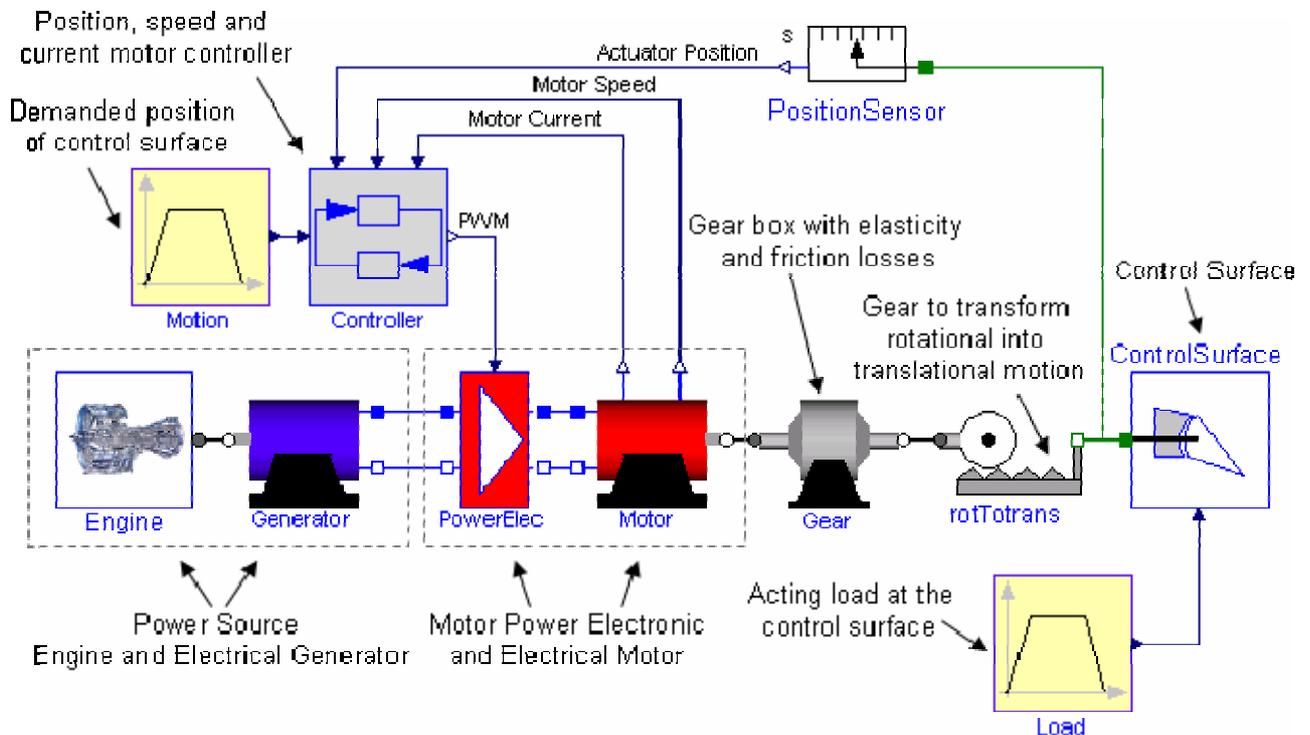


FIG 5. Direct Modelica model of an electro-mechanical actuator

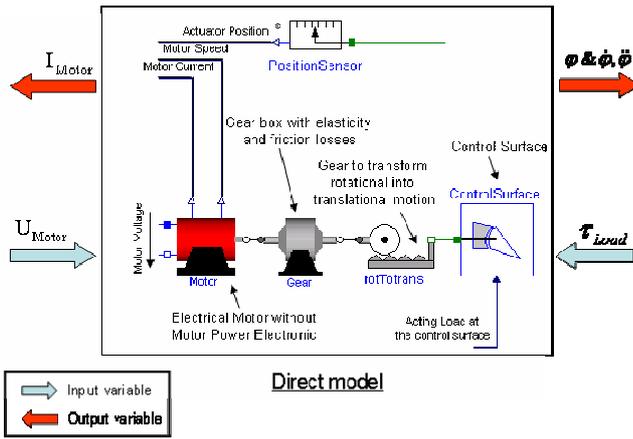


FIG 6. Diagram of the input and output variables of the direct electro-mechanical actuator model

Focusing on the electro-mechanical actuator (motor and gearboxes) and control surface model, the input variables for the direct simulation are the motor voltage  $U_{Motor}$  (derived from the actuator motor controller and motor power electronic) and the acting load  $\tau_{load}$  at the control surface (see FIG 6). The unknown variables are the motor current  $I_{Motor}$  and the real motion  $\varphi, \dot{\varphi}, \ddot{\varphi}$  of the control surface. On the basis of this direct actuator model, the electrical motor power and the dedicated motor power electronic losses can be computed by the actual motor voltage  $U_{Motor}$  and motor current  $I_{Motor}$ . The sum of the motor power and the power losses demonstrates the necessary electrical generator power to operate the electro-mechanical actuator. By means of the generator and engine models the resulting change in fuel consumption can be finally calculated for the total electrical actuator power.

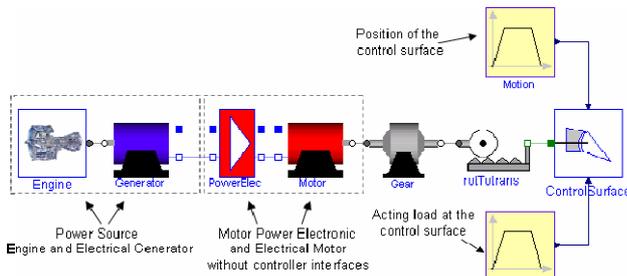


FIG 7. Inverse Modelica model of an electro-mechanical actuator

FIG 7 presents an inverse model in contrary to the direct model shown in FIG 5. The visible difference of these two models is that the inverse model does not require an actuator motor controller in order to impress the necessary motor voltage  $U_{Motor}$  at the

motor input. Based on the inverse modelling definition, the actuator motor voltage  $U_{Motor}$  will be determined by exchanging the meaning of input and output of the direct model. For the inverse electro-mechanical actuator and surface model, the input variables are the predefined position  $\varphi$  and load  $\tau_{load}$  found at the control surface. The output variables (unknown variables) are the motor voltage  $U_{Motor}$  and the motor current  $I_{Motor}$ . Comparing the direct actuator model (FIG 6) and the inverse actuator model (FIG 8), the meaning of inverse and direct interpretation is well visible. The resulting necessary power of the generator and engine can be calculated in the same manner as for the direct model.

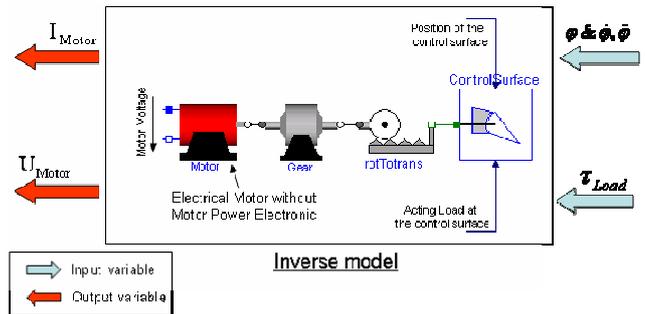


FIG 8. Diagram of the input and output variables of the inverse electro-mechanical actuator model

In Dymola, the DAE corresponding to the inverse model is being handled with the same methods like the DAE of any other (direct) model. The methods applied by Dymola are the Pantelides algorithm and the dummy derivative method. Since the Pantelides algorithm will differentiate equations, the known input functions may also be differentiated, which leads to the well known effect that the derivatives of the input functions must exist up to a certain order, see also [7].

In the present example in FIG 8, it is imperative that the input signal  $\varphi$  is at least twice continuously differentiable to compute the required signal derivations  $\dot{\varphi}, \ddot{\varphi}$  within the simulation model. To ensure that the model input signal is differentiable, the signal is treated by filters or spline-interpolation.

Due to the fact that in Modelica the models are described in an object-oriented and physical manner, an inverse model is almost identical to the corresponding direct model. As the only significant difference, the inverse model does not require any representation of the controller structure that exists in the real system or component, whereas the direct model generally comprises the controller structure for cal-

calculation of the motor voltage  $U_{Motor}$  as a function of demanded and actual actuator position, the actual motor speed, motor current and the generator voltage level. Because of the unavoidable control error and physical effects in the drive train (elasticity, friction) the actual control surface position  $\varphi$  is different from the demanded control surface position. Under the assumption that the angular position of the surface profile is treated as the demanded position, the direct model induces errors in the motor variables. This leads to a resulting error in the total power consumption.

In contrast to this behaviour the inverse model matches per definition exactly the surface profile  $(\tau_{load}, \varphi)$ . Therefore the inverse model describes correctly the power consumption. A further advantage of the inverse modelling approach is the lower model complexity due to the absence of possibly complicated or unavailable controllers.

For the above mentioned reasons inverse modelling is used as a general concept for all of the electrical, hydraulic and mechanical power consumers. For each of the consumers, operation profiles during a typical flight are available to drive a multi-domain inverse model for simultaneous computation of the power off-take from the engines.

## 5. POWER CRITERIA

To measure and assess the quality of an architecture simulation some criteria are needed which quantify energy consumption and peak power. Pre-defined flight profiles (movement of surfaces, landing gear, state of galleys) yield the power characteristics of the different physical domains such as hydraulics, electrics and mechanics from the architecture simulations. In the following the definitions of the criteria, which are related to the dynamic simulations, their implementation in Modelica and the results from an example are presented.

To evaluate the overall energy consumption during a flight profile, it is suitable to define the average power

$$P_{Average} := \frac{1}{t_e - t_0} \int_{t_0}^{t_e} P(t) dt$$

with the current power  $P(t)$  at the time  $t$ , the start time  $t_0$  and the terminal time  $t_e$  of the flight profile.

$P_{Average}$  describes, which integral averaged power is required for the operated manoeuvre in the time-

frame  $[t_0, t_e]$ . It is a measure for the overall power demand.

Beside average power there is also an interest on peak power which is relevant to the design of the aircraft components and systems. In a first step it is natural to define the peak power as

$$\max_{t \in [t_0, t_e]} P(t).$$

However arbitrary short peaks can unmeantly increase the value of the peak power, because only peaks holding a certain minimum duration  $T$  are of interest for evaluation. In order to achieve an appropriate numerical solution, it is helpful to define the peak power

$$P_{Peak} := \max_{t \in [t_0 + T, t_e]} P_{Filtered}(t)$$

for a fixed  $T \in (0, t_e - t_0]$ .  $P_{Filtered}$  denotes a filtered power characteristic determined from the original power  $P$ . As filter serves the *continuously moving average* filter which computes for every time point  $t$  the integral average of the power  $P$  over a moving time window with the length  $T$ :

$$P_{Filtered}(t) := \frac{1}{T} \int_{t-T}^t P(\tau) d\tau \quad (t \in [t_0 + T, t_e]).$$

In FIG 9 the effect of the filter with a time window of 5 seconds is shown for a power trajectory.

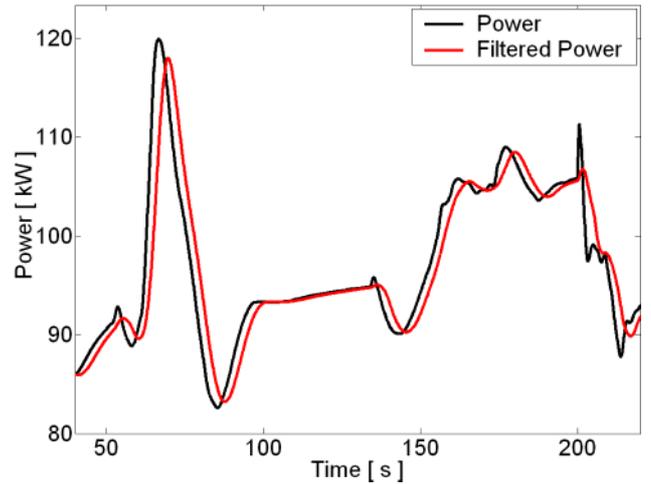


FIG 9. Results by moving average filtering,  $T = 5s$

Choosing  $T = t_e - t_0$  yields as special case the average power, and the equation  $P_{Average} = P_{Peak}$

holds. In this sense the peak power can be considered as generalisation of the average power.

For a Modelica implementation the definition of  $P_{Filtered}$  can be rewritten as differential equation:

$$(1) \quad \dot{P}_{Filtered}(t) = \frac{P(t) - P(t-T)}{T}$$

with initial condition  $P_{Filtered}(t_0 + T) = \frac{1}{T} \int_{t_0}^T P(\tau) d\tau$ .

It remains to find the maximum of  $P_{Filtered}(t)$ . The general problem is to compute

$$\bar{u} := \max_{t \in [t_0, t_e]} u(t)$$

for a time depending variable  $u$ . The corresponding Modelica model to determine  $\bar{u}$  creates a state event in the case that  $\dot{u}$  changes its sign. Then the value of  $u$  is compared with the maximum value up to this event and the greatest one is selected as new  $\bar{u}$ . In addition the values  $u(t_0)$  and  $u(t_e)$  can be defined for possible candidates of maximal values of  $u$  by setting accordant parameters in the model.

Due to the fact that all the time points  $t$  with  $\dot{u}(t) = 0$  are defined by state events, these points and the respective values of  $u$  are computed very accurately by root finding algorithms in Dymola.

It is remarkable on the definition and implementation of the criterion peak power, that maxima are computed with the help of derivatives, but no derivative of the power  $P$  is needed. The smoothed function  $P_{Filtered}$  has the derivative (1) which is a backward difference approximation of  $\dot{P}(t)$ .

To illustrate the criteria the example from FIG 7 is considered once again. The evaluation of the criteria are exemplified by the mechanical power at the engine shaft. For the simulation the data for load torque and moving angles of the control surface are used as input. The resulting power characteristics at the engine shaft are shown in FIG 10 for 50 s with  $T = 1$  s.

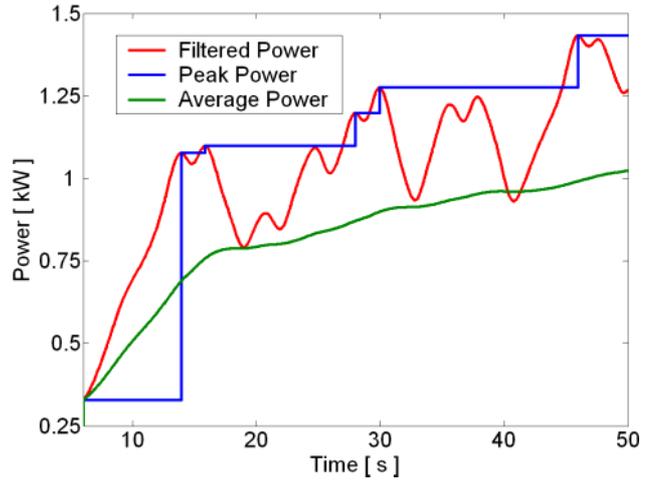


FIG 10. Power criteria for the electro-mechanical actuator

Beside the both criteria – average power and peak power – the filtered power  $P_{Filtered}$  is plotted as well. Please notice, that intermediate values of peak power do in general not correspond to the peak power up to the intermediate time, but only for  $t = t_e$ .

## 6. UNCERTAINTY MODELLING AND ANALYSIS

For reliable assessment of simulation results it is essential to know how accurate the generated figures are. An approach to estimate the accuracy of the aircraft architecture simulation results and its implementation on the VIB platform is presented in this section.

An aircraft architecture model consists of several component and system models (see Section 3). Each of the component models reflects real hardware behaviour only up to a certain accuracy. The uncertainty of the component models directly influences the overall architecture simulation results. In general these effects are not known a priori and therefore the accuracy of the architecture simulation results remains unidentified.

The following concept of uncertainty modelling is based on statistical information about each aircraft component model. At first only electrical consumers (e.g. electro-mechanical actuators, motors, galleys) are considered. Assuming that every consumer model defines (implicitly) the current  $I$ , which is necessary to operate itself, an additional uncertainty model yields an extended component model (see FIG 11).

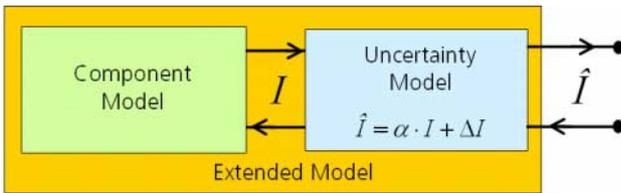


FIG 11. Extended uncertainty model for an electrical consumer component

The uncertainty model producing an updated current  $\hat{I}$  consists of a multiplicative part  $\alpha$  and an additive part  $\Delta I$ :

$$\hat{I}(t) = \alpha \cdot I(t) + \Delta I.$$

The factor  $\alpha$  can be interpreted as reciprocal modified component efficiency whereas  $\Delta I$  denotes an additional load. The values for  $\alpha$  and  $\Delta I$  are statistically distributed (e.g. Gauss or uniform distributions) and shall cover parametric and structural uncertainties of the component models. The power consumption of the power users is mainly described by the electrical current  $I$  flowing through the components, because the net voltage delivered by a generator is approximately constant during operation. On the whole it is true for every power consumer that the potential variable (angle resp. rotational speed, pressure) remains more or less constant and the flow dominates the power consumption. Thus, the principle can be applied to all power users and their accordant flow variables (mechanical torque, pneumatic and hydraulic flow).

The Modelica component models are extended by uncertainty models so that corresponding aircraft architectures can be used as nominal models (without uncertainty information) or as entire uncertainty models. The object-oriented modelling platform allows to switch from the nominal to the extended uncertainty model (and vice versa) only by one parameter change on top level of the model. In this note the VIB naturally offers uncertainty investigations.

In general, an aircraft uncertainty model is a nonlinear simulation problem with nonlinear statistical parameter dependencies. Monte Carlo simulation (see FIG 12 for the entire uncertainty analysis process) enables to find the statistical distributions of the results of interest like the power criteria average and peak power described in Section 5. For Monte Carlo simulation many dynamic time simulations of the aircraft uncertainty model have to be run with random values for the component parameters  $\alpha$  and  $\Delta I$  according to their statistical distributions. The simulation runs are independent to each other, consequently the computing time can considerably be

reduced by using a computing cluster for parallelisation.

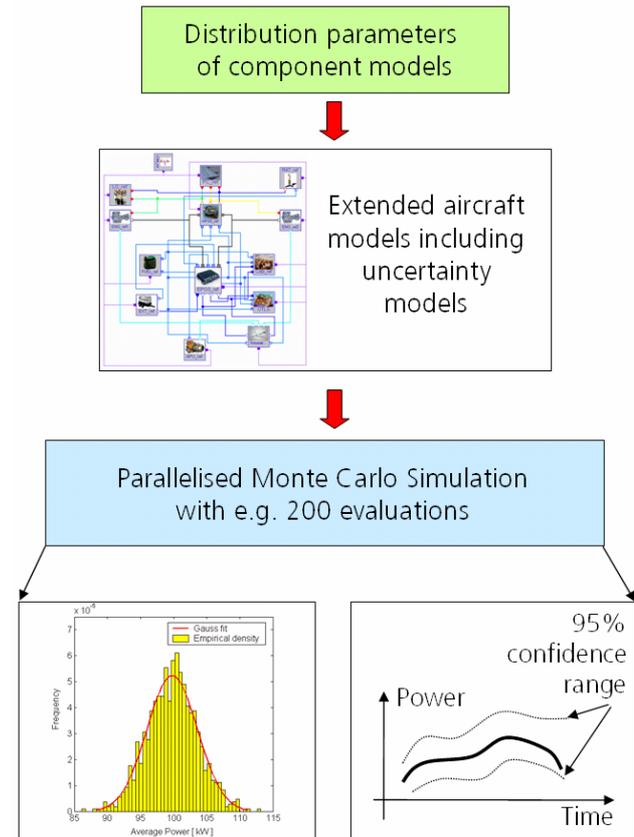


FIG 12. Process for VIB uncertainty analysis

The VIB implementation of Monte Carlo simulations is done by applying the parametric assessment tool MOPS [8] which has an interface to Dymola simulations. MOPS also provides a user-friendly possibility to parallelise the simulation runs. Additionally it gives a broad range of features for statistical analysis after the simulation runs. An interesting result is the empirical distribution of the power criteria, like the average power at a generator after 1000 seconds in FIG 13. The variance of the fitted Gauss distribution is a measure for the accuracy of the mean value corresponding to the most likely average power. For peak power the distribution analysis can be done in the same way.

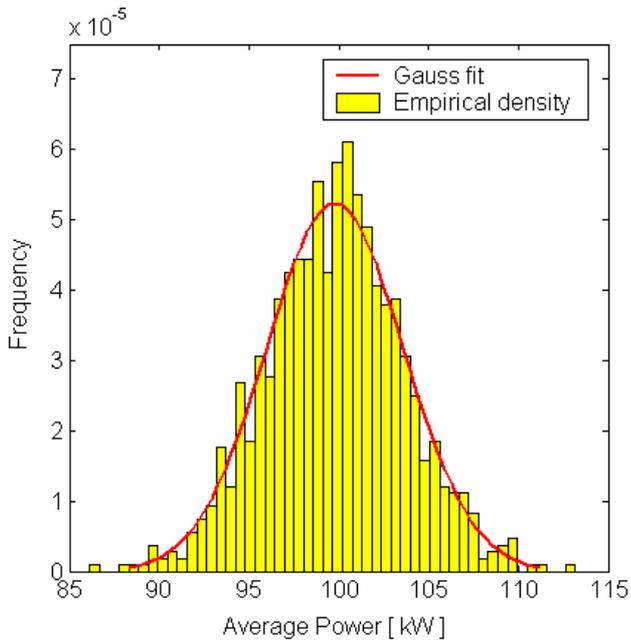


FIG 13. Empirical distribution of average power after 1000 s

Time dependent accuracy estimates can be generated by means of confidence intervals for each time point  $t$ . The output of a Monte Carlo simulation is a bundle of power trajectories each resulted by a different set of random uncertainty parameter values  $\alpha$  and  $\Delta I$  for the components. For every time point  $t$  a confidence interval (e.g. 95%) with lower bound  $b_l(t)$  and upper bound  $b_u(t)$  can be calculated using the bundle of power trajectories. In FIG 14 the result of such an analysis is shown. The lower and upper bound functions form an uncertainty band in which the real hardware measurements of the possible aircraft architecture will lie between with a probability of 95%. The most likely nominal simulation can be compared to the uncertainty band (or more uncertainty bands with different confidence probabilities) to estimate and assess the nominal simulation accuracy on each time point.

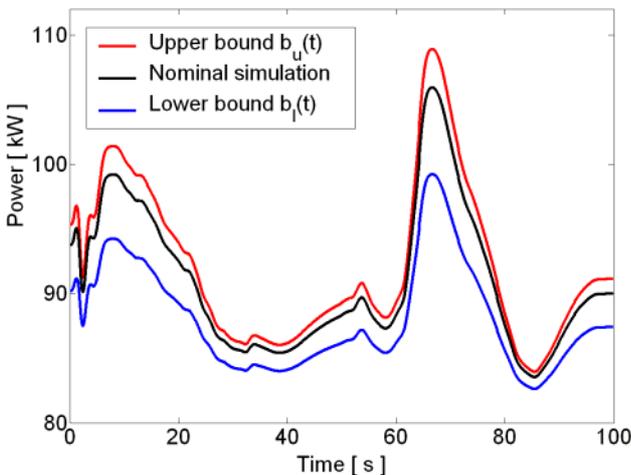


FIG 14. Result of Monte Carlo simulation: 95% confidence range of a power trajectory

## 7. CONCLUSION

The Virtual Iron Bird serves as a modelling, simulation and analysis platform to predict and assess the power demands caused by the systems installed on a large civil aircraft. The underlying model library is set up as a hierarchically structured Modelica library enabling inverse modelling for power demand simulations. The inverse modelling approach is described by an elementary modelling example. In order to evaluate the power consumption of different aircraft architectures two power criteria – average and peak power – are introduced as well as their implementation in Modelica. Reliable assessment of the simulation results is guaranteed by Monte Carlo simulations of aircraft architecture uncertainty models. The necessary uncertainty modelling and analysis tools are also incorporated in the Virtual Iron Bird environment.

## 8. LITERATURE

- [1] L. F. Faleiro: Power Optimised Aircraft – The Future of Aircraft Systems. AIAA/ICAS International Air and Space Symposium and Exposition: The Next 100 years, 2003.
- [2] Power Optimised Aircraft, contract G4RD-CT-2001-00601 under the European Communities 5th framework Programme for Research – Promoting Competitive and Sustainable Growth – Key Action 4: 'New Perspectives in Aeronautics'. [www.poa-project.com](http://www.poa-project.com)
- [3] Modelica Language: [www.modelica.org](http://www.modelica.org)
- [4] Dynasim Dymola: [www.dynasim.se](http://www.dynasim.se)
- [5] H. Elmqvist, S. E. Mattsson, M. Otter: Modelica – The New Object-oriented Modeling Language, The 12th European Simulation Multiconference ESM'98, Manchester, UK, 1998.
- [6] M. Thümmel, G. Looye, M. Kurze, M. Otter, J. Bals: Nonlinear Inverse Models for Control, 4th International Modelica Conference, pp. 267-279, March 7-8, 2005.
- [7] M. Thümmel, M. Otter, J. Bals: Control of Robots with Elastic Joints based on Automatic Generation of Inverse Dynamics Models. IEEE/RSJ Conference on Intelligent Robots and Systems, pp. 925-930, 2001.
- [8] H. D. Joos, J. Bals, G. Looye, K. Schnepper, A. Varga: A multi-objective optimisation-based software environment for control systems design. IEEE International Symposium on Computer Aided Control System Design Proceedings, pp. 7-14, Glasgow, Scotland, 2002.