# A NLP based reentry flight guidance algorithm

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## ABSTRACT

A major cost driving factor for space transportation systems, especially for reusable systems, are the operation costs. The Guidance, Navigation and Control (GNC) system of a vehicle determines the amount of autonomy and ground support required. Current systems demand high manpower effort from the ground, which makes a mission costly and inflexible. Next generation space transportation systems demand a high cost saving in order to be commercially successful. One possibility to cut down costs is a highly autonomous and flexible guidance system. The paper addresses an approach to achieve this goal by using onboard flight path prediction in combination with numerical optimisation routines to guide a vehicle in its reentry mission. Some numerical results are given to demonstrate the capabilities of such an approach.

## 1 INTRODUCTION

Guiding an un-powered low lift vehicle over a distance of several thousand kilometres and from hypersonic to subsonic speed is a high sophisticated task. Uncertainties of vehicle properties and especially atmospheric conditions, which can not be predicted very accurately in advance, require a flexible and adaptive algorithm. Additionally, path constraints such as the critical aero-thermodynamic heating have to be addressed. Currently used guidance algorithms use reference trajectories, to which the state of the vehicle is controlled to.

The only algorithm for lifting body or winged vehicles in service and proven to be capable is the shuttle orbiter algorithm. It is known, that the manpower needed to prepare a mission is a major cost driving factor. A factor of 12% of the total mission costs is given in literature [1]. Future space transportation systems will need smarter, independent solutions in order to save cost and to gain flexibility and autonomy for the vehicle. Adaptive algorithms can not only save cost, but if also adaptive to different mission scenarios, they can guide the vehicle during abort scenarios, thus gaining a great safety aspect for the vehicle and possible crew.

The development of guidance algorithms at the Institute of Space Systems (IRS) focused on an algorithm that offers a high degree of autonomy and generality to fulfil the previously mentioned demands. Originally intended for the COLIBRI capsule [2] the core of the guidance algorithm was further developed and under investigation in the last years within the German TETRA and ASTRA technology programs (technology for future space transportation systems [3]; advanced systems and technologies for future space transportation applications [4]). The reference missions have been the X-38 demonstrator and the Hopper vehicle. For X-38 the guidance algorithm was not only applied to the hypersonic but also to the terminal area flight phase (known as terminal area energy management; TAEM). Simulation results that will be presented within this paper encouraged further developments. Currently, the guidance algorithm is being applied to the Hopper vehicle, which demands special guidance solutions due to its suborbital flight. Initial results show a very promising performance not only for the descent, but also for the ascent of the vehicle [5].

The paper will outline the working principle of the algorithm and give some performance insight for the example X-38.

## 2 GUIDANCE ALGORITHM

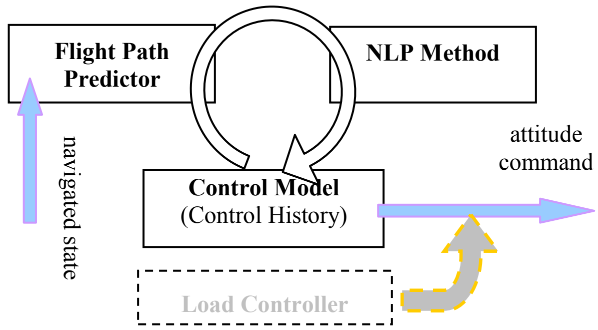


*Fig. 1: General guidance working scheme*

The proposed guidance algorithm is using a simplified NLP method to optimise control histories for the reentry trajectory. The flight path of the vehicle concerning the control history is computed by numerical integration of a set of equations of motion modelling full 3D translational motion (3DOF simulation). The advantage of this in respect to older approaches is that down- and crossrange are not decoupled. On the other hand, the complete integration of the equations of motion and additionally the use of accurate environmental and vehicle models demands a high numerical effort. Therefore the future state of the vehicle can be predicted very accurately in the order of model uncertainties. This overcomes the uncertainties of simple state estimations.

*Fig. 1* depicts the working principle. The three main objects to be discussed are the path predictor, the NLP method and the parameter model for the control history. Also illustrated is an auxiliary element, the load controller, which is necessary, if the parameter model is not sufficiently detailed.

### The Flight Path Predictor

The core element of the guidance algorithm is a numerical flight path predictor depicted in *Fig. 2*. Due to the accuracy of the models for environment and vehicle used, computational effort can be become unacceptably high with respect to the real time demands of an onboard algorithm. While equations of motion (eqm) are established for the three dimensional translational motion and guarantee a reliable prediction, the model for the Earth atmosphere can be obtained with less effort, because a highly complex model does not seem to be appropriate due to the unpredictability of the conditions for a special day. Single models like that of gravitation do not require a high computational load. For the aerodynamic modelling of the vehicle, a model of relatively high accuracy is chosen. It consists of several data arrays depending on Mach number and angle of attack mainly and can be corrected for other effects (e.g. base drag due to “engines on” in ascent flights). A linear interpolation within these arrays is used to obtain the drag and lift coefficients. The prediction is solved numerically using a 4th order Runge-Kutta Scheme with constant time steps.

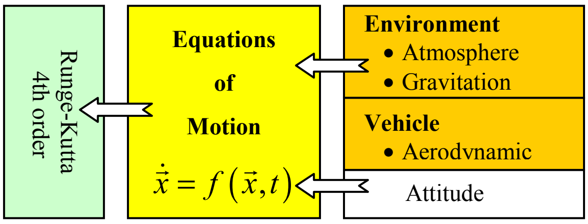


*Fig. 2: Scheme of flight path predictor*

While prediction is the most time consuming factor of the algorithm, time steps of the integration scheme can be adopted with drawbacks in prediction accuracy. While in the beginning of the flight, total flight distance and thus integration time is high, a greater time step can be applied to save computational time and a higher inaccuracy of the predicted final state can be tolerated, while in the end of the reentry flight, when only a short distance is left to fly, integration steps can be decreased to obtain a higher accuracy in the prediction without increasing the computational effort, because total integration time left is smaller.

### The NLP Method

A very simplified accelerated gradient projection algorithm [6] is used within this guidance scheme.
The task of the optimisation routine is to solve the parameter optimisation problem given by a set of parameter $\vec{p}$ of the control model and the dynamic system described within the flight path predictor to fulfil in-flight and final constraints $\vec{g}$ and minimise a cost function $F$.
Modification of the parameters is obtained by eq. 1,

$$\vec{p}^{k+1} = \vec{p}^k + \alpha^k \cdot \vec{s}^k \tag{1}$$

while search direction $\vec{s}^k$ and step size $\alpha^k$ are calculated in two consecutive steps, a restoration and an optimisation loop (superscript $^k$ indicating number of loop). In the restoration loop, only final constraint violations $\vec{g}$ and their local gradient $\vec{g}_p$ are respected, which are calculated by forward differences of the final state of the predicted flight path for modified parameters (eq. 2)

$$\vec{p}_{pred} = \vec{p} + \Delta\tilde{p}_i \,. \tag{2}$$

With the Jacobian matrix $\vec{g}$ of the final constraint violations the search direction is calculated using eq. 3.

$$\vec{s}^k = -\bar{H}^k \, \vec{g}_p^{k^T} \left( \vec{g}_p^k \, \bar{H}^k \, \vec{g}_p^{k^T} \right)^{-1} \vec{g}^k \tag{3}$$

In eq. 3 the inverse of the Hessian matrix $\bar{H}$ can be assumed to be the identity matrix $\bar{I}$ (uniform weighting of all constraint violations) or will be updated in the optimisation loop by a DFP (Davidon-Fletcher-Powell) scheme. Step size $\alpha^k$ is assumed to be 1 (the restoration becomes then a Newton-Rapson-Scheme with quadratic convergence properties) or will be updated in the optimisation step. After successful restoration is obtained (final constraint violations are below a tolerance level), the optimisation step is initiated, in which search direction $\vec{s}^k$ is obtained by eq. 4 applying a modified cost function $\tilde{F}$ of eq. 5 combining the cost function formulated for the problem with the constraint violations $\vec{g}$ using Lagrange multipliers $\vec{\lambda}$ according to eq. 6.

$$\vec{s}^k = -\bar{H}^k \left( \bar{\vec{F}}_p^k \right) \tag{4}$$

$$\bar{\vec{F}}_p^k = \vec{F}_p^k + \vec{\lambda}^T \, \vec{g}^k \tag{5}$$

$$\vec{\lambda} = -\left( \vec{g}_p^k \, \bar{H}^k \, \vec{g}_p^{k^T} \right)^{-1} \vec{g}_p^k \, \bar{H}^k \, \vec{F}_p^k \tag{6}$$

Step size $\alpha^k$ is found by means of a 1-dimensional minimum search. A Golden Search algorithm is applied. After each optimisation step, the inverse Hessian can be updated with the DFP-formula. Optimisation steps are repeated until the improvement of the cost function is converged or the restoration step is initiated again if the constraint violations increase beyond a given limit.

### The Control Model

The function of the control model is to give a continuous time history of the vehicles attitude during the complete entry flight by only a set of few parameters. These are angle of attack and bank angle at in the case of X-38, but could also be a speed brake setting or in case of ascent flight a thrust vector. The number of parameters affects the computational effort for the flight path optimisation, because for each parameter a variation calculation has to be performed. The parameter model is defined in a velocity, Mach number or time frame. Velocity has proven to be advantageous compared to time, because we know initial and final velocity of the vehicle more or less exactly and time may vary in a great range, depending on cross and downrange conditions for different missions.

Actually the control models are using fixed grid points and the parameters only influence the value of an attitude angle at the given grid point. In case of reentry flight we are using either a linear or a piecewise constant model to interpolate the attitude between grid points (compare Fig. 3). A small number of model parameters is favoured for real time reasons, while a high number of parameters is preferred to reproduce complex control histories. For real flight application a compromise has to be found between both. If a complex parameter model is necessary but numerical performance is restricting the parameter number to only few, a load control module can be used to overwrite the guidance command in critical phases.

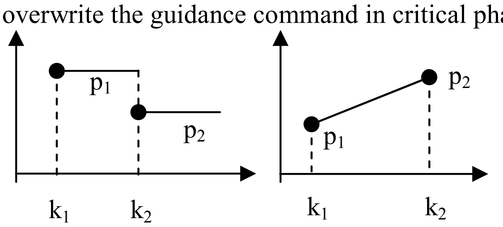


*Fig. 3: Principle of control model interpolation*

**The Load Control**

As depicted in *Fig. 1* the guidance command can be modified by a control element. This may become necessary if the trajectory is demanding to fly along any boundary constraint over a long time. The control module itself is a simple state tracker using navigated or model based information to e.g. control heat flux by bank angle modulation. This implicit method to control reentry leads to a hybrid guidance solution in combination with the explicit NLP-based approach.

**Guidance Algorithm Sequences**

The guidance is initiated with a complete optimisation of the flight path at the beginning of the considered flight phase or in the flight phase before, (i.e. in a coasting phase). This optimisation phase starts with the restoration loop to obtain a solution fulfilling all final constraints. Afterwards this solution is modified in the optimisation loop of the algorithm to minimise a cost function which is in most cases either a control effort or any load. If the modification of parameters by the optimisation loop become too large and the final constraints are not met any longer, the algorithm returns in the restoration loop, again. This initial sequence is repeated until convergence of final constraint satisfaction and minimisation of cost function is obtained.

During the guided flight phase itself, this initial solution is used as a reference for the control of the vehicle. Repeatedly flight path predictions are performed from the actual state of the vehicle to identify final constraint violations. If the predicted final constraint violations become too large, restoration steps are initiated again to compensate for these errors by modifying the parameters of the control model.

## 3 GUIDANCE ALGORITHM PERFORMANCE

The performance of the guidance algorithm is described in two steps. The first performance analysis discusses the general advantage of autonomous NLP based algorithms, promising a high flexibility and reliability. In a second step, the real performance on the basis of numerical simulations and Monte Carlo analysis is shown, applying the algorithm on the X-38 vehicle and mission.

### 3.1 General Performance Description

General performance is described under consideration of following main aspects:

- autonomy
- reliability / safety
- adaptability / applicability
- cost saving
- accuracy and mission constraint satisfaction

**Autonomy**

An autonomous guidance algorithm as described above is able to plan the trajectory on its own. The flight path optimisation at the initiation of the algorithm should be able to find an initial solution (reference solution) for the upcoming flight path, respecting all mission specific trajectory and final constraints as far as physically feasible. This reference solution would guide the vehicle to its destination within mission constraints if the models applied and environmental conditions assumed are exact and no disturbance occur in-flight. Due to the extend unpredictability of environmental conditions and uncertainties in vehicle properties, the regularly performed updates in-flight are necessary and compensate for insufficient and uncertain simulation models respectively. Autonomy is achieved due to the onboard implementation of the restoration loop. Further autonomy is gained because the restoration loop can also modify the control history given by the control model to guide the vehicle e.g. to a different landing site the change of which may become necessary during the reentry flight. Changes in the mission scenario have not to be addresses pre-flight due to the board autonomous flight planning. Thus mission changes are not restricted to calculated reference trajectories for only a few circumstances as in the case of currently used systems.

**Reliability and Safety**

Reliability and safety are the major design drivers for any guidance algorithm. In case of any onboard trajectory optimisation, a convergence problem may concern the safety of the vehicle. It has to be assured that there is always an initial solution. In the actual algorithm a very simple algorithm is used but offering a wide radius of convergence. This assures always an initial solution in the restoration step of the optimisation (as proven for X-38 Monte Carlo runs, see chapter 3.2). A further improvement during restorations steps in-flight is achieved starting with the initial solution to guide the vehicle to the desired landing site or way point. The drawback of the GPA algorithm used is its low convergence rate, taking up computational effort in the beginning. Otherwise, a very high convergence level is not intended due to that fact, that the initial solution will be modified during the flight anyway, due to differences of reality and predictor as well as disturbance.

In-flight, there is always a control history to control the vehicle trajectory in the computer memory, which is only updated if the restoration loop finds a better solution, thus if restoration fails due to any circumstances, there is still a proper guidance command left in the memory.

Safety is not only a relevant topic for the guidance in any nominal reentry flight but becomes even more an important part of the guidance algorithm if any occasion in the flight demands an abort or emergency scenario. While in other guidance approaches emergency scenarios have to be investigated in detail in advance to offer proper reference trajectories for any (or a majority of) cases, the discussed guidance algorithm does not need reference cases. Only path constraints and final constraints have to be rearranged do the emergency situation and a new optimisation step will find a new trajectory to be flown. The decision e.g. which landing site is to be chosen in case of an ascent abort, can be assessed by the onboard prediction routine for the modified vehicle properties by means of several flight path predictions to calculate the achievable area (the general application to ascent abort scenarios has already been performed with the example HOPPER in [7]).

**Adaptability and Applicability**

The terms adaptability and applicability refer to the capability of the algorithm to compensate for major changes in the vehicle configuration or even a different vehicle as well as different mission phases.

The capability for adaptability is important for safety and cost and has been addressed before in case of changes of landing site or flight path limitations.

The guidance concept itself is also applicable for different missions and vehicles. The guidance algorithm has been proved to be applicable to guide an ascent flight (shown for HOPPER) including the orbit insertion phase, was applied to an orbit transfer vehicle and for the reentry flight in the hypersonic and terminal area guidance phase for X-38 (next chapter). Actually it is applied to the HOPPER skip trajectory reentry and the terminal area guidance phase [5].

**Cost Saving**

While adaptability is important for safety reasons, applicability is reducing development cost if a new vehicle has to be guided. A further advantage is, that for nearly all mission phases of a future RLV the same core guidance system can be applied. Thus only one concept has to be developed, tested and verified, reducing further cost and also increasing safety. Personal, which are trained for the entry guidance scheme are also trained for the ascent guidance, because the same guidance scheme is used for different flight phases. In the operational costs, the autonomous algorithms are advantageous, because there is only minor pre-flight effort to prepare a mission, because all reference trajectories and control histories are generated and modified onboard and in real time.

**Accuracy and Mission Constraint Satisfaction**

The major task of any guidance algorithm is to guide the vehicle to its desired final state. Therefore not only the position of the vehicle has to be accurate but also its energy level (i.e. velocity and altitude) and heading. The accuracy of the fulfilment of these constraints is on the one side depending on the conformance of models used in the predictor, on the other hand the capability to compensate for any disturbances. If the control model is chosen properly, the algorithm will always obtain enough freedom to counteract deviations and leave a safety margin for upcoming disturbances. Thus accuracy is also depending on the proper choice of the number of parameters and control elements (e.g. in the terminal area guidance phase bank angle control alone is not satisfactory, but angle of attack has to be modulated and even speed brakes may be required). The fulfilment of load constraint (e.g. heat flux) is hardly depending on the number of parameters used. In case of very critical or sensitive constraints, a load controller can be applied as discussed previously. These load controllers performs very accurately in nominal cases, but may fail with modifications of the mission, which is a major drawback.

### 3.2 Example X-38 Reentry

Within the technology program TETRA, extensive work has been put onto the X-38 mission. One main topic was Guidance Navigation and Control. A high fidelity flight simulator CREDITS [8] was developed to test and verfy GNC algorithms. The guidance scheme introduced above was applied to X-38 and in parallel modern control algorithms have also been developed, applied and tested in combination with the guidance algorithm [9]. Therefore, CREDITS offers a real 6DOF fully dynamic (including actuators, thrusters) real time capable simulation environment, supporting Monte Carlo analyses with a high number of uncertainties and model deviations.

**Guidance Application to X-38**

The guidance algorithm was applied to the X-38 reentry mission, covering the atmospheric flight from 120km down to 7km altitude. The X-38 – a lifting body – offers a lift to drag ratio of about 0.95 in the hypersonic flight regime and 1.2-1.3 in the subsonic regime. For landing a parafoil system is used, deployed at an altitude of 7km (not discussed here). The mission was divided into two phases, the hypersonic reentry (120km – 24km altitude), the most important problem of which is the thermal load on the vehicle, and the terminal area guidance (TAG from 24 to 7km), which covers the supersonic to subsonic regime initiated. In the hypersonic flight phase bank angle was the only modulated command, while angle of attack was given as a function of Mach number. In the TAG phase the control model modulated angle of attack and bank angle. In both phases, bank angle was modelled in a velocity frame, angle of attack in the Mach number frame.

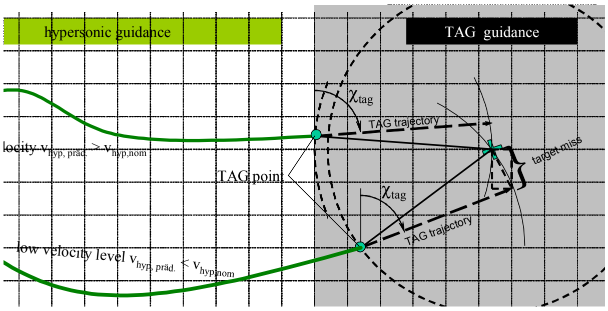


*Fig. 4: Flexible final constraint definition for the hypersonic guidance phase*

The final constraints for the hypersonic flight phase have been defined in an adaptive kind, to respect demands of the following TAG phase. The predicted state at the end of the hypersonic flight phase (prediction is terminated at an altitude of 24km) is extrapolated to a final state at 7km altitude. This approach depicted in *Fig. 4* renders the definition of any waypoint unnecessary, increasing the flexibility of the guidance algorithm. The extrapolation is obtained by starting at the predicted position of the vehicle in 24km altitude ($\lambda_{24}$, $\delta_{24}$) and adding a linear way section in the predicted heading in 24km altitude ($\chi_{24}$), the length (s, eq. 8) of which is calculated respecting the predicted flight path velocity ($v_{24}$) in 24km altitude. Using this method (see eq. 7) the extrapolated position at 7km altitude ($\lambda_7$, $\delta_7$) is compared to the target point defined to obtain the target miss.

$$\lambda_7 = \lambda_{24} + s \cdot \sin \chi_{24} \qquad (7)$$
$$\delta_7 = \delta_{24} + s \cdot \cos \chi_{24}$$

$$s = f_{scale} \cdot v_{24} \qquad (8)$$

In fact, a way point is automatically defined to be the target point of the hypersonic flight (called TAG point), which can move during the reentry flight to be an optimal way point. The point will be located on a circle around the final target point, the radius of which is s (eq. 8), varying with predicted velocity. This offers the possibility, that if the vehicle has a high energy (i.e. velocity) in 24km the following TAG flight is assumed to be at a longer distance and the TAG point is moved further away from the target point and closer if the predicted velocity of the vehicle is low. The position of the TAG point on the circle in turn is dependent on the flight path azimuth in such a manner that at 24km the vehicle is always heading to the landing point. A further improvement or safety margin can be obtained, if a miss pointing $\Delta\chi$ is added to the predicted heading to force not a straight but turning flight in the TAG. If this is implemented the scaling factor $f_{scale}$ (eq. 8) has to be adapted to compensate the downrange loss. The final constraint of the TAG phase is target miss in longitude and latitude during the optimisation loops. For the restoration loops in the TAG flight phase, the absolute target miss (distance to target) is used while additionally the velocity error at 7km altitude is respected in TAG restorations. Bank angle control effort is chosen as cost function in the hypersonic guidance while for TAG optimisation the final velocity of the vehicle to assess drogue chute deployment is applied. Additionally a heat flux controller was applied for the hypersonic guidance phase.

**Simulation Results**

For nominal flight conditions all mission constraints are fulfilled within allowable tolerances. The bank angle control history is depicted in *Fig. 5* showing also the initial solution of the optimisation step. It can clearly be seen, how the control profile is changed by the restoration routine, if the heat flux controller is overruling the bank command of the control model.

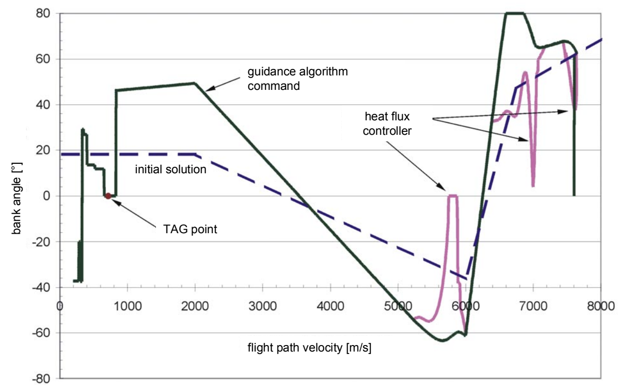


*Fig. 5: Modifications of initial bank angle control history by restoration steps*

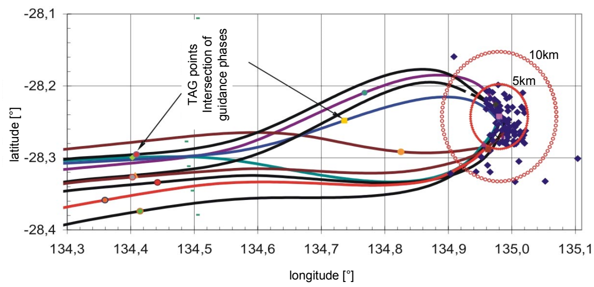


*Fig. 6: Target accuracy (inner circle 5km outer 10km)*

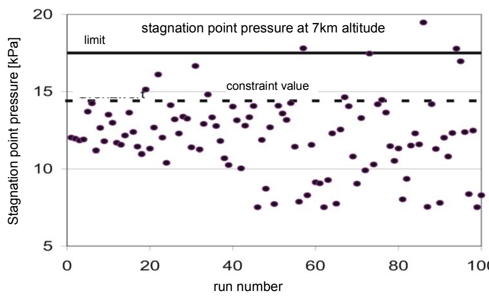


*Fig. 7: Accuracy of final stagnation point pressure*

The performance in non-nominal cases has been evaluated in Monte Carlo runs applying uncertainties and deviation in atmosphere, aerodynamic, navigation and vehicle mass. The results (*Fig. 6* shows the final position of the vehicle in 100 Monte Carlo runs) show a mission success (final position within the 10km circle requirement) of over 95%, while still some Monte Carlo cases are not very realistic. As one can see from the ground tracks (only 10 are depicted), target approach is achieved from different directions according to flight conditions and optimal criteria. The accuracy of the stagnation point pressure at the initiation of the parafoil system is depicted in *Fig. 7*. Excluding a few extremes, it is well fulfilled. The heat flux controller worked well also. A higher heat flux is in some cases (e.g. a higher vehicle mass) not avoidable, but still violations are in the range of 2-3% of the nominal value, only.
The flexibility of the algorithm is depicted in *Fig. 8*, where the ground track obtained for different initial entry conditions and for several different landing sites are shown, always using the unmodified guidance algorithm.

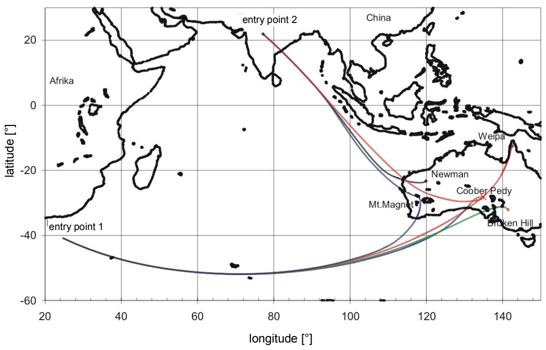


*Fig. 8: Ground tracks for different entry states and landing sites*

## 4 SUMMARY

An onboard autonomous NLP-based guidance algorithm has been developed at IRS intended to be applied to a complete RLV mission including ascent and return flight as well covering abort guidance and emergency scenarios. It offers a high degree of autonomy and self solving capability due to its NLP onboard trajectory optimisation which is necessary to obtain cost saving as well as safety and flexibility options in future RLV applications. Still, onboard computer performance is restricting the use of very complex optimisation algorithms within the guidance loop. This problem has to be overcome by either simplification in the models used in the flight path predictor or by applying control modes which lack the adaptability the guidance algorithm itself is offering. Further improvements of onboard computers may help to overcome these problems.
The algorithm was successfully applied and Monte-Carlo tested for the X-38 reentry mission. Simulation results show in general good performance comparable to other X-38 simulations published.
The greatest advantage has become obvious when different entry states or landing sites are chosen. The algorithms adapts automatically without intervention by the user. However the control model for the load control also showed a disadvantage to be overcome.
Further work applying the algorithm to the complete HOPPER mission has been started and shows very promising results. The HOPPER mission is difficult in a special kind, because ascent and descent are related to each other directly and the entry flight includes a skip phase. Additionally abort scenarios are also under investigation.

**Acknowledgments**
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