Chapter 17
Multi-objective 4D Trajectory Optimization for Online Strategic and Tactical Air Traffic Management

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Abstract Significant evolutions of aircraft, airspace and airport systems design and operations are driven by the continuous increase of air transport demand worldwide and by the concurrent push for a more economically viable and environmentally sustainable aviation. In the operational context, novel avionics and air traffic management (ATM) systems are being developed to take full advantage of the available communication, navigation and surveillance (CNS) performance. In order to attain higher operational, economic and environmental efficiencies, the generation of 4-dimensional trajectories (4DT) shall integrate optimisation algorithms addressing multiple objectives and constraints in real-time. Although extensive research has been performed in the past on the optimisation of aircraft flight trajectories and very efficient algorithms were widely adopted for the optimisation of vertical flight profiles, it is only in the last few years that higher levels of integration were proposed for automated 4DT planning and rerouting functionalities. This chapter presents the algorithms conceived for integration in next generation avionics and ATM Decision Support Systems (DSS), to perform the multi-objective optimisation of 4DT intents. In particular, the algorithms are developed for 4DT planning, negotiation, and validation (4-PNV) in online strategic and tactical operational scenarios, and are conceived to assist the human flight crews and ATM operators in planning and reviewing optimal 4DT intents in high air traffic density contexts. The presented implementation of the multi-objective 4DT optimisation problem includes a number of environmental objectives and operational constraints, also accounting for economic and operational performances as well as weather forecast information from external sources. The current algorithm verification activities address the Arrival

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Manager (AMAN) scenario within a Terminal Manoeuvring Areas (TMA), featuring automated point-merge sequencing and spacing of multiple arrival traffic in quasi real-time.

17.1 Introduction

In order to achieve the ambitious objectives set by national and international organisations for capacity, efficiency, sustainability and safety of flight operations in the future, substantial technological and operational evolutions are required. A key area of improvement for attaining the higher capacities necessary to cope up with the steady growth of air transport demand and at the same time to enhance the levels of safety, efficiency and sustainability of flight operation consists in the adoption of 4-dimensional trajectory (4DT) functionalities in an intent-based operations (IBO) environment (The ATM Target Concept—D3 2007). The conventional operational paradigms involving the manual dispatch via voice communications of route clearances consisting of a limited set of flight path descriptors are in fact constraining the available capacity and affecting operational efficiencies in an ever-growing number of airspace regions. Furthermore, voice communication channels are quickly saturating the available aeronautical very high frequency (VHF) spectrum in high air traffic density areas. Data-link communications feature a more efficient exploitation of the available aeronautical radio spectrum, and enable a secure high-integrity and seamless networking and extensive information sharing. An automation-assisted planning and negotiation/validation of 4DT intents will permit the full exploitation of the enhanced navigation and surveillance performances provided by modern ground, avionics and satellite-based systems, as it will be natively capable of processing more complex route clearances and higher amounts of shared information supplied by data-link communications, presenting them to the human operators in user-friendly formats. In order to operationally deploy the 4DT-IBO functionalities, novel avionics and air traffic management (ATM) systems are required. These advanced airborne and ground-based decision support systems (DSS) will assist human operators in the generation, validation, execution and monitoring of optimised 4DT intents in real-time. Enhanced traffic separation and spacing standards will be made available in high performance communication, navigation and surveillance (CNS) airspace regions, thanks to the extensive deployment of 4DT capabilities. In particular, two DSS are being developed at present to implement 4DT-IBO: a Next Generation Flight Management Systems (NG-FMS) for manned and unmanned aircraft, and the 4DT planning, negotiation and validation (4-PNV) assisting ATM operators on the ground. (Sabatini et al. 2015; Gardi et al. 2015; Ramasamy et al. 2015). In order to promote a higher efficiency and environmental sustainability of flight operations, the generation and negotiation of 4DT shall integrate multi-objective trajectory optimisation (MOTO) software algorithms, addressing all environmental and economic impacts of the generated trajectories. MOTO algorithms are thereby a key feature of avionics and ATM DSS in the future. This chapter reviews the state-of-the-art of trajectory optimization for aviation applications and presents the customised MOTO algorithm that was developed to meet the stringent requirements of online strategic and tactical ATM timeframes. The MOTO algorithm attempts the optimisation of the planned flight path with respect to multiple objectives and constraints and is based on the timeframe convention for offline and online air traffic operations previously adopted (Gardi et al. 2014). The adopted formulation of the multi-objective 4D trajectory optimisation (MOTO-4D) problem includes a number of environmental objectives and operational constraints such as flight time, fuel consumption, multiple engine emissions, noise and contrails. The novel avionics and ATM DSS are capable of generating multiple intents in real-time based on a set of environmental performance criteria, allowing more sustainable air traffic operations.

17.2 Statement of the Problem

A number of operational aspects and environmental impacts associated with the aircraft mission have significant dependencies on the flown trajectory (Gardi et al. 2016). On-board trajectory optimisation algorithms were investigated as early as the 1970s (Sorensen et al. 1979), and deployed in larger civil transport aircraft during the following two decades in the form of new automatic flight and flight director modes for most phases of flight, targeting in particular the vertical guidance and optimised standard turns. Although the savings derived from these measures were very significant with respect to the previous operational paradigms, it has been proposed that more substantial gains can be attained by adopting real-time optimisation algorithms for strategic and tactical replanning of 4D flight trajectories in an intent-based network-centric ATM scenario. Figure 17.1 represents the concept of MOTO to tackle multiple operational, economic and environmental criteria in the aviation context. In order to obtain optimal 4D intents with respect to the set optimality objectives, the MOTO suite comprises a number of essential aircraft, environmental and operational models. These models include local/global weather, operational costs, pollutant emissions, airspace structure, contrails and aircraft noise. As the emphasis is on the noise perceived by the population on the ground, the aircraft noise model must be complemented by suitable demographic distribution and digital terrain elevation databases.

Significant research activities and outcomes on multi-objective 4DT optimisation algorithms are being achieved as part of the major research programmes worldwide. The progresses in optimal control theory and nonlinear programming for trajectory optimisation are leading to substantial improvements to the numerical solution methods for real-time applications. A considerable opportunity for direct

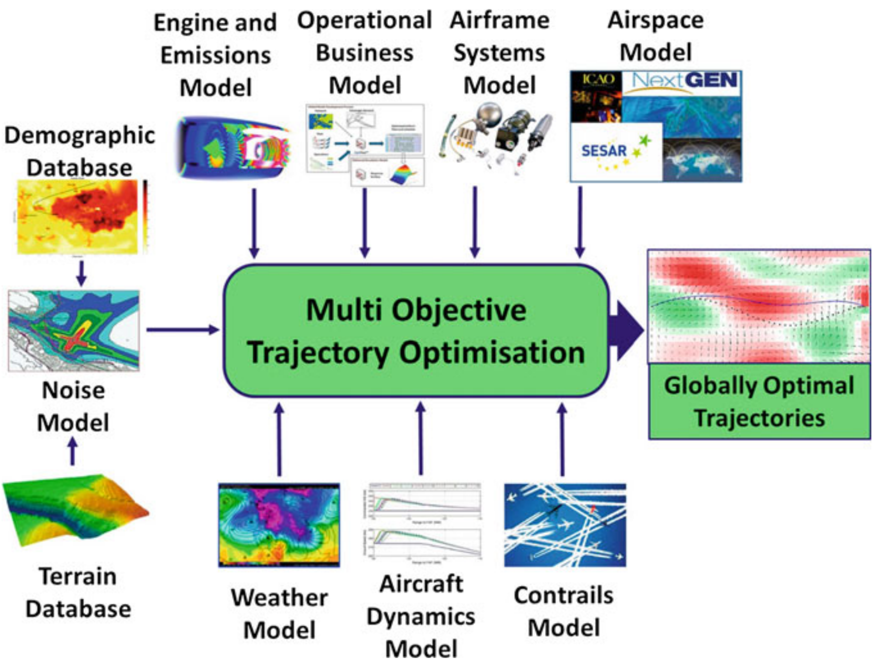

Fig. 17.1 Multi-objective trajectory optimisation concept (Sabatini et al. 2014)

exploitation of these research outcomes into the next generation avionics and ATM systems is emerging. The adoption of computational algorithms for optimal 4DT planning represents a substantial evolution from the conventional flight planning methodologies currently in place and their associated limitations. The conventional flight plan is, in fact, an essentially static entity, hence unforeseen weather and air traffic perturbations have the effect of progressively compromising its optimality. Furthermore, only fuel and time costs are normally considered in traditional optimisation methods. Reducing fuel consumption leads to reduced carbon dioxide (CO_2) emissions with current generation turbofan engines but, unfortunately, most of the noxious emission such as carbon monoxide (CO), nitrogen oxides (NO_X) and unburnt hydrocarbons (UHC) are not typically addressed. Growing R&D efforts are therefore addressing practical implementations of real-time trajectory optimisation algorithms as well as pollutant and noise emission models for the optimization of flight trajectories with respect to multiple objectives, while encompassing constraints that also entail strategic and tactical ATM and air traffic flow management (ATFM) directives in an evolving airspace (Visser and Wijnen 2001; Jardin 2003; Wijnen and Visser 2003; Hartjes et al. 2009; Torres et al. 2009; Soler et al. 2010; Sridhar et al. 2011; Vaddi et al. 2012).

17.3 Mathematical Formulation

Although different formulations of the trajectory optimisation problem (TOP) were adopted for aeronautical applications, partly due to the considerable dependence on geographic descriptors to characterise the flight path in three dimensions, in the mainstream literature a considerable emphasis is given to the optimal control problem (OCP) formulation. This is mainly due to the consideration of the aircraft as a dynamical system and to the conspicuous mathematical framework guaranteeing the optimality of theoretical optimal control results. The theoretical framework of optimal control and its application to aerospace vehicles and systems is extensively presented in Ben-Asher (2010) and Betts (2010). Adopting the formulation of Bolza, the TOP is analytically stated as (Rao 2010a):

> *"Determine the states* $\boldsymbol{x}(t) \in \mathbb{R}^n$*, the controls* $\boldsymbol{u}(t) \in \mathbb{R}^m$*, the parameters* $\boldsymbol{p} \in \mathbb{R}^q$*, the initial time* $t_0 \in \mathbb{R}$ *and the final time* $t_f \in \mathbb{R} |\ t_f > t_0$*, that optimise the performance indexes*
>
> $$\boldsymbol{J} = \boldsymbol{\Phi}\left[\boldsymbol{x}\left(t_f\right), \boldsymbol{u}\left(t_f\right), \boldsymbol{p}\right] + \int_{t_0}^{t_f} \mathcal{L}[\boldsymbol{x}(t), \boldsymbol{u}(t), \boldsymbol{p}]\mathrm{d}t \quad (17.1)$$
>
> *subject to the dynamic constraints*
>
> $$\dot{\boldsymbol{x}}(t) = \boldsymbol{f}[\boldsymbol{x}(t), \boldsymbol{u}(t), t, \boldsymbol{p}] \quad (17.2)$$
>
> *to the path constraints*
>
> $$\boldsymbol{C}_{\min} \leq \boldsymbol{C}[\boldsymbol{x}(t), \boldsymbol{u}(t), t; \boldsymbol{p}] \leq \boldsymbol{C}_{\max} \quad (17.3)$$
>
> *and to the boundary constraints*
>
> $$\boldsymbol{\Phi}_{\min} \leq \boldsymbol{\Phi}\left[\mathbf{x}(\mathrm{t}_0), \mathbf{x}\left(\mathrm{t}_f\right), \mathbf{u}(\mathrm{t}_0), \mathbf{u}\left(\mathrm{t}_f\right); \mathbf{p}\right] \leq \boldsymbol{\Phi}_{\max}{''} \quad (17.4)$$

For the solution of TOP, two mainstream strategies have been extensively investigated in the literature, namely *direct methods* and *indirect methods* (von Stryk and Bulirsch 1992; Visser 1994; Betts 1998; Rao 2010b). In the first class, also defined by the paradigm "*discretise then optimise*" the determination of the unknown control function is attempted directly, and this involves the discretisation of the infinite-dimensional TOP into a finite-dimensional nonlinear programming (NLP) problem. In the indirect methods, which historically emerged beforehand and are defined by the paradigm "*optimize then discretise*", analytical manipulations based on the theory of the calculus of variations are exploited to transform the OCP into a nonlinear boundary value problem (BVP).

17.3.1 Numerical Solution

Due to their higher versatility and to the recent emergence of very efficient computational implementations, direct solution methods are currently favoured in a considerable number of applications. The transcription into finite-dimensional NLP problem can be performed either by introducing a control parameterisation based on arbitrarily chosen analytical functions, as in *transcription* methods, or by adopting a generalised piecewise approximation of both control and state variables based on a polynomial sequence of arbitrary degree, as in *collocation* methods. In both cases, the transcribed dynamical system is integrated along the time interval $[t_0; t_f]$. The search of the optimal set of discretisation parameters is formulated as a NLP problem, which is solved computationally by exploiting the most efficient numerical NLP solution algorithms available. In direct transcription methods, a basis of known linearly independent functions $q_k(t)$ with unknown coefficients $\boldsymbol{a}_k$ is adopted as the parameterisation in the general form:

$$z(t) = \sum_{k=1}^{N} \boldsymbol{a}_k q_k(t) \tag{17.5}$$

Considerable research on computationally efficient TOP solution algorithms based on direct transcription and collocation was performed in the last two decades (Betts and Cramer 1995; Betts and Huffman 1998, 1999, 2004; Betts et al. 2000, 2002, 2007; Gherman et al. 2006; Engelsone et al. 2007; Benson et al. 2006; Huntington and Rao 2008; Garg et al. 2010, 2011; Rao et al. 2010; Darby et al. 2011a, b; Patterson and Rao 2012). Although most diverse implementations of direct solution methods are currently researched and developed, global orthogonal collocation methods are considered the state-of-the-art for the solution of large nonlinear OCP, particularly on longer timeframes, and show remarkable computational performances, provided the constraints are carefully defined and the initial guess supplied to the algorithm lies sufficiently close to the global convergence region. In global collocation methods, the direct solution of the OCP is attempted by enforcing the evaluation of the state and control vectors in discrete collocation points across the problem domain by means of orthogonal (spectral) polynomial basis functions. Since pseudo-spectral methods were developed from this very principle, global orthogonal collocation methods are also widely known as pseudo-spectral optimal control methods or simply pseudo-spectral methods (PSM). These methods consist in the following steps. The original time variable is replaced by the scaled and normalised $\tau \in [-1, 1]$ as in:

$$t = \frac{t_f - t_0}{2}\tau + \frac{t_f + t_0}{2} \tag{17.6}$$

The differential operator is consequently modified as follows:

$$\frac{\mathrm{d}}{\mathrm{d}t} = \frac{2}{t_f - t_0}\frac{\mathrm{d}}{\mathrm{d}\tau} \tag{17.7}$$

If the final time is not known a priori (i.e. it is either unconstrained or inequality-constrained in the boundary conditions), t_f will be an additional unknown variable to be determined by the NLP solver. The states and control variables of the OCP are approximated by a set of polynomials of order N, and the problem is thereby discretised in $N + 1$ nodes. These interpolation polynomials must be an orthogonal basis in the discretised space. Hence, they have to satisfy the null scalar product property:

$$P_i\left(x_j\right) * P_k(x_l) = 0 \quad \forall i \neq j,\ \forall k, l \in \{1, \ldots N + 1\} \tag{17.8}$$

Various families of interpolating polynomials can be successfully adopted and comprehensive dissertations may be found in Boyd (2000) and Funaro (1992). At present, the most computationally efficient implementations of PSM adopt simple interpolation polynomials in conjunction with a careful selection of the collocation nodes distribution. For such reasons, the basic Lagrange polynomials are most frequently adopted for the interpolation of states and controls. A Gaussian quadrature rule ensures the exact results of discrete integral evaluations. Adopting the interpolation polynomials $P_k(\tau)$ on the $N + 1$ nodes τ_k, the states are approximated as:

$$\tilde{x}_i(\tau) = \sum_{k=1}^{N} \tilde{x}_i(\tau_k) \cdot P_{i,k}(\tau) \tag{17.9}$$

and the controls are approximated as:

$$\tilde{u}_j(\tau) = \sum_{k=1}^{N} \tilde{u}_j(\tau_k) \cdot P_{j,k}(\tau) \tag{17.10}$$

The evaluation of the dynamic constraints (i.e. the state equations) is then performed in the nodes only, leading to a problem of finite dimensions. The dimension of the discrete problem is not the same in all cases, though. Lagrange polynomials of order N are expressed as:

$$P_k(\tau) = \prod_{j \neq k} \frac{\tau - \tau_j}{\tau_k - \tau_j}, \quad \forall j \in [0, N] \tag{17.11}$$

Chebyshev pseudo-spectral methods (CPM) adopt Chebyshev polynomials of order N. An application of the CPM to aircraft dynamics is discussed in Bousson and Machado (2010) and involves the evaluation of the Chebyshev trigonometric polynomials:

$$P_N(\tau) = \cos\left(N \cos^{-1} \tau\right) \tag{17.12}$$

in the $N + 1$ nodes:

$$\tau_k = \cos\frac{k\pi}{N}, \quad k \in [0, N]. \tag{17.13}$$

Two recently adopted PSM variants are the Gauss PSM and the Legendre–Gauss–Lobatto (LGL) PSM (Basset et al. 2010). Gauss PSM are based on the Gauss–Legendre quadrature, whereas the LGL PSM are based on the LGL quadrature, also simply known as Lobatto quadrature. Gauss PSM are specifically conceived to ensure that the Karush-Kuhn-Tucker (KKT) conditions are identical to the discretised first-order optimality conditions. Legendre polynomials may be calculated by using the Rodrigues formula:

$$P_N(\tau) = \frac{1}{2^N k!} \frac{\mathrm{d}^{(N)}}{\mathrm{d}\tau^{(N)}} \left[\left(\tau^2 - 1\right)^N\right] \tag{17.14}$$

The LGL nodes are the $N + 1$ zeros of the polynomial:

$$L_N(\tau) = \left(1 - \tau^2\right) \dot{P}_N(\tau) \tag{17.15}$$

where $\dot{P}_N(\tau)$ is the first derivative of the Legendre polynomial of degree N (Brix et al. 2013).

In Gauss PSM, the dynamic constraints are not collocated at the boundary nodes, whereas in the LGL PSM the evaluation of states and controls is performed also at the boundary nodes, thereby the dimension of the NLP problem is increased by two additional nodes. For further reference the reader may refer to Rao (2010b) and Rao et al. (2010).

17.3.2 MOTO-4D Algorithm Implementation

The real-time MOTO-4D algorithms implemented in the 4-PNV system adopt the same dynamic and path constraints implemented in the NG-FMS (Ramasamy et al. 2015). Aircraft dynamics data are shared between the NG-FMS and the 4-PNV through the Next Generation Aeronautical Data-Links (NG-ADL), along with the relevant aircraft and airspace information, to ensure synchronisation and, consequently, mathematical consistency. In order to characterise the flyable envelope of the aircraft, a flight dynamics model is adopted as part of the dynamic constraints in the OCP formulation. The three degrees of freedom (3DOF) point-mass model with variable mass traditionally adopted as flight dynamics in NG-FMS and 4-PNV is:

$$\dot{\boldsymbol{x}} = \begin{cases} \dot{v} = \frac{\tau \cdot T_{\mathrm{MAX}} - D}{m} - g \sin\gamma \\ \dot{\gamma} = \frac{g}{v} \cdot \left(N \cos\mu - \cos\gamma \right) \\ \dot{\chi} = \frac{g}{v} \cdot \frac{N \sin\mu}{\cos\gamma} \\ \dot{\phi} = \frac{v \cos\gamma \sin\chi + v_{w_\phi}}{R_E + z} \\ \dot{\lambda} = \frac{v \cos\gamma \cos\chi + v_{w_\lambda}}{(R_E + z)\cos\phi} \\ \dot{z} = v \sin\gamma + v_{w_z} \\ \dot{m} = -FF \end{cases} \tag{17.16}$$

where v is the true airspeed, $\boldsymbol{v_w}$ is the wind velocity vector, γ is the flight path angle, χ is the track angle, m is the aircraft mass, ϕ λ and z are, respectively, the geodetic latitude, longitude and altitude, g is the gravity acceleration, R_E is the geodetic Earth radius, D is the aircraft drag, T_{CL} is the maximum climb thrust. The control variables are $\boldsymbol{u} = \{N, \tau, \mu\}$, which, respectively, represent the load factor, the throttle and the bank angle. The drag is calculated with the conventional parabolic approximation as:

$$D = \frac{1}{2}\rho v^2 S C_{D0} + \frac{2 C_{D2} m^2 g^2}{\rho\, v^2 S} \tag{17.17}$$

where ρ is the local air density, and S, C_{D0}, C_{D2}, respectively, represent the aircraft reference area and the two parabolic drag coefficients. These parameters are typically available for the most commonly flown aircraft, and for instance may be obtained from the Eurocontrol's Base of Aircraft Data (BADA) database. The drag coefficient increases to account for flaps and landing gear are also available (BADA 2013). Adopting the formulation from BADA, the maximum climb thrust and the fuel flow of a turbofan engine are calculated as (BADA 2013):

$$T_{\mathrm{CL}} = C_{T1} \cdot \left(1 - \frac{H_P}{C_{T2}} + C_{T3} \cdot H_P^2 \right) \cdot \left[1 - C_{T5} \cdot (\Delta T - C_{T4}) \right] \tag{17.18}$$

$$FF = \max\left[\tau\, C_{f1} \left(1 + \frac{v_{\mathrm{TAS}}}{C_{f2}} \right), C_{f3} \left(1 - \frac{H_P}{C_{f4}} \right) \right] \tag{17.19}$$

where $C_{T1} \ldots C_{T5}, C_{f1} \ldots C_{f4}$ are the thrust and fuel flow coefficients from the BADA empirical models (BADA 2013). The emission of a generic gaseous pollutant (GP) is modelled as:

$$\mathrm{GP} = \int_{t_0}^{t_f} EI_{\mathrm{GP}} \cdot FF \, \mathrm{d}t \; [\mathrm{Kg}] \tag{17.20}$$

The specific CO and UHC emission indexes are empirically modelled as:

$$\mathrm{EI}_{\mathrm{CO/UHC}} = c_1 + \exp(-c_2\tau + c_3) \; [\mathrm{g/Kg}] \tag{17.21}$$

Similarly, the $\mathrm{NO_X}$ emission index is empirically modelled as:

$$\mathrm{EI}_{\mathrm{NO_X}} = c_1\tau^2 + c_2\tau + c_3 \; [\mathrm{g/Kg}] \tag{17.22}$$

Equations (17.6) and (17.7) are accurate nonlinear fit of the ICAO Emissions Databank.[1] The fitting parameters $c_{1,2,3}$ accounting for the pollutant emissions of 165 currently operated civil turbofan engines which are $\boldsymbol{c} = \{0.556, 10.21, 4.068\}$ for CO, $\boldsymbol{c} = \{0.083, 13.2, 1.967\}$ for UHC and $\boldsymbol{c} = \{7.32, 17.07, 3.53\}$ for $\mathrm{NO_X}$. Linearized models can be introduced to enhance computational performance when required.

17.3.3 Multi-objective Optimality

In line with the requirements for online tactical replanning, the weighted sum method, belonging to the category of a priori articulation of preferences, is adopted for the identification of a combined performance index $\boldsymbol{J}$ (Gardi et al. 2014; Marler and Arora 2004). The a priori multi-objective optimisation approach is conceptually represented in Fig. 17.2. The performance weightings can be dynamically modified along the flight and as part of an ongoing collaborative decision-making (CDM) process between the AOC and ANSP when required. multiple optimal 4DT are generated on-board each traffic, and then using a rule-based algorithm, a conflict free set of trajectories is found for all aircraft.

17.4 4DT Optimisation Algorithm

The numerical algorithm for the solution of the single (combined) objective optimal control problem is represented in Fig. 17.3. A mathematically optimal 4DT is generated by means of a numerical solver based on a direct method of the family of

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[1] ICAO. ICAO Aircraft Engine Emissions Databank [Online]. Available http://easa.europa.eu/node/15672.

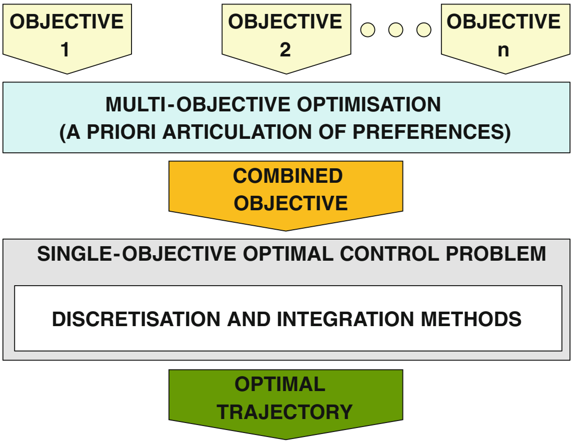


Fig. 17.2 Block diagram of multi-objective optimisation with a priori articulation of preferences (Gardi et al. 2014)

global orthogonal collocation (pseudo-spectral). This 4DT is a discretised version of a continuous/piecewise smooth (CPWS) curve, which in general may not be flyable by human pilots nor by conventional automatic flight control systems (AFCS), as it includes transition manoeuvres involving multiple simultaneous variations in the control inputs. Moreover, the discretised CPWS consists of a very high number of overfly 4D waypoints, which would have unacceptable impacts on the Next Generation Airborne Data-Link (NG-ADL) bandwidth usage. Therefore, an “operational smoothing” post-processing stage is introduced, which employs manoeuvre identification algorithms to segment the trajectory in conventional flight legs, including straight and level flight, straight climbs and descents, level turns, and climbing/descending turns. The final result is a concisely described 4DT consisting of operationally feasible flight segments.

17.5 Simulation and Results

The sequencing of dense arrival traffic towards a single approach procedure was extensively evaluated as a representative case study of online tactical Terminal Manoeuvring Area (TMA) management. The results of one representative simulation run are depicted in Fig. 17.4. The 4-PNV identifies the best arrival sequence among the available options. Longitudinal separation is enforced at the merge-point to ensure sufficient separation upon landing and to prevent separation infringements in the approach phase itself. The 4-PNV is capable of performing point-merge at

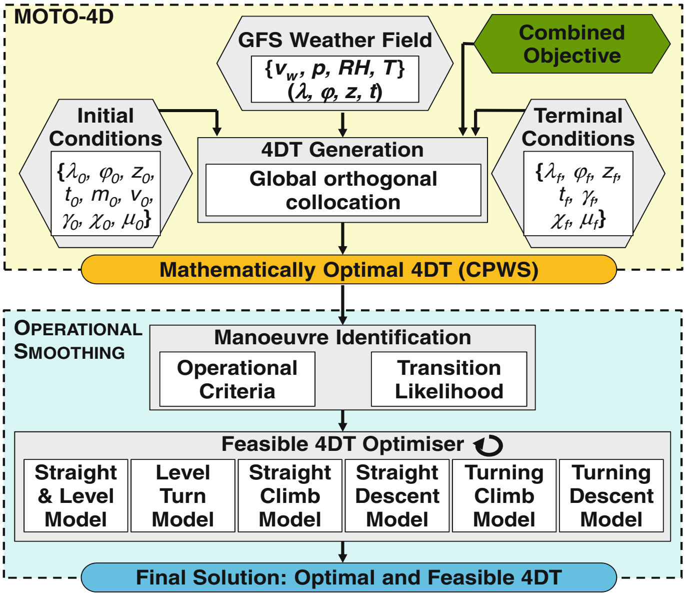


Fig. 17.3 Diagram of the MOTO-4D algorithm (Gardi et al. 2015)

any metering point. After the initial intents have been stored in the 4-PNV, the point-merge sequencing algorithm allocates the available time slots accordingly. The assumed minimum longitudinal separation is 4 nautical miles on the approach path for medium category aircraft approaching at 140 knots. Therefore, the generated time slots are characterised by a 90–160 s separation depending on the wake-turbulence categories of two consecutive traffics.

Figure 17.5 depicts the computed 4DT in the Arrival Manager (AMAN) schedule display format. Waypoints and lines depicted in magenta represent the flyable and concisely described 4DT consisting of a limited number of fly-by and overfly 4D waypoints, obtained through the smoothing algorithm.

Monte Carlo simulation was performed, resulting in an average of 41 s for single newly generated 4DT intents (and consistently less than 60 s). The 4DT post-processing allowed to reduce discretised CPWS trajectories of 150–450 points into a number of fly-by and overfly 4D waypoints consistently below 20. These results meet the set design requirements for tactical online data-link negotiation of the 4DT intents.

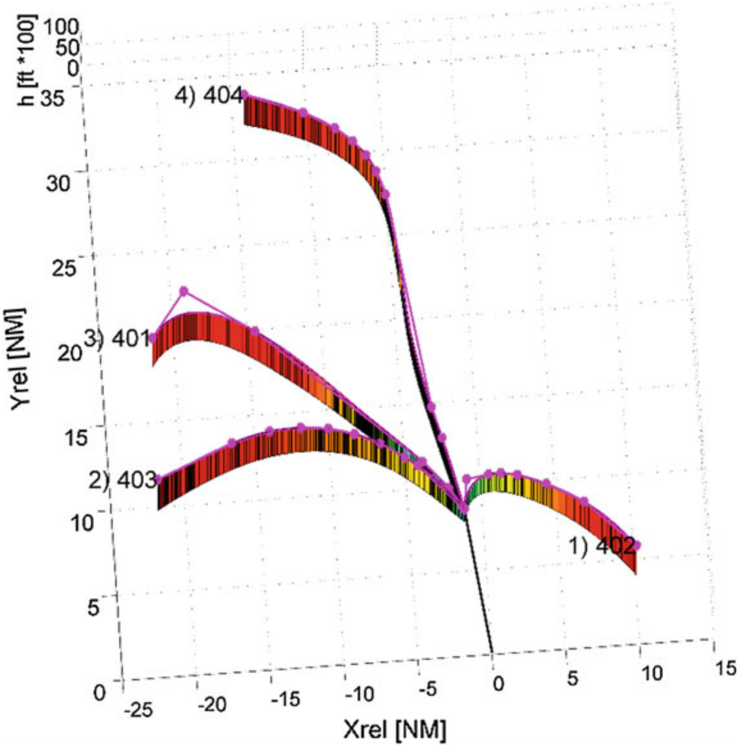
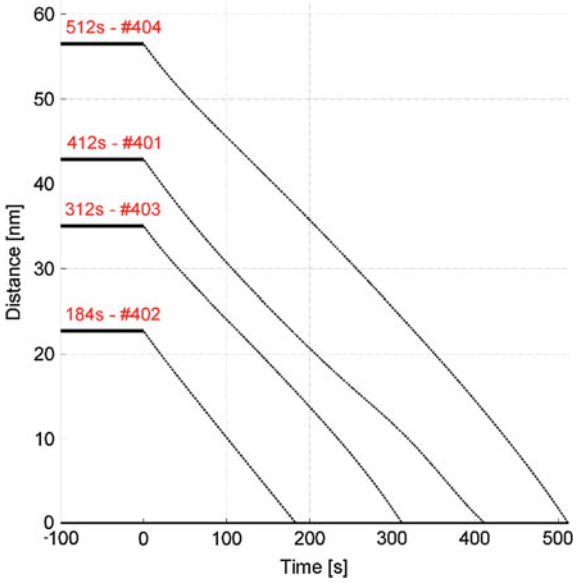


Fig. 17.4 Results of the 4-PNV exploiting the operational 4DT smoothing

Fig. 17.5 Traffic sequencing represented in an AMAN scheduler plot



17.6 Conclusions

This chapter presented the key aspects of Multi-objective Trajectory Optimisation (MOTO) currently being developed for integration in future airborne avionics and ground-based air traffic management (ATM) decision support systems (DSS). The MOTO algorithms are specifically conceived to reproduce the dependency of various aircraft emissions on its particular 4-dimensional flight trajectory (4DT) in space and time, to ultimately improve the environmental sustainability of air traffic, while at the same time enhance the operational and economic performances. The presented MOTO algorithms are at the core of 4DT planning functionalities in the novel avionics and ATM systems, which are the Next Generation Flight Management System (NG-FMS) for manned and unmanned aircraft, and the 4DT Planning, Negotiation and Validation (4-PNV) system on the ground. The MOTO functionalities are designed to meet the stringent requirements for strategic and tactical online air traffic operations in the presence of dense air traffic, whenever airspace or air traffic reorganisation is required due to dynamically changing conditions. The chapter presented a number of MOTO algorithm design aspects and some algorithm verification activities involving sequencing and spacing of arrival traffic within a Terminal Manoeuvring Area (TMA). These simulation activities consistently meet the requirements set for online tactical routing/rerouting tasks, generating 4DT intents consisting of a limited number of overfly and fly-by waypoints. Future verification activities will address the en-route ATFM context, also implementing the Dynamic Airspace Management (DAM) functionalities currently being researched.

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