Control of Future Air Traffic Systems via Complexity Bound Management

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The complexity of the present system for managing air traffic has led to "discreteness" in approaches to creating new concepts: new concepts are created as point designs, based on experience, expertise, and creativity of the proposer. Discrete point designs may be highly successful but they are difficult to substantiate in the face of equally strong substantiation of competing concepts, as well as the state of the art in concept evaluation via simulations. Hybrid concepts may present a compromise – the golden middle. Yet a hybrid of sometimes in principle incompatible concepts forms another point design that faces the challenge of substantiation and validation. We are faced with the need to re-design the air transportation system *ab initio*. This is a daunting task, especially considering the problem of transitioning from the present system to any fundamentally new system. However, design from scratch is also an opportunity to reconsider approaches to new concept development. In this position paper we propose an approach, Optimized Parametric Functional Design, for systematic development of concepts for management and control of airspace systems, based on optimization formulations in terms of required system functions and states. This reasoning framework, realizable in the context of *ab initio* system design, offers an approach to deriving substantiated airspace management and control concepts. With growing computational power, we hope that the approach will also yield a methodology for actual dynamic control of airspace.

I. Introduction

Large technological systems, such as the air transportation system and the Internet, have never been designed. They evolved incrementally, in response to stimuli. Reactions to accidents have been especially instrumental in advancing the technical development of the air transportation system. However, the incremental evolutionary approach to improving the air transportation system – a highly complex network of diverse interacting systems – no longer suffices in the face of growing demand and the changing nature of airspace. Dramatic future increases in commercial passenger demand are arguable when viewed in light of upcoming advances in realistic immersive telepresence. However, the need to ensure airspace access for enormous numbers and variety of autonomous safely coexisting vehicles with independent, cooperative, and non-cooperative missions appears necessary and imminent. Human control places hard bounds on feasible directions available for incremental system development. A need for active and rigorous *ab initio* system design methods is becoming evident.

In this position paper, we propose a methodology for approaching design of the transportation system from scratch.

Needless to say, designing an air transportation system *ab initio* is an immensely difficult undertaking. A detailed list of the technical gaps in bringing about a completely new system is outside the scope of this paper. We mention only several difficulties salient to the present methodological discussion.

Traditional active design of complex engineered systems necessitates identification of independent (design) variables, objectives, and constraints whose functional dependence on the design variables has been established analytically and experimentally. In other words, active design requires predictive models. Agent-based approaches (see, e.g., Meyn et al.[1]) form the state of the art in modeling airspace dynamics. However, agent-based models cannot be viewed as predictive in the sense that high-fidelity physics-based models are predictive, especially when modeling radically new architectures. At best, akin to low-fidelity physics-based models, they can filter out unsuccessful designs. Granted, with growing computational capacity, agent-based simulations will model large

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adaptive systems with increasing levels of fidelity[2]. Nonetheless such simulations are tools for evaluation and analysis, rather than design, pointing to a clear need for developing mathematical models conducive to large-scale active system design.

Another significant challenge in concept development for airspace design is the discrete nature of the concepts. That is, new concepts are traditionally created as "point designs", based on experience, expertise, and creativity of the concept developer. Distributed system control and centralized system control (see, e.g., Krozel et al.[2] and references therein) are examples of alternative system point designs for controlling air traffic. Discrete point designs may be highly successful but they are difficult to substantiate in the face of equally strong substantiation of competing concepts, both usually evaluated via simulations. An intuitive view is that the best solution may be a compromise – a hybrid of several alternatives. Yet alternative concepts may be incompatible, in principle; the degree of hybridization may be *ad hoc*; and finally, any hybrid again represents a point design that faces the challenge of substantiation and validation. Finally, as successful as any particular concept may be, it is difficult to substantiate rigorously why it is the best possible solution; why another "best" solution may not have been missed when the concept appeared in the mind of the designer.

The two outlined challenges – the lack of predictive modeling and traditional point design approach to development – need to be resolved, among others, to enable *ab initio* design. We conjecture that predictive modeling is possible at right scales, with appropriately developed variables, functions and degrees of resolution. We are also cautiously optimistic that framing the design problem in terms of functional optimization will facilitate moving away from point designs to rigorously derived and substantiated designs.

Re-designing the air transportation system *ab initio* also presents a problem from the perspective of transitioning from the current basic architecture to any radically new one. The working assumption is that the coming state-of-the-future-art powerful simulation tools may provide sufficient validation, so that the present system may be "turned off" at some point and the new one "turned on" safely; but such a solution is not definite. Safety validation and the ensuing certification of massively automated systems are open technical problems.

However, we conjecture that the *perceived degree* of difficulty is an artifact of the present human-centric control system: designing the system without the constraints of the established infrastructure and human control is likely to simplify design significantly. Moreover, design from scratch is an opportunity to reconsider fundamental approaches to new concept development. To this end, we propose a framework, Optimized Parametric Functional Design (OPFD), for systematic derivation of concepts for management and control of airspace systems. OPFD is based on optimization formulations in terms of required system functions and states. The framework, realizable in the context of *ab initio* system design, offers an approach to deriving substantiated airspace management and control concepts. With growing computational power, we hope that the approach will also serve as a methodology for actual dynamic control of airspace.

The remainder of the paper outlines the principles of OPFD and gives an example of its use in an ongoing investigation of functional allocation of control. It should be emphasized that at the current stage of development, OPFD is a general methodological approach, rather than a single algorithm. The aim of the present paper is to start the discussion on the need for a paradigm shift in design methods for future airspace. OPFD is one potential solution.

II. Problem Setting

A fundamental feature of air traffic control is the need to enable safe, efficient, and affordable movement of multitudes of independent entities in a multi-participant system. The present system comprises the airport infrastructure and routes, aircraft, commercial and private operators, air traffic controllers, pilots, passengers, and so on. All system components already have a real degree of autonomy. Thus the design problem appears different from that of designing even vastly complicated mechanisms, such as modern aircraft or spacecraft, where the multitudes of components are united into a single machine. However, we propose that the problem is not completely different and we can make use of design principles used for complex machinery. This section attempts to set the airspace design problem in a simplified perspective, to frame the OPFD approach described in the next section.

A. Lessons from Active Design of Mechanical Systems

[2] See, for instance, a new NASA initiative in high-fidelity simulations for airspace, SMART-NAS (Shadow Mode Assessment using Realistic Technologies for the National Airspace System): https://www.fbo.gov/index?s=opportunity&mode=form&id=3c09168be9748d17b9169da5a37525e0&tab=core&_cview=1

Methods for designing complex engineered mechanical systems, such as vehicles, usually belong to one of three categories; two amenable to formal optimization strategies and one termed "heuristic" here.

In *inverse design*, a target for an objective is stated. Then models and algorithms are applied to produce steps that will take the current system to the target design or, at least, minimize the distance between the candidate design and the desired target; subject to constraints of the system. This approach presupposes that the target design is realizable, as are the steps toward reaching the target. In the context of airspace, we could say, for example: design all aspects of the National Airspace System (NAS) so that the capacity is increased tenfold, compared to the current capacity.

In *direct design*, there is no assumption of a target. Instead, one encodes the properties of the desired system into objectives and constraints and takes the system through a succession of steps toward improving the objectives, while satisfying the constraints. This approach relies on the ability to define sensible objectives and presupposes the existence of steps toward improving the objective. To continue the example, a corresponding direct design problem statement would be: design all aspects of the NAS so that its capacity is maximal.

In both inverse and direct approaches, the lack of feasible directions indicates reaching an optimum, local or global. In the case of a local optimum, further exploration of the design space entails taking large steps to move away from the local optimum. An airspace analog of such a step may involve a radically new control paradigm. If the optimum is global, the only way to improve the system is to remove some of the constraints. Human control in the current air transportation system places a hard constraint of feasible concept domain and the system is approaching saturation. There are certainly degrees of freedom left in the current system[3], but the hard constraint of human control means that the system will not be able to absorb orders of magnitude increase traffic required to ensure universal access to airspace, i.e., mobility on demand.

In contrast to the first two approaches, in *heuristic design*[4], one works to improve subsets of the system via methods aimed at producing better subsystem performance and hopes that the entire design evolves to a better one with respect to stated objectives. In other words, one hopes that the system will evolve to be *somehow* better. Arguably, this is the current approach to the evolution of the NAS. To continue our example, a corresponding sample problem might be: optimize algorithms for arrival scheduling; reduce the size of buffers around vehicles via better wake prediction; enable autonomous flight rules; and hope that capacity improves.

The first two approaches rely on predictive modeling for quantification of the objectives, constraints, and the system state, as well as on analyzable algorithms. The benefit is the ability to progress toward solutions, evaluate the progress toward solution, actually identify an optimal solution, and detect infeasible directions not leading to solutions. The direct design method is preferable, because it makes no *ad hoc* assumptions about the target design, instead attempting to reach the best design possible, given the constraints and limitations in modeling.

The heuristic method relies instead on an intuitively sensible approach: the sum of better parts should yield a better whole. However, this approach is valid only if the components of the system are separable or weakly coupled. One of the properties of complex systems is that the strength of component coupling may be difficult to detect and predict. In our example, a better wake prediction may be immaterial in the presence of runway operation capacity limitations. The ability of aircraft to de-conflict autonomously and take charge of their departure in the face of, say, inclement weather may not yield benefit if too many autonomous aircraft compete for landing. In summary, in a highly complex coupled system, progress on subsystem objectives may be deceptive when a subsystem is viewed in sufficient isolation; and the system objectives may be impacted adversely. Moreover, it is difficult to detect when the system has limited or no more degrees of freedom for improvement.

With all its drawbacks, the heuristic approach has been a necessity and has resulted in a very safe and reasonably efficient system. Until now, neither the straightforward inverse or direct design had been possible. However, even without formal methods, it is becoming evident that the present system has limited degrees of freedom and we must begin the introduction of direct and inverse design methodological components into designing the future system that will enable mobility on demand – the target beyond NextGen.

B. Complexity

Complexity is one of the most overused, yet least clear terms. Some concepts of complexity have definite technical meaning. For instance, in the analysis of algorithms, complexity measures bounds on the minimal amount

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[3] Current NASA's Airspace Systems Program activity titled "Choke Point Analysis" includes an effort to determine the degrees of freedom remaining in the NAS. See NASA ARMD Research Opportunities in Aeronautics (ROA-2013), http://www.aeronautics.nasa.gov/nra.htm

[4] This is the author's term for denoting the described approach. To the author's knowledge, the approach does not have a widely accepted name.

of time needed to solve a problem via an algorithm (see, e.g., Goldreich[3] for a review). In other domains, the notions are not as clear and definitions of complexity proliferate (see examples[4-9]). In the context of complex systems, complexity is usually associated with notions such as non-intuitive system behavior; the inability to predict the system effects of individual actions because of high interconnectivity; massive amounts of computation and analysis needed to put a dent in prediction of system behavior and so on. Some of the fundamental characteristics of complexity are uncertainty, high dimensionality and information structure constraints – all relevant in the context of transportation.

We conjecture that the notion of complexity in itself is interesting only from a descriptive perspective. In engineering design, complexity, whether it is measured by the number of components, their connectivity, or other metrics, is an outcome of the system design, not an objective *per se*. That is, the system should be designed for a set of performance objectives; the resulting complexity is a byproduct of the optimal design.

A more useful notion in operating a complex system, such as transportation, is controllability or the ability to reach desired states and avoid undesired ones. In this context, controllability and complexity are tied to a more tangible ability to solve specific problems. For instance, in moving a vehicle from point A to point B, an efficient and safe trajectory has to be computed and re-computed to avoid conflicts along the way. Controllability then has to do with the ability to compute and re-compute the trajectory, while maintaining overall efficient traffic flow in the transport network. These are clear and computable entities that have to do with the work needed to solve a fundamentally computational problem. In fact, in the present NAS, complexity often refers to cognitive complexity, i.e., the workload of the air traffic controllers (see, e.g., Kopardekar et al.[10] and references therein). Other notions of complexity deal with uncertainty of intent addressed via flexibility preservation in trajectories (e.g., Idris et al.[11]) – again, relevant to the ability to compute a viable trajectory, but viewed through several steps ahead.

Even though designing for low complexity as an explicit objective is not a promising exercise, maintaining manageable complexity of airspace, in terms of the ability to compute feasible trajectories, is a necessary target. In fact, the ability to solve any problem computationally implies bounding the problem complexity. In the present NAS, complexity is bounded to accommodate human cognitive faculties. With automated control, complexity will also have to be bounded, but at a different level.

An intuitive view is that increased autonomy and density breed complexity and that the future system with mobility on demand will be faced with unprecedented complexity. We conjecture that this would only be true in the presence of human control. (In fact, massive autonomy would be technically infeasible under human control, if only from the perspective of safety.) Control under machine intelligence may reduce problem complexity significantly because bounding the uncertainty of machine behavior is an easier task than bounding the uncertainty of human actions.

In addition to safety, efficiency is a bounding factor for complexity. Given even infinitely good capabilities for resolving traffic conflicts, avoiding conflicts in sufficiently dense autonomous traffic can lead to Brownian-like motion of vehicles, impeding efficiency. With finite algorithmic speeds, ensuring safety, without compromising efficiency, calls for rigorous, provably operational traffic management tools with quantified uncertainties and risks.

C. Autonomy, Automation and Design ab Initio

Many motivation factors lead to the conclusion that system design from scratch is the only feasible approach for ensuring on-demand mobility and the implied autonomy. Here are some of these factors.

As mentioned already, the cognitive bottleneck of human control places an absolute bound on the volume and variety of controllable traffic. It is well known that injection of automation to assist control does not remove the cognitive bottleneck: to maintain controllability by humans, traffic must not contain scenarios more complex than humans can handle, no matter the machine assistance (see references in, e.g., Tsonis[12]). Moreover, human-machine interaction makes for a more difficult control problem than human or machine control alone.

On-demand mobility requires that operation of large numbers of small vehicles must be amenable to pilots with no skills. This can only be achieved via machine autonomy or automation authority, necessitating a complete re-design of the transport system.

One of the difficulties of incremental evolution is the need to inject ever growing degrees of automation into a system which can, in principle, handle only limited automation. When the ultimate goal is, arguably, complete machine control, artificial maintenance of human control along the transition path will prevent optimal system design. On the other hand, transition has to happen. We conjecture that *ab initio* design approached via principles outlined in the next section will provide a framework for continual development of the overall design, without excluding transitional versions.

III. Approach: Optimized Parametric Functional Design

The idea of OPFD rests on the fact that controlling air traffic on all temporal and spatial scales – from a single aircraft to the entire airspace – can be formally stated as a dynamic, high-dimensional optimization problem with many objectives and constraints based on physics, economics, information, and other considerations. Attempting to find optimal solutions to such problems, especially in a future, densely populated NAS would violate practical constraints, such as those on computational and communication resources. The proposed approach addresses the problem of finding solutions to problems of air traffic control subject to real-world limitations on the computational/ communication cost of finding that solution.

Formal optimization approaches have been proposed for actually controlling future air traffic (e.g., Schouwenaars et al.[13]). We propose that an optimization formulation for control also be used for transportation system design *ab initio*. The following subsections outline the components of OPFD.

A. Functional Description

In designing from scratch, we disregard the constraints of the present infrastructure for now and focus on what is needed to get a vehicle from origin to destination:

1) A mathematical formalization of the trajectory; the points on the trajectory are the independent design variables, for which the flight is optimized.
2) A set of functions that evaluate the quality of the trajectory, e.g., time traveled, deviation from the shortest path, deviation from expected time, fuel expended, quality of airspace traversed in terms of current and anticipated obstacles, quality of the ride, any other functions intended for optimization.
3) A set of constraints; e.g., the safety buffer around the vehicle, rules of the road; the need to resolve the problem within temporal and spatial horizons; constraints on physical performance characteristics of participating aircraft; and any other limitations.
4) A set of dependent outputs that may serve to inform the design; for instance, cumulative merit functions describing the performance of the system at various levels of resolution; composition and density of traffic in airspace.
5) Quantification of uncertainty in independent variables.

B. Parameterization

The distinction of OPFD is that all objectives and constraints in computing the trajectory must be expressed as a function of both the independent variables (trajectory itself) and of parameters that encode the technological entities necessary for the aircraft to complete its mission. All parameters must be equipped with uncertainty quantification. Examples of relevant parameters are:

1) The bandwidth of communications;
2) The quality of communications (related also to security of communications);
3) The speed of communications;
4) The availability of position information;
5) The accuracy of position information;
6) The availability of intent information;
7) The time horizon of intent information;
8) Computational resources;
9) Availability of trusted decision making algorithms;
10) Computational complexity of optimization algorithms used to compute trajectories continually;
11) Physical properties of aircraft; e.g., maneuverability, speed, sensors;
12) Availability of high-fidelity phase transition modeling.

In actual traffic control specific values of these parameters are fixed to available technologies. We propose that for the purposes of system design, traffic control problems be solved for *optimal trajectories in terms of the parameters*. The resulting control concept is no longer an *ad hoc* point design (a matter of conviction), but a rigorously derived optimal design with explicit dependence on the state of the art in technology at any point in time.

C. Optimization Problem Formulations

The overall optimization problem formulation for control of trajectory for a single aircraft is a general multiobjective non-linear programming problem:

$$\min_{x(p)}\{f_i\big(x(p), p, u(x,p)\big), i = 1, \cdots, N\}$$
$$s.t.\, C_I(x(p), p, u(x,p)) \;\leq 0$$

$$C_E(x(p), p, u(x,p)) = 0$$
$$x_L(p) \le x(p) \le x_U(p).$$

Here $u(x(p), p))$ may be computed by solving a set of state equations $S(x(p), p, \big(u(x,p)\big) = 0$. In this formulation, $\{f_i\}$ are a set of objective functions; x is a vector of (ordinarily) independent design variables; C_I and C_E are vectors of general inequality and equality constraints, respectively; and the bound constraint expresses simple geometric constraints on the trajectory. The general constraints represent functional performance, safety, cost, and other requirements.

Of course, at any time, a control system has to solve as many of these problems as there are moving vehicles[5]. However, there is no need to know *a priori* who needs to solve the problems, i.e., the locus of information collection and control. These aspects also become derivable from the formulation.

Solving the formulation for parameters is now under investigation. One of the immediate standard questions is how to handle multiobjective decision making (see, e.g., Chankong and Haimes[14], for an overview) present in the problem. Traditional multiobjective optimization usually contains an *ad hoc* aspect in selecting a single solution from a set of Pareto optimal solutions, but that solution is selected once and for all. In solving the proposed formulation, modeling the relative importance of multiple objectives should be handled stochastically: for independent autonomous missions, system participants will chose different objectives as most important at different times.

Given the present state of the art in optimization, solving the general optimization problem (even with fixed parameters) in real time is not a tractable option. Methods for separation assurance that rely on optimization usually limit the number of feasible directions to discrete choices[11]. This is why we view the formulation as feasible only as a design approach. However, as computational capacity grows, solving the problem at any step in time will become practical. For now, computational complexity remains one of the parameters that can be used to bound complexity and ensure controllability.

As mentioned earlier, to avoid phase transition to "Brownian motion" of getting out of each other's way at the expense of moving toward destination, the airspace must remain on the safe side of phase transition to uncontrollability (e.g., Helbing et al.[15]).

Note that the general problem formulation may have to be viewed in conjunction with other models of the overall system design, such as the transportation network model (e.g., Alexandrov et al.[16]). Whether this is necessary or the general trajectory control problem can subsume network considerations (or if network considerations are relevant) is an open question.

D. Projection onto Technology State of the Art

Once the optimization formulation is solved for technology parameters, we can project the solution to the state of the art in technology at any time of interest, either actual technology levels at a point in present or a model of anticipated technology in the future. We conjecture that a series of projections in time will facilitate a smoother transition between the present transportation system and the steps toward the future system. The idea is to develop technologies that are as much backward-compatible and forward-compatible as possible. An example of such a technology is the TASAR[17] concept currently under development at NASA. TASAR will supply pilots with advisories for trajectories that are more beneficial than the planned ones. However, at the present level of automation in the system, the pilots have to obtain permission to change the trajectory from air traffic control. In a future system, when a centralized permission from the ground is no longer needed, the TASAR function is still applicable and useful; the step of asking permission will disappear.

Here are examples of how projections onto technology state of the art (SOA) would impact system designs at any time.

In a state of limited ability of algorithms to resolve conflicts in time (parameters: computational complexity, speed of computation, speed and quality of communication, availability and quality of information), the complexity of airspace must remain sufficiently bounded to enable safe conflict resolution and strategic efficiency. The implication is limiting traffic density and/or maintaining human presence in control. Projection onto actual parameter estimates would yield the degree of density limitation and degree of control.

Should communications acquire unlimited capacity, complete security, and become virtually error-free, the ability to provide accurate navigational and intent information in real time would enable automated decision making, in principle. Massive increases in computational power (parameter: computational resources) would then enable optimization via relatively simple search algorithms. Alternatively, breakthroughs in fast optimization algorithms

[5] We are not addressing multimodal transportation here, but the general principles are applicable to multimodal systems as well. Functional description and parameters would be expanded, but the approach is unchanged.

could enable real-time optimization even in the absence of quantum leaps in computing power. In either case, automated control is enabled.

In a state of limited knowledge and modeling of phase transitions (parameters: computational complexity, speed of computation, availability and quality of information, speed and quality of communication), various levels of control (tactical, strategic, order-of-hours management) may be needed. The ability to sense (parameter: sensors) and predict (parameter: model availability) an approach to various stages of controllability in dense airspace may obviate the need for longer temporal control. The idea is that multi-level control structure does not need to be taken as an assumption and remain unchanged. Solution for optimal parameters and then projection of the parameters derives the degree of multilevel control for the given SOA.

This is the salient feature of the approach: a general solution in terms of parameters does not force us to choose a specific method of handling system functions. Instead it tells us explicitly how the system depends on these salient parameters. Then design decisions can be made based on the SOA under investigation. For instance, algorithmic developments in machine decision making may yield methods for spontaneous formation of "flocks" of autonomous vehicles if they share a destination or share a target of avoiding a particularly congested region. The solution for parameters will not dictate how such communal, self-organizing behavior is realized; but it will suggest that the performance of the system is strongly dependent on the ability to form multi-level control structures.

How difficult is it to project parameters onto SOA? For some parameters, it is as easy as assuming the available communication bandwidth for a new technology (e.g., optical communications). Other parameters may require quantitative model development (e.g., predictive models for phase transition). This area is a subject of ongoing research.

IV. Example Problem: Functional Allocation of Control

We are currently applying the OPFD approach to a subset of the overall control system – the problem of functional allocation (FA) of control.

Two competing concepts of controlling the air traffic are the *centralized* control and *distributed* control. In its pure form, centralized control means that information gathering and control decisions and directions are made at a single point of authority, possibly for subsets of airspace or the entire airspace. Purely distributed control (or autonomy) means that each entity collects its own information and arrives at its own control decisions and directions. In the present system, traffic control possesses some degrees of distribution and centralization. The overall control of aircraft trajectories is exercised by air traffic control centered on the ground. Pilots control the aircraft subject to the constraints imposed by the air traffic controllers, but do have the ultimate physical control. Another axis of control is *human vs. automation*. The overall system is viewed as human-centric, centralized and ground based.

Some researchers hold the view that realistic control of complex systems, such as the air transportation system, will always involve some degree of distribution and some degree of centralization, as well as a mix of human and machine control. Exactly what degree is appropriate for what conditions is the main area under study in FA.

In the interests of admitting bias, the author's current opinion is that the ultimate system with on-demand mobility will require automated distributed control. From a list of supporting arguments, we mention only Ashby's Law of Requisite Variety[18, 19] as a motivation for this opinion. In popular terms, the law states that only variety destroys variety. The term "variety" denotes the total number of states of a system. An intuitive explanation of the law is that system stability requires that the number of states of control scheme exceed the number of states of the controlled system. Colloquially speaking, the number of ways for fixing the system needs to be greater or equal to the number of ways in which the system can break. The likelihood of a centralized control's successful handling the multitude and diversity of events in the entire system appears lower than the likelihood of successful implementation of local control, where local sensing provides better situational awareness to the system participant.

The present investigation may serve to validate or disprove this opinion. An additional benefit is (we hope) that the study will clarify the sequence of steps in progressive introduction of automation, assisting in transitioning from human control to control via machine intelligence. Whereas the progressively sophisticated simulations may ease transition, it is not clear whether the transition to complete automation can take place abruptly. Moreover, we hope the technique will assist in nearer-term injection of automation as well.

The proponents of both approaches – centralized and distributed – have conjectured and studied properties that support the benefits of each approach. In particular, the centralized approach is viewed as supportive of system stability, while the distributed approach is viewed as promoting system robustness and flexibility. Definitive comparative analysis and the analysis of functional allocation are difficult for a number of reasons:

- The centralized approach emphasizes system-level objectives and functions.

- The distributed approach focuses on individual user objectives and function.
- Conjectures about hybrid approaches make assumptions about the extreme point designs (fully centralized and fully distributed) and seek a beneficial combination; but the very assumption of the asymptotic point designs limits the hybrid solution to an *ad hoc* choice of weights for each of the two contributing concepts.
- Given the present complexity of describing the problem in the NAS, the tool of choice is a simulation of aircraft moving in the system. Almost invariably, in such simulations, the need to represent the concepts faithfully leads to continual complication of the processes and leaves open the question of how much fidelity is sufficient in each concept to perform a fair comparison, yet capture all features that are the source of benefit for each concept.

Under the conjecture that to understand the basic properties of approaches to FA, the fundamental control problem must be considered mathematically, we initially dispensed with the notion of fidelity of a specific concept and instead moved in the direction of abstracting the control problem. The abstract problem then serves to investigate problem formulations, leading to various levels of centralization and distribution, based on a variety of system and individual system participant parameters and variables. Once fundamental formulations were established, the ensuing analysis and experimentation allowed us to arrive at a static model and then a dynamic model.

To-date, we have modeled the basic control problem in terms of local (aircraft and individual user based) and global (system-based and region-based) variables and functions. Individual functions include: fuel consumption; time to specified points/delay; the existence of feasible directions for maneuvers (flexibility); conflicts; computational time/resources necessary to calculate a conflict-free move from the current point to the next. For system-level functions, we have considered system stability, flexibility, computational time/resources, overall environmental impact (to start, in terms of fuel consumption), capacity and throughput, flexibility, approach to phase transitions, and robustness. For both individual users and the system, we account for sensitivity of all functions to perturbations (congestion, weather).

The first conjecture under study is the belief expressed by a number of NAS researchers[6], stating that in the absence of uncertainty and limitations on communications bandwidth and quality, solutions to the centralized and distributed control problems would be identical. We have verified, both theoretically and computationally, that under a set of simple assumptions, this conjecture does not hold. This was accomplished by analyzing the basic differences between the two control strategies assuming zero uncertainty and perfect communications. Experiments with abstract centralized and distributed control/optimization problem formulations indicate significant differences in performance between distributed and centralized control in terms of selected objectives. Details can be found in Alexandrov et al.[20].

In analyzing the formulations, it became apparent that the conjecture would have been true if there existed a single “original” problem formulation (i.e., the centralized one) and then the distributed formulation would be a reformulation for distribution of computation. Such problem decomposition is well studied in optimization and the solution of the distributed problem can be shown to be a solution of the original problem under some assumptions, and conversely[21]. However, we claim that the centralized, global control problem is not the “original” problem to be decomposed. Instead, even under the assumptions of zero uncertainty and perfect communications, the centralized and distributed concepts will exhibit different characteristics, because both are multiobjective problems, and they will be different for both approaches[20].

The next steps in the investigation involve introduction of constraints for communication quality and bandwidth, as well as explicit uncertainty, at the basic one-step control problems, followed extensions in time. Simultaneous with optimality and performance analysis are efforts to understand parameters salient to phase transition in the system and the appropriate functional allocation.

V. Conclusion

This position paper is aimed at advancing the idea that *ab initio* design of a new air transportation system is technically feasible if we pose the overall design problem in terms of functional parameterized optimization formalisms. The idea is that we can get away from point designs that are difficult to substantiate and instead *derive* substantiated designs by solving decision making/optimization problems with information content, projecting solutions onto technology SOA under investigation. Such an approach has implications for many system aspects. For instance, it calls for changing the notion of designing for safety because it is impossible to use the usual safety

[6] Private communications.

standards (e.g., the number of mishaps per unit of time or miles flown) as explicit design objectives. Instead, we propose designing for performance objectives that include avoidance of uncontrollable (or inefficient) states. Projecting the optimal design onto available technologies would assure the realism of resulting concepts.

Having formulated the approach in general terms, we are now taking first steps in developing computational algorithms, using subsets of the overall system design as a development platform, with focus on functional allocation of control. Details of the initial investigation are available in another publication[20].

We would like to emphasize, again, that the proposed approach is in its infancy, at the level of fundamental research. We are now working on improving the components of the formulation to solve for more realistic functional allocation. The open problems are numerous and difficult. To most important one is a satisfactory approach to resolving the safety and security questions in the presence of machine autonomy.

Finally, solving the *ab initi*o design problem requires the application of techniques from many domains, including information theoretic, network theoretic, machine intelligence, safety, economics, among others. We find the transdisciplinary approach[22] of necessity and particular help in this investigation.

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