A Framework for Assessment of Autonomy Challenges in Air Traffic Management

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***Abstract*— Traditionally, air traffic management services have been provided by air traffic controllers and managers stationed in ground facilities, employed or contracted by the public sector, and supported by automation. These centralized, human-centric air traffic management services do not scale to accommodate increasing demands from conventional and new entrant operations for access to the national airspace system. One transformation that provides much needed scalability is increasing the level of autonomy of air traffic management by enabling edge agents of the system, including vehicles, operators, and third-party service suppliers, to collectively self-manage independently from the centralized service providers and enabling the automation to also take on more independent traffic management responsibility from the human agents. This paper identifies challenges to increasing the level of autonomy of air traffic management services. It describes a framework to enable a systematic identification of these challenges. The framework consists of a functional breakdown of air traffic management services and several dimensions characterizing different autonomy scales. The autonomy dimensions include the automation level between human and machine agents, the locus of control between centralized and distributed edge agents, cognitive activities for autonomous situation awareness and decision making, intelligence levels ranging from skill-based to expertise-based autonomous behavior, and uncertainty levels of the dynamics and environment in which autonomous agents operate. Several challenges are identified and categorized using the different dimensions of the autonomy framework.**

Keywords—automation; autonomy framework; collective autonomy; air traffic management;

I. INTRODUCTION

Aviation operations in the National Airspace System (NAS) continue to increase in number and complexity, resulting in greater stress on limited resources and facilities. New entrants with diverse performance and mission profiles are anticipated to enter the same airspace in the next few decades including supersonic flights over land, commercial space missions, unmanned and autonomous aircraft, high-altitude long-endurance (HALE) vehicles, and short-haul, on-demand urban air mobility (UAM) operations. Some of the new missions require access to airspace where air traffic management (ATM) services have not been provided in the past, such as HALE and supersonic flights above 60,000 feet. UAM operations are expected to reach traffic volumes orders of magnitude higher than the current use of the NAS by commercial and general aviation.

Traditionally, ATM services have been provided by air traffic controllers and managers stationed in ground facilities and employed or contracted by the public sector. They ensure safe, orderly, expeditious, and secure operations by issuing traffic advisories to pilots. These advisories include, for example, trajectory modifications that are issued to maintain safe separation between aircraft and ensure conformance to procedures and flow restrictions. Human service providers are often assisted by automated decision support that generates alerts and recommends mitigations for potential conflicts at different time horizons. This centralized (ground-based) system, relying heavily on human providers, cannot scale with the increase in demand for high-tempo operations. In particular, UAM operations are expected to reach high volumes that preclude a human ability to control the traffic. The ATM system must transform to enable and scale to these unprecedented needs.

One transformation that provides much needed scalability is increasing the level of autonomy of ATM by both enabling edge agents of the system, including vehicles, operators, and third-party service suppliers, to collectively self-manage independently from the centralized service providers and enabling the automation to take on more independent traffic management responsibility from the human agents. Enabling vehicles and their operators to participate in providing ATM functions, in addition to or in lieu of the ground-based service providers, facilitates greater scalability as new growing demand becomes capable of self-managing and furnishing its own services. Automation to assist human agents can alleviate some capacity limitations, but such automation needs

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to reach higher levels of autonomy in order to scale as independent agents. Therefore, independence—and hence autonomy—from the human, centralized (i.e., ground-based) service providers is a key mechanism to achieve scalability of services with increasing demand by new entrants and to accommodate increased operations tempo and complexity by expanding the capacity of the current centralized human-based system. Such transformation is becoming increasingly possible with a convergence of technological advances including digital connectivity, big data analytics, the internet of things, artificial intelligence, and machine learning enabling increasingly autonomous systems, empowering the participation of users, and spawning new on-demand seamless mobility services.

The purpose of this paper is to help ATM researchers, concept developers, system designers and practitioners identify autonomy challenges and corresponding research needs for developing an ATM system that is resistant to disruption, capable of dynamically scaling to safely meet demand and complexity, and inclusive of new entrants and use cases in the NAS. The ATM system is a complex system of systems with many heterogeneous actors, including vehicles, pilots, operators, and service providers, working together to ensure all mission and business needs are achieved in a safe, stable, and efficient manner. A framework is introduced herein to enable the identification of challenges and solutions of an autonomous ATM system. The framework consists of a simplified functional breakdown of the ATM system and several dimensions that characterize levels of autonomy in performing these functions. The dimensions include human versus machine, centralized versus distributed, cognitive activities, intelligence levels, and uncertainty levels. The framework draws on a number of models and scales that have been used by the scientific community to represent levels of automation and of functional allocation. These are referenced throughout the paper as the framework is described. The paper starts with the ATM functional breakdown and follows with describing the autonomy framework dimensions. It then outlines a list of challenges that were identified as barriers to effectively increase ATM autonomy.

II. Functional Decomposition

ATM services form a layered set of functions that close many control loops around the air traffic system, as shown in Fig. 1, ensuring that the operation is safe, orderly, expeditious, and secure, among other performance objectives. Example functions are listed in Fig. 1 under several functional groups or services. A set of communication, navigation, and surveillance (CNS) services underlies all other ATM functions, enabling the measurement of the states of the system through surveillance, the generation of trajectories along navigational aids, and the communication of these trajectories and other commands to the aircraft. Then a layer of trajectory management services overlies the CNS services and provides functions such as trajectory prediction, generation, execution, and conformance. These trajectory management functions produce trajectories that are commanded to the aircraft.

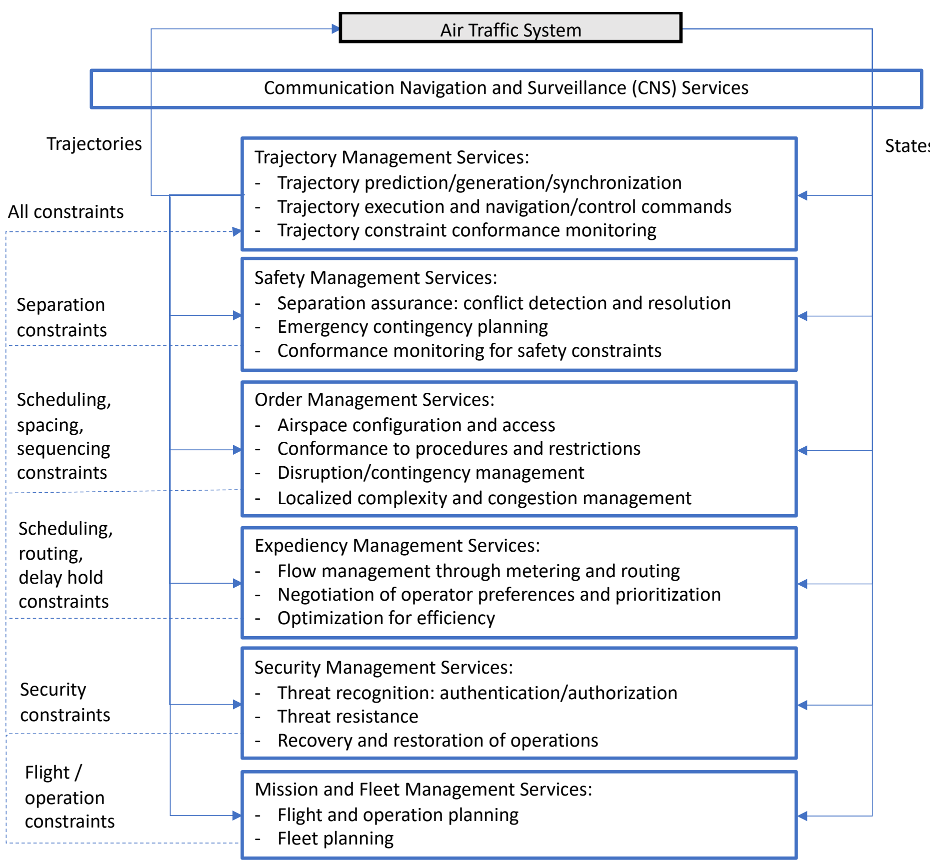

Fig. 1. ATM Functional Framework

Building on top of the trajectory management services, numerous ATM functions close outer control loops for different performance objectives of the system and at different time horizons. The example functions in Fig. 1 are grouped by five objectives: safety, order, expediency, security, and mission planning. Safety functions include collision avoidance, separation assurance, and contingency management. Order functions include providing orderly airspace structure and access, conformance to procedures and restrictions, and disruption management. Expediency functions include flow management, metering traffic, and accommodating mission preferences and timely needs. Security functions include identification and mitigation of security threats. Finally, mission and fleet planning form the most strategic loop with functions related to flight operation and fleet planning. Additional services not included in Fig. 1 include, for example, environment (noise and pollution) management, and community concern management. Functions may also be innovated by human providers, to deal with new events based on their expertise. Fig. 1 shows trajectory management services supplying trajectories as control input to the traffic. Safety, order, expediency, security, and planning services all provide different types of constraints to the trajectory management services to produce trajectories that satisfy these constraints.

III. Autonomy Dimensions

To analyze how the ATM functions depicted in Fig. 1 may be performed autonomously, a number of dimensions representing different autonomy scales are introduced. Fig. 2 shows that the ATM functions of Fig. 1, and potentially many other functions (hence the "…" function name notation in the figure), close a continuum of control loops around the traffic system ranging from the shortest tactical time horizon, for example through collision avoidance, to the longest strategic time horizon through mission planning. In-between, functions such as separation assurance, conformance monitoring, merging, spacing, scheduling, and flow management occupy different ranges of the control time horizon. Fig. 2 depicts the following dimensions of autonomy: (1) Control locus: A function may be performed by the centralized service provider or increasingly distributed to other agents including vendor service suppliers, operators, pilots, and other actors; (2) Automation level: Each agent may consist of a team of humans and machines with increasing machine responsibility (note that machine and automation are used interchangeably in this paper); (3) Cognitive activity: Each function may be broken down to activities such as information acquisition, impact assessment, solution planning and action implementation, where different agents may undertake different activities within a function; (4) Learning level: As an agent performs a function or an activity, learning increases the level of proficiency in performing the function from skills, to rules, to knowledge, to expertise and hence increasing the agent's ability to perform the function autonomously without assistance; (5) Uncertainty level: Autonomy may be possible under limited predictable conditions such as without weather disruptions but may be increasingly difficult under higher levels of uncertainty.

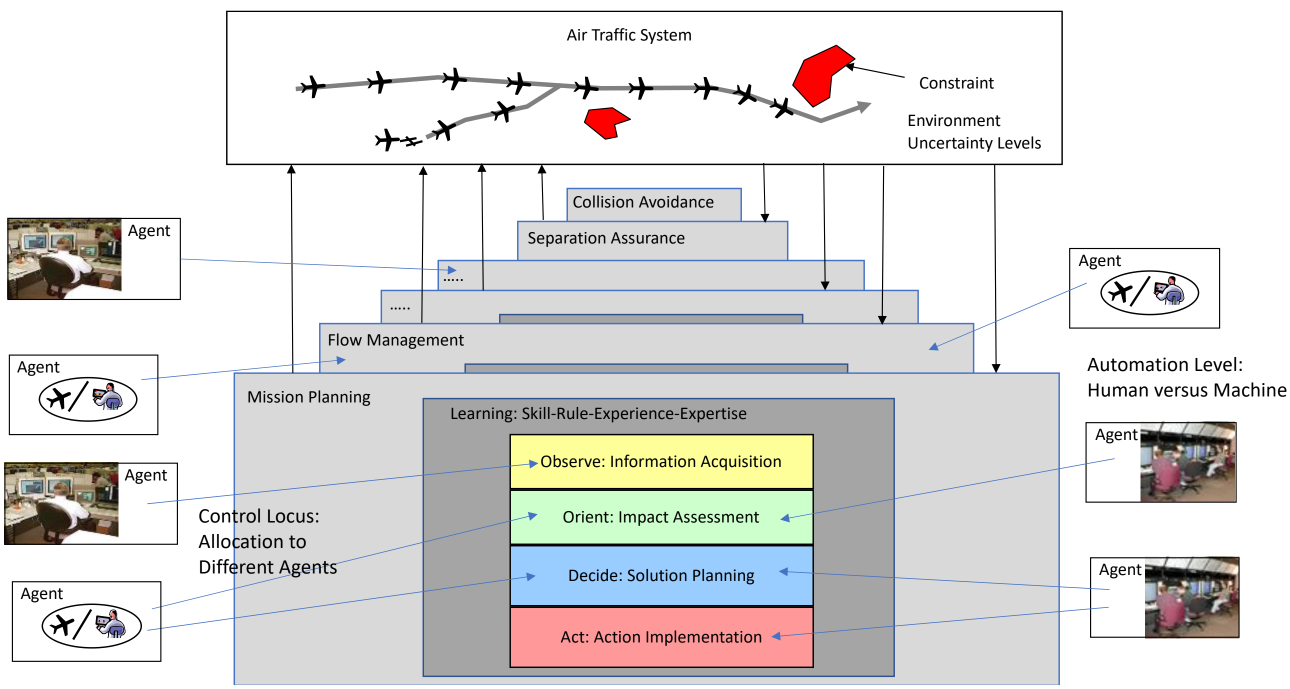

Fig. 2. Cognitive Abstraction of Different Autonomy Dimensions

In Fig. 3, the operational aspects of the framework are depicted in a multi-dimensional space: the functional groups are shown in the center on a vertical axis, with the automation levels and control locus forming the horizontal plane. These three dimensions may be termed an operational space highlighting the roles of each agent, human or machine, in performing each function. The two autonomy dimensions are described below along with a choice of a scale along each.

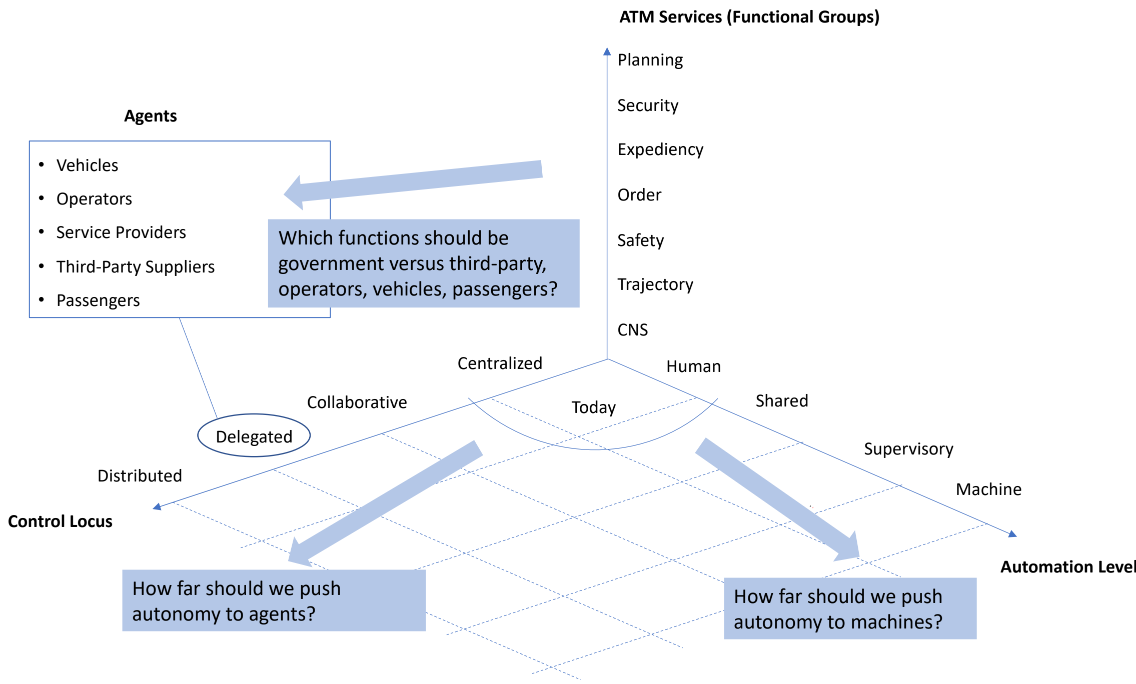

Fig. 3. Operational Space: ATM Functions, Control Locus and Automation Levels

A. *Control Locus*

Autonomy of ATM functions includes the performance of these functions by agents other than a centralized ground-based service provider, including by vehicles and their operators, which may be called edge or distributed agents. Distributed schemes for several ATM functions such as separation assurance and flow management have been studied in the literature [1-6]. The framework includes a control locus dimension for different levels of distribution of functions among agents. A scale of four levels is identified on this dimension (more levels may be identified for a higher-resolution scale):

1. Centralized control whereby a function is performed by the central authority (the ground-based service provider).
2. Collaborative control whereby a function is performed by a central authority (the ground-based service provider) with input from other stakeholders, such as vehicles and their operators. Collaborative decision making has been a key feature of the traffic flow management system historically and under NextGen [7-9].
3. Delegated control whereby a function is performed by edge agents, such as the vehicles or their operators, while some rules and oversight are maintained by a central authority (the ground-based service provider). For example, safety critical functions such as separation assurance may only be delegated to vehicles and their operators under conditions dictated by the centralized authority.
4. Distributed control whereby a function is performed by edge agents, such as the vehicles and their operators, with no involvement from any centralized authority (the ground-based service provider).

The collaboration, delegation and distribution of functions may involve different agents (as shown in the figure for "delegated" as an example). Five of these agents are:

1. Vehicles, which may be flown by human or autopilot.
2. Operators, who perform functions such as remote piloting and higher-level operation of the vehicle or fleet of vehicles.
3. Public navigational service providers of air traffic management functions.
4. Third-party service suppliers (other than operators and government) of traffic management services. Third-party service provision has been a key feature of the UAS traffic management system (UTM) [10].
5. Passengers, who may also affect traffic management functions as they are empowered by edge technologies to make decisions such as route and mission changes.

There may also be new agents, such as local governemnts, that are involved in ATM services under new concepts such as UAM and total multi-modal mobility paradigms.

B. *Automation Level*

Each agent in the system may include a human-machine team. The autonomy level increases as more responsibility is taken by the machine relative to the human in the performance of a function or activity. Levels of automation have been studied extensively in the literature, for example by Sheridan's ten levels of automation and the many subsequent variations on it [11-12]. While more levels can be incoporated as needed, the framework includes a scale of four levels for simplicity, defined as follows:

1. Human control, whereby the function is performed manually.
2. Shared control, whereby the human and the machine perform the function in a cooperative manner (e.g., with decision support from automation) [13].
3. Supervisory control, whereby the function is performed by the machine with monitoring, teaching, and intervention from the human as needed [11].
4. Machine control, whereby the machine performs the function independently without any involvement from the human except when the machine decides.

The horizontal plane in Fig. 3 depicts 16 cells of combinations of automation and distribution levels. Autonomy levels are increased by extending how far each function can be pushed or allocated along these two axes. For each function, the collaboration, delegation, or distribution can be pushed to different agents of the system as depicted for the delegated level as an example. A main question here is which functions may be best performed by pilots, operators, government, or third-party agents. This may be different for the different types of vehicles and missions that aspire to access the NAS.

Fig. 4 shows the other three dimensions of cognitive activity, learning level, and uncertainty level applied to each of the ATM services functional groups (shown for the security services as an example). These dimensions may be termed a cognitive space, which break down ATM functions into a higher level of detail to highlight more autonomy challneges. For each function, autonomy may be at different levels for the range of cognitive activities for that function, where autonomy may achieve self-planning, for example, but not self-awareness. Learning can increase from acquiring skills to gaining expertise for each of the cognitive activities and for all human or machine artificial intelligence. Finally, higher levels of autonomy are achieved when the autonomous agent—be it human or machine—can perform a function or activity under the highest levels of uncertainty. The following subsections describe each of these dimensions with a suggested scale.

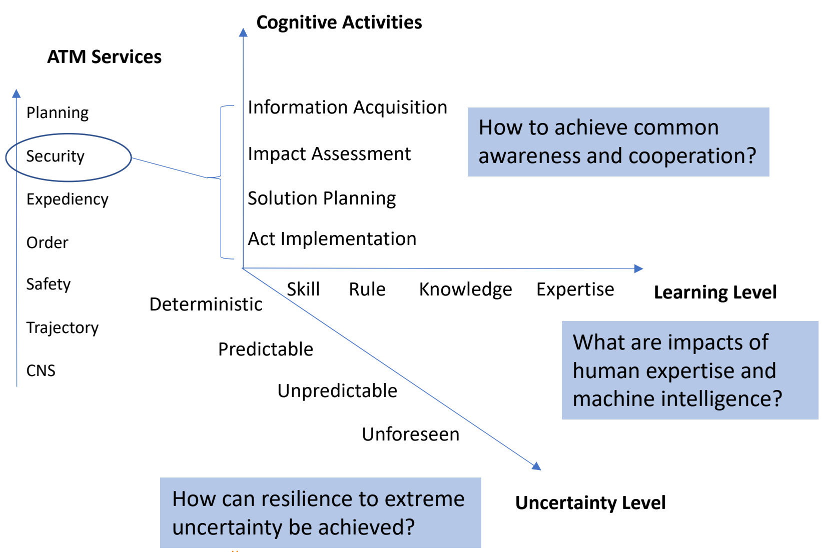

Fig. 4. Cogntive Space: Cognitive Activity, Learning, and Uncertainty

C. *Cognitive Activities*

In this framework, we break each function into four cognitive activities that are needed to accomplish an ATM function [14]:

1. Information acquisition: acquisition of information needed to perform the function.
2. Impact assessment: assessment of impacts requiring mitigation based on performance metrics.
3. Solution planning: computation of solutions to mitigate the identified impacts.

4. Action implementation: implementation of computed solutions by performing the needed actions.

The first two activities are typically associated with situation awareness by acquiring information, analyzing it, interpreting it, and computing any metrics and impacts to establish awareness. The third and fourth activities are associated with planning and executing solutions for any problems identified through situation awareness. These cognitive activities are commonly used in cognitive modeling and task analysis, with many variations in terminology and interpretation. For example, the observe, orient, decide, and act model, known as OODA, is commonly used as a four-stage breakdown of functions [15].

Any ATM function can be decomposed into the activities listed above, and agents can own or share the responsibilities for performing them. The level of autonomy increases as an agent is able to perform more or all of the cognitive activities associated with a function independently. For example, an agent may be able to only acquire information or only execute a plan independently. The term "self" is often associated with the independent conduct of functions or activities. Table 1 includes examples of self-properties from the literature grouped under each activity [16].

Table 1. Autonomous System Characteristics

	Self Property	Examples from Literature
Situation Awareness	Self-Acquisition	Self-awareness, context/environment awareness, mission awareness, self-monitoring
	Self-Assessment	Anticipatory, self-critical, self-diagnosis, self-reflecting, self-simulation, self-defining
Planning and Execution	Self-Planning	Self-optimizing, self-healing, self-protecting, self-adapting, self-destructing, self-governing, self-recovery,
	Self-Execution	Self-actuation, self-control, self-regulating

D. *Learning Level*

The higher the complexity of the tasks that an agent is able to perform independently, the higher the required level of autonomy. Many factors contribute to task complexity; Gill and Hicks provided a literature review of many of these factors [17]. It categorizes these factors into objective complexity, which is dependent on characteristics of the task itself independent of the task performer, and several factors that depend on the agent performing the task, including experienced complexity, information processing complexity, problem space complexity, and lack of structure complexity. As an agent—human or machine—performs a function or activity, intelligence accumulates through learning increasing the agent's proficiency in performing the function. Gill and Hicks suggested that while objective complexity may stay constant over learning, the other complexity attributes that are dependent on the performer are reduced through learning as expertise increases. Through learning, the expertise transitions from a cognitive stage where performing the task requires conscious activity, to an associative stage consisting mostly of associating knowledge, and finally to an autonomous stage where the agent expertise is highest and enables autonomous performance, based on intuition and instinct.

Another possible scale for task complexity uses the skill-based, rule-based, knowledge-based behavior levels by Rasmessen, which were expanded to an expertise-based level by Cummings [18-19]. Cummings associated these levels mainly with the ability to deal with different levels of uncertainty. Based on these models, these levels can be defined as follows:

1. Skill-based: routine activity, reactive to signals, dealing with deterministic events
2. Rule-based: programmed activity, matching signs, dealing with predictable stochastic events
3. Knowledge-based: planning activity, using symbology, dealing with unpredictable events
4. Expert-based: goal-generation activity, using meta-knowledge, dealing with unforeseen events

Table 2 describes some examples of tasks that may be classified under each of these categories.

E. *Uncertainty Level*

The ability of an agent to perform autonomously depends on the task environment, often known as the operating domain, particularly the level of uncertainty that the agent has to deal with. Four levels of uncertainty are highlighted:

1. Deterministic: no uncertainty is present and prediction can be perfect (known knowns).
2. Predictable: uncertainty may be represented by stochastic models of known events and dynamics (unknown knowns).
3. Unpredictable: uncertainty involves known but unmodeled events and dynamics (known unknowns).
4. Unforeseen: uncertainty includes unknown events and dynamics that popup unexpectedly (unknown unknowns).

Higher levels of intelligence and expertise are needed to handle higher levels of uncertainty, both from human and machine agents.

Table 2. Behavior Level Examples

	Skill	Rule	Knowledge	Expertise
Acquire	Receiving standard well-structured information, e.g., air traffic control (ATC) messages.	Collecting information according to well-defined rules, e.g., sampling instruments at desired rates.	Deciding what to observe, e.g., observing off-nominal weather with prioritized attention; detecting unfamiliar objects and events.	Observing and detecting unfamiliar objects and events.
Assess	Routine analyses, e.g., Filtering out noise; check list.	Simple mostly deterministic and well-defined analyses, e.g., projecting a state; comparing value to threshold.	Complex analyses involving uncertainty, e.g., determining risk tolerance; nuisance events.	Anticipating unforeseen events.
Plan	Planning reactionary routine responses, e.g., planning a maneuver according to a well-defined ATC instruction.	Planning according to if-then rules, well-structured algorithms, well-defined metrics and constraints, e.g., planning an approach procedure; planning a trajectory that meets a time.	Making complex plans under uncertain conditions using intuition and experience, e.g., contingency planning especially using other than pre-planned actions.	Planning actions under unforeseen and rare situations using innovative reasoning, e.g., selecting landing site with all engine failure
Execute	Reactionary and routine responses, e.g., acknowledging an ATC instruction; entering flight control commands.	Executing a plan according to well-defined rules or procedures, e.g., closing the loop on altitude or heading change using a control law; modulating power to maintain speed.	Executing a plan using adaptive methods under uncertain conditions, e.g., tracking a trajectory using adaptive behavior that accounts for changing dynamics.	Executing a plan using innovative methods under unforeseen conditions, e.g., controlling aircraft trajectory under full engine failure.

IV. Autonomy Challenges

Operational and technical challenges were identified for each functional group and across the different dimensions. They were then rolled up into several high-level challenges. Some high-level challenges were highlighted on the diagrams in Figs. 3 and 4 along each of the dimensions, namely: how far along the different dimensions should the ATM system extend in order to handle the anticipated levels of traffic and its diversity? The following list summarizes these challenges per dimension.

A. *Control Locus*

1) ***Coordination of Collective Autonomous Behavior***

As ATM functions progress towards more delegated (federated) and distributed schemes to enable scalability, an increasing need for coordination between autonomous agents develops. The system will need coordination mechanisms among distributed teams of vehicles, operators, service providers (public), and service suppliers (third-party) acting collectively to ensure safe and orderly operations (See Fig. 5). The agents may also include passengers as they become increasingly connected and empowered to make traffic management decisions in the mobility network. Fig. 5 (left side) shows that vehicles may belong to fleets operated by one operator (the orange, blue and green vehicles), while some (the black vehicles) may be operated individually. It also shows that vehicles may subscribe to receive services from different, and possibly multiple, service suppliers (vehicles within the dashed circles) while some vehicles may receive services only from the public central authority.

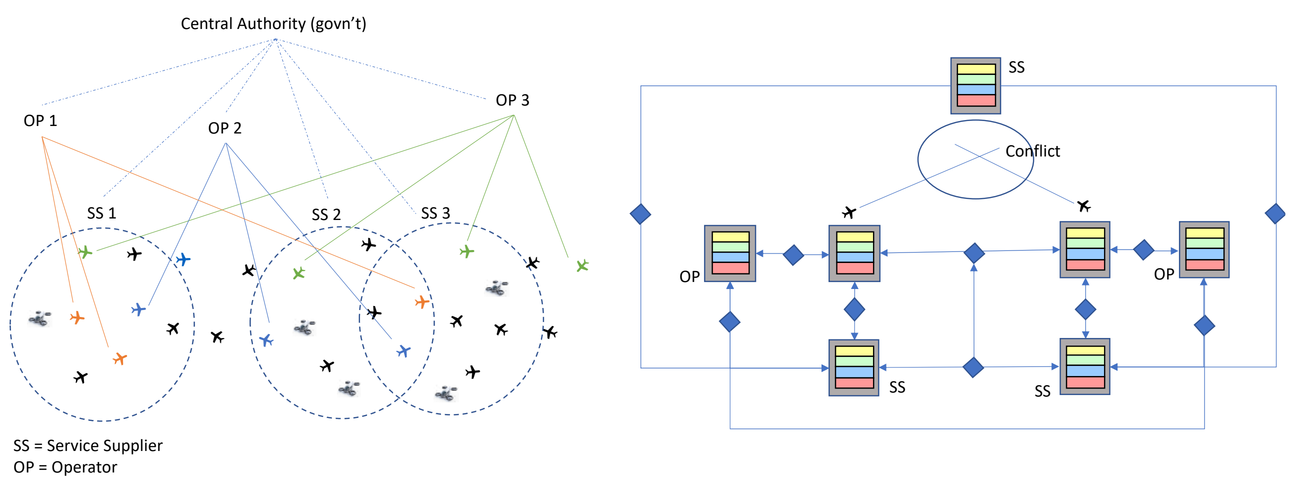

Fig. 5. Collective Coordination among Heterogenous Autonomous Agents

As vehicles subscribe to different service suppliers and are managed by different operators as part of different fleets, the coordination may involve coupling between heterogeneous sub-systems and dynamics. Several potential types of coordination are shown in Fig. 5 (right sides): (1) vehicle-vehicle coordination, where vehicles coordinate their behaviors directly; (2) vehicle-service supplier coordination, where each supplier induces coordinated behavior among the vehicles under their service; and (3) supplier-supplier coordination, where service suppliers need to coordinate among each other in order to resolve any conflicts, for example in accessing shared airspace. Similarly, Fig. 5 shows types of coordination between vehicles and their operators, between operators, and between suppliers and operators, where the service suppliers can coordinate vehicle behaviors through the vehicle operators. The diamonds on each connector line indicate that the coordination can be controlled as needed between the respective agents. Fig. 5 shows that each agent exhibits the four levels of cognitive activities (yellow for information acquisition, green for impact assessment, blue for planning and red for implementation) enveloped by a learning layer (grey boundary) as outlined in the framework in Fig. 2. Using the cognitive activities, coordination mechanisms can be classified as collective situation awareness including sharing of observations, states, and intents and sharing individual agent and system impacts, or collective decision-making including negotiation between agents and integration of their distributed plans and actions. To provide maximum flexibility when possible, the coordination may be dynamic, where tighter coordination is applied as the situation necessitates [6].

2) *Dynamic and Graceful Transition of Responsibility*

ATM functions may be delegated or distributed to different agents, such as the vehicle, operator, or third-party service suppliers. It is important to ensure the proper allocation of responsibilities to these different agents based on their capabilities, the complexity of functions, and the uncertainties in the environment. These allocations may be dynamic as the complexities and uncertainties of the functions and the environment change. An important challenge is to ensure the graceful transition of responsibility under dynamic conditions. Both procedural and technological support is needed to ensure these transitions of responsibility occur gracefully.

3) *Clear Responsibilities and Sufficient Oversight*

As ATM functions are delegated and distributed to human and/or machine agents, one important challenge is to ensure clear lines of responsibility between the agents and proper oversight from the centralized authority. It is very important for centralized, human service providers to know where their responsibilities start and end. For some functions (such as safety critical functions) and under certain conditions (such as degraded, off-nominal conditions), only centralized, collaborative or delegated schemes may be appropriate, leaving the responsibility to the centralized service provider. Even under delegation and distribution of functions, the appropriate level of oversight should be provided by the centralized authority.

4) *Seamless Access and Services*

ATM functions will be provided by a network of government providers and third-party suppliers, along with services that may be delegated or distributed to operators and vehicles. In this federated architecture, a key challenge is to determine which services are inherently governmental (such as safety-critical services), which may be delegated to a single supplier, and which may be offered by multiple suppliers. These allocation decisions may also be dynamic depending on the airspace, time, and traffic situation. They should be seamless to users as they travel through the airspace and receive uninterrupted services from multiple agents.

B. Automation Levels

1) *Digital Air-Ground-Cloud Integration*

Historically, many ATM functions have been automated to varying degrees with decision support automation providing advisories to human pilots, operators, and service providers. However, even as more functions have been automated, the integration between them has remained centralized and human-based. As the ATM automation level increases along the automation scale from decision support to the ability to perform functions under human supervision or independently from the human, the coordination needs to be transformed from human-based integration to digital-based integration. This digital connection enables automation systems to be integrated without the mediation of human flight operators or service providers. It also allows these systems to coordinate information and solutions and to support a higher level of function allocation to the machine from the human. Fig. 6 shows the current level of ATM automation (in the top left corner cell) and three increasingly autonomous ATM operations (in the other three cells), simplifying the horizontal plane in Fig. 3 from sixteen cells to four cells.

1. The current system shown in the top left diagram is human-centric where most integration between ground-based and airborne agents is performed by the human agents using voice communication while machines support the human agents. The coordination is achieved primarily by the ground-based coordination among the human service providers (solid arrows) while the communication between pilots/operators plays a secondary role (dashed arrows).

2. The top right diagram shows a transition to a digital, machine-based system that is still ground-based, but where the integration between all the airborne and ground-based agents is performed via machines exchanging digital information and negotiating decisions. The ground-based human agents depend on their machines to provide primary coordination with voice as secondary. The ground-based agents still maintain a major centralized role in performing all ATM functions with only secondary coordination among the airborne agents. While the machines perform most coordination, the human agents act in a supervisory role to the machines, intervening when needed.

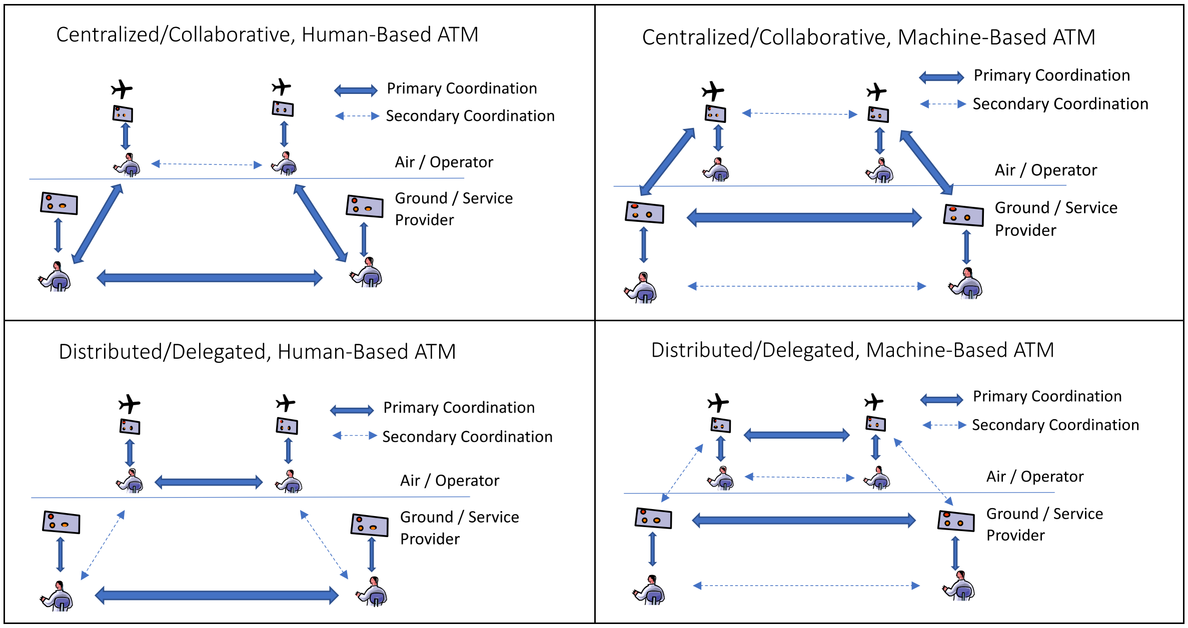

Fig. 6. ATM Distribution and Automation Schemes

3. The bottom left diagram shows a delegated or distributed architecture where the airborne agents (the vehicles and their operators) are able to self-manage and perform all of the ATM functions, either in a delegated (under supervision from the ground-based service provider) or a distributed manner (without supervision from the ground-based service provider). Integration is still human-based, where the human pilots and operators interact among each other to provide primary coordination. The ground-based human service providers also interact among each other to coordinate their behavior, but provide secondary coordination to the vehicles and operators, through delegation and oversight.

4. The bottom right diagram shows also a delegated or distributed architecture where the airborne agents self-manage and perform all of the ATM functions. Integration, however, is all digital and accomplished via the machines. The airborne agents include piloted, remotely operated, and autonomous vehicles that support all required vehicle-to-vehicle, operator-to-vehicle, and operator-to-operator machine-based interactions. The ground-based service providers also coordinate digitally through their automation, but provide only secondary coordination to the airborne agents, through supervision and oversight.

As part of the digital transformation, automated functions may be hosted in the digital cloud, potentially provided by third-party suppliers. The digital integration needs to include not only airborne and ground-based agents, but also cloud-based agents.

2) Human-Autonomy Teaming

As ATM functions are increasingly automated, most functions will continue to be performed by teams of human and machine agents working together to ensure safe, orderly, expedient and secure operations. This is true across the automation scale where some functions or activities may require cooperation between human and machine agents, some a supervisory role by the human, while other functions and activities may be performed equivalently by either the human or machine agents. Therefore, it is critical to facilitate an effective human-machine teaming relationship by establishing seamless understanding and robust human-machine interfaces. This teaming relationship must be maintained between human-automation teams of service providers and with/among autonomous, remotely-operated, and piloted flights. Shared understanding must also be maintained under nominal and downgraded conditions such as loss of digital communication, which may require technologies for intelligent machines to interpret voice as well as digital communications. Finally, measures to assess effective team performance will need to be developed and validated to evaluate proposed teaming structures, and to possibly determine the composition of teams, as well as when they should be formed.

3) Dynamic Function Allocation

Determining which functions to delegate to machines and what role the human plays is a significant challenge to ATM autonomy. The roles of the human and machine agents should be dynamic, varying under different conditions such as traffic densities, complexities, and off-nominal events. This allocation also depends on the level of trust that can be achieved by the machine for different functions under different conditions. Technologies must be developed to support dynamic function allocation between the human and the machine.

4) *Graceful Transition between Automation Levels*

Another challenge is to ensure graceful transition between different automation levels, particularly for degradation from higher machine autonomy levels to lower ones as the human may need to intervene or take over from the machine. Procedures and technologies that ensure human continued awareness and engagement to enable graceful takeover are needed across all functional groups and time horizons. For example, seamless integration of autonomous machines into the ATM system may lead to complacency in human oversight, loss of situation awareness, and loss of skills, leading to potential adverse outcomes in failure situations that require special handling due to the lack of human operators. Design of autonomous machines, artificial intelligence, and distributed schemes needs to account for the possibility of partial or complete human takeover.

5) *Supervisory Human-Machine Ratio*

As the automation level of ATM functions increases to supervisory schemes where the human responsibility is reduced to monitoring and intervening only when needed, the human agent may be capable of supervising multiple machines. For example, one human operator may be able to operate multiple vehicles that can perform many vehicle functions autonomously and potentially multi-vehicle coordination functions. Many schemes with reduced ratios of human operators to autonomous vehicles are being considered as a gradual transition towards higher levels of autonomy.

C. *Cognitive Activities*

1) *Autonomous Collective Perception and Situation Awareness*

Higher levels of autonomy are achieved when distributed agents and autonomous machines are able to establish situation awareness independently by acquiring information and analyzing it to assess any impacts that require attention. Situation awareness involves capabilities that are more typical for human agents than machines. For example, while automation may surpass the human ability to maintain vigilance in monitoring a particular situation or to compute some complex metrics, artificial intelligence technologies are still lacking in determining what relevant information to acquire and sample and what impacts and metrics to assess. It is also more difficult for distributed agents to establish shared awareness and build a common understanding of system impacts that are more visible to a centralized agent. This requires considerable intelligent perception capabilities in edge and machine agents to not only acquire and share observations but to fuse and interpret this information into a collective situation awareness.

2) *Characterizing Autonomous System Performance*

The impacts of increased levels of autonomy on the performance of the ATM system in terms of, for example, safety, security, order and expediency, need to be characterized and well understood. When assessing the impacts of a certain event or behavior on system performance, these impacts are different when the system consists of highly autonomous human-machine teams acting collectively. For example, the response time of autonomous systems is different than the response time of a centralized system with dominant human roles. This poses implications on the safety and stability of the system and its robustness to disruptions such as failure events. Therefore, the design of autonomous systems and human-machine teams should account for response times and stability margins across different time horizons. Some performance metrics that may be associated with autonomous systems include:

1. Scalability: the ability of autonomous services to scale with increased demand.
2. Seamlessness: the ability of autonomous systems to integrate in the airspace transparently without noticeable impacts.
3. Flexibility: the ability of autonomous systems to provide more solutions to meet mission needs and mitigate disruptions.
4. Resiliency: the ability of autonomous systems to anticipate, resist, and recover from unforeseen threats.
5. Trustworthiness: the ability of autonomous systems to be understood, trusted and certified.

3) *Cooperative Autonomous Collective Decision Making*

Distributed, autonomous agents acting collectively to manage traffic are more susceptible to non-cooperative behavior such as gaming. As multiple autonomous agents make independent decisions, a key challenge is to reconcile their individual utilities and mission objectives with the overall system performance objectives. Reaching consensus on plans and actions among distributed, autonomous agents takes more time and may result in instabilities such as deadlock and racing conditions. Agents such as operators and service suppliers acting at more aggregate levels may promote cooperative behavior among the vehicles in their systems. Special rules for autonomous systems with effective oversight may also be needed to induce fair and efficient collective behavior.

D. *Learning Level*

1) *Enabling Knowledge/Expertise-Based Autonomy*

Automation has long been considered effective for skill- and rule-based behaviors where a machine is able to independently perform routine repetitive tasks (skill-based) and tasks that can be programmed into a set of rules or well-defined algorithms (rule-based). Machines can surpass the human ability to perform some of these tasks which often require vigilance or heavy computation. Examples of these tasks include the automatic digital communication of routine control clearances. It is more challenging to increase machine autonomy for knowledge and expertise level behaviors, where the human abilities still outperform those of the machine. For example, artificial intelligence is still lacking in providing behaviors for determining what information to acquire, what goals to pursue, what objectives to maximize, and what priorities to place on tasks. The machine learning technologies still expect the human to teach such parameters to the machine, while the machine can then learn and perform computations, optimizations, and control using these parameters. These characteristics of human behavior draw on human abilities such as abstraction, generalization, instincts, and intuition, which may be called upon in unforeseen situations. An example of this situation is handling uncommon failure situations such as losing all engines and selecting an emergency landing site (the Captain Sully case [18]).

2) *Autonomy Emergent Behaviors*

Autonomy of multiple distributed agents that include human-machine teams can lead to emergent behaviors that are difficult to anticipate and trust by centralized human agents providing oversight. The addition of machine learning increases the potential of emergent behavior by autonomous machine-based entities. The complexity of the behavior of distributed intelligent systems is often beyond the comprehension abilities of human teaming and oversight. This is increasingly true as machine intelligence progresses towards generalization using deep and transfer learning. In addition, increasingly autonomous agents can potentially perform more functions at higher resolutions and at farther time horizons than possible by the human-centralized agents. While these added capabilities are beneficial to increase scalability and often improve performance, technologies are needed to ensure that emergent autonomous behaviors can be understood, trusted, and safely managed particularly when humans may interact with the system.

3) *Seamless Autonomous Operations and Training Implications*

Another challenge is whether autonomous systems, working in teams with human agents (with different levels of responsibility allocations), should be designed to minimize the need for human training or if the human should be trained to operate according to the autonomous system desired design. This issue has implications on the effectiveness of graceful degradation in the case the human agent (pilot, operator, or air traffic controller) has to intervene or take over from the automation. Seamless operation of autonomous agents such as vehicles may not require any additional human training, and hence may be desired from a cost perspective. However, seamlessness may lead to compromising safety in situations that require human attention where a human is not present.

E. Uncertainty Level

1) *Adaptive and Robust Autonomous Operations*

The ability of distributed autonomous agents to perform functions independently depends on the environment in which the function is performed. Higher levels of autonomy are associated with the ability to perform ATM functions under more challenging operational domains, including high levels of disruptions and uncertainties. It is therefore essential to design the autonomous systems to exhibit the adaptive and robust characteristics needed to respond in a timely manner to volatile environments. Adaptive behavior can be increased by incorporating dynamic parameters that can be adjusted based on the changing environment. Robustness can be increased by building stochastic models of uncertain dynamics into the autonomous system design. For example, weather uncertainties can be modeled and factored into the decision making of autonomous agents. One advantage of increasing autonomy is enabling more adaptive and robust behavior towards disruptions and uncertainties. As ATM functions are distributed to human-machine teams, more redundancies are created because the distributed multi-agent system provides more alternative paths to accomplish a function than a centralized human-centric system. These alternatives can also provide more flexibility in accommodating dynamic environment and mission needs, such as on-demand flight planning.

2) *Resilient Autonomous Operations*

Higher levels of autonomy are expected to perform in extreme levels of uncertainty where unforeseen events that cannot be predicted may occur. These incidents may not be possible to prevent due to their unforeseen nature and may have drastic outcomes on system performance. Such events include, for example, loss of communication and complete engine failure. Dealing with such situations is typically a trait of human agents who can resort to their expertise-based behavior and intuition to manage them with innovative solutions and enduring will. To achieve high-levels of autonomy, the autonomous agents must be designed with resiliency to such events. The resiliency includes autonomously anticipating, resisting, and recovering fully from their effects.

F. Functional Groups

1) *Autonomous Dynamic CNS*

Scalability of CNS services can be achieved by increasing the level of autonomy in the provision of CNS services. For example, the allocation of communication bandwidth may be transformed from current static practices to dynamic allocation, where a volume of airspace is assigned different frequencies based on traffic demand for the airspace. Such high-frequency dynamic allocations are often prohibitive for human management and require high levels of automation and machine intelligence.

2) *Safety Assurance of Autonomous Operations*

Proving the safety case for autonomy to enable certification and rule making for autonomous systems is critical and still elusive. Safety-critical functions such as separation and contingency management are harder to make autonomous, whether to different agents or to machines. The level of autonomy for safety-critical functions may remain lower than other functions, maintaining a significant oversight and authority role for the centralized human service provider.

3) Autonomous Order and Disruption Management

While the automation and distribution of separation assurance and flow management functions have been studied to some extent, increasing autonomy for other functions such as maintaining orderly flow and managing disruptions are less understood and still pose a challenge. For example, notions of "roadmanship" in human behavior, which are key to maintaining orderly traffic flows that avoid disruptions and gridlocks, are not well understood and difficult to teach to machines. The ability of autonomous ATM systems, distributed and machine-based to mitigate and manage disruptions without human assistance is a major challenge and key to increasing autonomy to levels where autonomy can operate "everywhere."

4) Flexibility and Scalability to User and Mission Demands

One challenge is to develop ATM services that scale to high-volume operations containing a diversity of missions and vehicle types. More scalability can be achieved by moving more functions from centralized agents towards edge agents and from the human to automation. Through moving the locus of control towards users, more flexibility is provided to users and missions to accomplish their objectives expediently. The flexibility afforded by higher levels of autonomy needs to be balanced by the appropriate levels of structure and predictability to maintain safe and orderly operations.

5) Cyber-Physical Security of Autonomous Security

Security threats, cyber and physical, pose a major challenge to autonomous systems, distributed and machine-based, that cannot be overlooked. Autonomous systems, especially if distributed, can offer redundancies that reduce the impacts of threats and help in recovery, but they also increase the exposure to threats that may propagate through the system. The ability to authenticate services and information, and to be resilient to threats in the sense of anticipating them, resisting them, and recovering fast from their effects to restore full operations, needs to be researched and incorporated in autonomous systems.

6) Autonomous Dynamic Mission Planning

Mission, flight and fleet planning need to accommodate a wide variety of operations including scheduled operations, which may feature high levels of accuracy in their flight plans and on-demand operations, which require the flexibility to accommodate volatile changes in time and location. These variations pose challenges to increased autonomy, which needs to accommodate dynamic replanning under poorly defined missions, volatile flight plans, and changing environments.

V. CONCLUSIONS

To conclude, the challenges that were identified and described in the previous section are depicted graphically along the different framework dimensions in Figs. 7 and 8. This depiction shows how a framework such as the one presented in this paper helps to analytically and systematically identify autonomy challenges for a system. This is particularly important for ATM, which is a complex system of systems with many functions, facets, and stakeholders. While the presentation in the paper is rather analytical, the framework can also serve as a basis to communicate and socialize ATM autonomy challenges with experts and solicit their feedback in a methodical manner. It can be used to develop operational scenarios, perform functional allocation, formulate human-machine teams, and design automation and machine intelligence. Finally, the framework provides abstractions, such as the cognitive activities, levels of expertise and levels of uncertainties for modeling autonomous multi-agents and their collective behavior. Current research activities are developing such models based on these abstractions to assess the performance of different levels of autonomy in ATM.

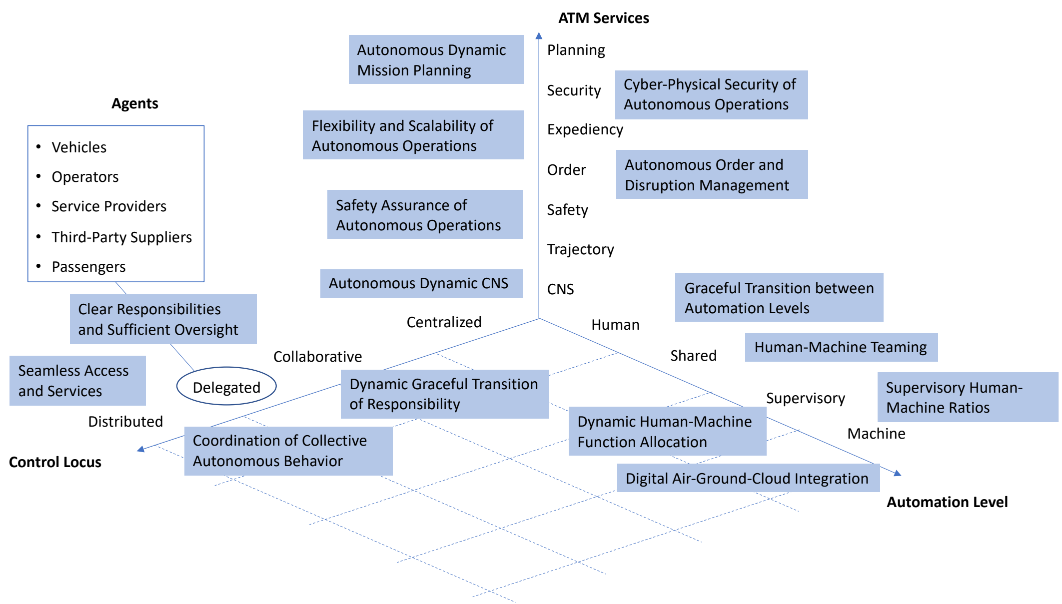

Fig. 7. Challenges per Abstraction Framework

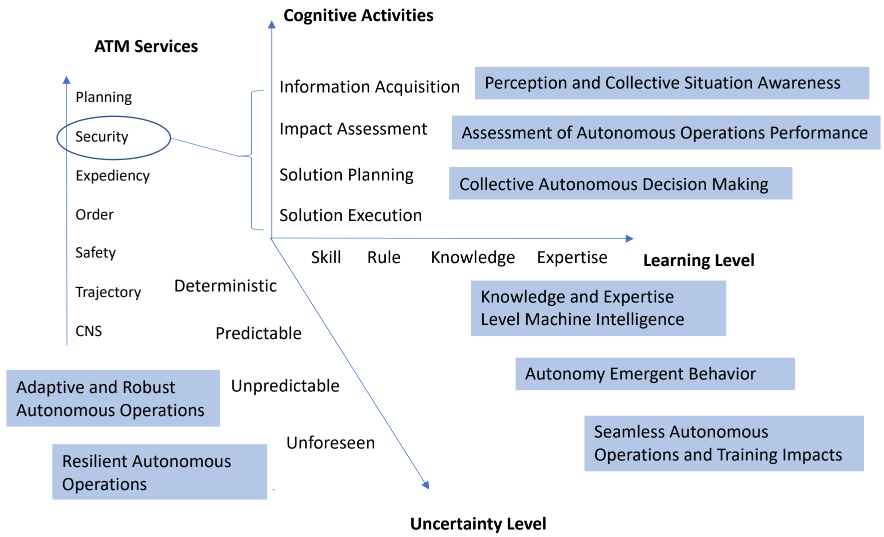

Fig. 8. Challenges per Abstraction Framework

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