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A Framework for Predicting the Mission-Specific Performance of Autonomous Unmanned Systems

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Abstract— **While many methodologies have been proposed for calculating a quantitative level of autonomy for intelligent Unmanned Systems (UMS), no one definitive measure of autonomy or autonomous performance has been validated and adopted by the UMS community. Particularly for military applications, a simple performance metric that is based on the UMSs mission profile and is comparable between UMS systems is critical. This metric would not only help define the features a UMS needs to successfully perform its mission, both in terms of hardware and software, but also enable the use of UMS for a broader range of applications at an increased level of autonomy. This paper presents the development of a new methodology for calculating a single-number performance metric for autonomous UMS, and this metric is called the Mission Performance Potential (MPP). Rather than a retroactive measure of UMS performance and autonomy level for one iteration of a given scenario, the MPP separates autonomy level and mission performance to provide a predictive measure of a UMS's expected performance for a mission set and level of autonomy. As an example application, the MPP is calculated for an Unmanned Aerial Vehicle (UAV) performing a target tracking mission, and this MPP value is compared to the results of field-testing with this system.**

I. INTRODUCTION

The field of robotics and intelligent systems has grown explosively over the last decade, and Unmanned Systems (UMS) are being fielded with increasing frequency for military applications. However, as a consequence of this rapid advancement, a lack of agreed upon standards, definitions, and evaluation procedures for UMS exists. Specifically, no agreed upon method for assessing an intelligent UMS's level of autonomy has been established. Furthermore, while a wide range of both autonomous and semi-autonomous UMS are available for use, no measure yet exists to measure what the impact increased or decreased autonomy has on UMS performance.

Several models have been proposed for assessing UMS level of autonomy and autonomous performance, and these models are briefly discussed in the following section. The major drawback to these models is that they do not assess, specifically, the mission-specific fitness of a UMS. For military operations, the user will often have several UMS assets available for a given mission, and the current models do not provide a simple answer for which asset is "best." Furthermore, none of the current models address, quantitatively, the impact on mission-specific performance of changing a given UMS's level of autonomy.

Therefore, a critical need exists for a simple, quantitative metric for measuring the mission-specific fitness of a UMS that is a function of the UMS's level of autonomy. With this need in mind, such a metric was developed. The new metric for measuring autonomous performance is designed to predict the maximum possible mission performance of a UMS for a given mission and autonomy level and is named the Mission Performance Potential (MPP). Section III presents a detailed description of the MPP, including the data needed to calculate a UMS's MPP and the method in which the MPP is calculated.

Another major shortcoming of the present autonomy level/autonomous performance methodologies is that they have not been fully implemented and applied to "real world" UMS operations. To bridge this gap from theoretical to practical, the MPP was implemented in software and applied to a simple example UMS and mission: an Unmanned Aerial Vehicle (UAV) performing a target acquisition and tracking mission. The MPP for the UAV was computed and then compared to the UAV's true performance during a field-testing exercise. Section IV presents the results of this experiment. Lastly, Section V offers some conclusions and plans for future MPP development.

II. RELATED WORK

As of this writing, several models have been proposed for assessing UMS performance and autonomy level. In general, these models can be divided into two categories, contextual and non-contextual.

A. *Contextual Performance Evaluation Tools*

The most developed and commonly referenced contextual model for assessing autonomous UMS performance is the Autonomy Levels for Unmanned Systems (ALFUS) framework [1] [2]. The ALFUS is not a specific test or metric, but rather a model of how several different test metrics could be combined to generate an autonomy level. The ALFUS workgroup continues to develop and refine the ALFUS, and recent advancements can be found in [3] and [4]. The framework includes the following both a Detailed Model and a Summary Model for Autonomy Levels as described below.

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The Detailed Model for Autonomy Levels tool was envisioned to satisfy the need for accurately assessing the autonomy level of a UMS. It assesses autonomy level using a tool called the Contextual Autonomous Capability (CAC), which is described in detail in [1]. The CAC is a three-axis system wherein each axis refers to a metric group, which can be Mission Complexity, Environmental Complexity, or Human Independence. These axes comprise scores from bench tests. For a given mission and environment, metrics are measured for the mission complexity, environmental complexity, and human independence of the UMS (measured during mission performance), and these metrics are combined to form a level of autonomy.

The Summary Model for Autonomy Levels aspect of the ALFUS methodology consists of a simpler, easier to reference model that was developed to be used for general reference purposes. It consists of a 0 to 10 numeric scale that characterizes the autonomy level of a given UMS. It uses the outputs of the detailed model as its main inputs, as presented in [3].

The ALFUS framework provides the capability of estimating the level of autonomy of one robot or a team of robots. However, this methodology still has some drawbacks that prevent its direct implementation. The ALFUS methodology does not provide the tools to:

- Decompose the tasks in a commonly agreed-upon, standard way
- Test all possible missions, tasks, and sub-tasks
- Assess the interdependency between the metrics, as some of the subtasks can apply to more than one metric
- Allow metrics to be standardized in scoring scales; this will cause subjective evaluation and criteria to influence the results across different robots, users, or competing companies
- Integrate the metrics into the final the autonomy level

Another important issue with the implementation of the ALFUS is the fact that the highest level of autonomy might not be the most desirable operational level for several UMS, missions, and/or environments. It is of critical importance that an autonomous performance assessment tool not only evaluate the UMS's level of autonomy but also the impact that autonomy has on the UMS's ability to perform its mission. Sometimes supervised autonomy or direct control over the robot will guarantee the best mission performance; for example, a fully autonomous ground vehicle will probably behave worse than a teleoperated robot in a bomb deactivation mission. Or, for a UAV, a fully autonomous intelligent asset does not assure the best mission completion status in the case of a changing or time-sensitive scenario.

Other contextual-based measures of autonomy have been proposed, namely those focused on measures of human-robot interaction [5] and those designed to determine "optimal" performance through adjustable autonomy [6] [7]. While these methods do provide the benefit of a rigid definition of UMS autonomy levels, they still suffer from many of the same drawbacks of the ALFUS. Specifically, any performance measure derived from human operator performance fails to produce a firm result that is comparable between systems and tests, especially for tests aimed at defining what sensor, hardware, and software requirements are "optimal " for a given UMS.

B. Non-Contextual Performance Evaluation Tools

The drawback to the use of the ALFUS and other contextual measures of autonomy is that they are highly context-sensitive methods which require metrics to be measured not only for the UMS's hardware platform but also for its operator and mission environment. Moreover, many of the metrics needed to evaluate environmental and operator concerns for the ALFUS have yet to be determined. A simpler method for measuring a UMS's autonomy level which is derived from only the robotic platform itself is desirable because such a measure could be calculated without first performing extensive operational level testing, and this measure could be compared across platforms without the added caveats of environmental factors.

Using a generalized model of UMS architectures, a non-contextual methodology for measuring UMS autonomy level was developed. This framework, called the Non-Contextual Autonomy Potential (NCAP), was first presented in [8] and [9]. The NCAP provides a predictive measure of a UMS's ability to perform autonomously rather than a retrospective assessment of UMS autonomous performance. Furthermore, the UMS autonomy level is determined outside of a mission or environmental setting. The NCAP treats autonomy level and autonomous performance separately. A UMS that fails completely at its mission but does so autonomously still operates at the same autonomy level as another UMS that succeeds at the same mission.

The NCAP defines four Autonomy Levels (AL). The AL ranges from 0, no autonomy/fully radio controlled or teleoperated, to 3, fully autonomous. A UMS's AL is defined within the context of a generic UMS architecture model as follows. A UMS that only contains perception, i.e., a teleoperated Unmanned Ground Vehicle (UGV) with an onboard camera, has no autonomy. A UMS that generates some sort of world model or retains an internal knowledge base of its surroundings is considered semi-autonomous. At this level, the UMS is interpreting the raw sensor data on its own and has the beginnings of intelligence. A UMS that further uses its world model to form a plan of action is considered autonomous. At this level, the UMS is making a judgment based on its internal knowledge base. Finally, a UMS that chooses a best action based on its modeling and planning and performs that action without operator input is considered fully autonomous.

The NCAP is based solely on the UMS platform itself. Metrics based on component level testing of the UMS are combined to provide the final NCAP score, and the NCAP is meant to serve as a tool for predicting autonomous performance potential. While the NCAP does offer some benefits over the ALFUS in terms of ease of implementation, it does not provide a complete solution to the problem of measuring mission performance or measuring the impact of autonomy on mission performance. Thus, a new metric for UMS performance is needed, i.e., one that fuses both contextual and non-contextual performance assessment methods.

III. The Mission Performance Potential

It is impossible to accurately determine a UMS's mission performance without testing the UMS in the field, and determining performance is further complicated by the fact that a UMS could be used for multiple missions, each with different tasks and environments. While the methods presented in the previous section have their own strengths and weaknesses, none of them address the core problem of determining a UMS's mission performance and the impact of autonomy on mission performance.

A contextual performance tool that can predict mission performance potential without full scale testing would provide the critical tool missing in the UMS evaluation process. Without full scale, in-theater testing, the true mission performance of a UMS cannot truly be determined. Therefore, a tool that predicts performance potential for a particular mission given the UMS hardware, software, and operational environment is needed. Specifically, a new tool is needed that provides the following:

1) A single, numeric value, comparable between UMS systems, that provides a predictive measure of UMS performance for a given mission, environment, and autonomy level.
2) A fixed UMS autonomy level, and UMS performance is measured as a function of that autonomy level.
3) An input data set that can be evaluated using only the UMS system and mission description.

A performance assessment tool was developed in accordance with these requirements and was dubbed the Mission Performance Potential, or MPP. The MPP methodology provides a snapshot of a UMS's potential to perform a mission (or mission set) at a set autonomy level and not a measure of how the UMS performed or what the UMS's autonomy level was for one single, full-scale instance of that mission. The following sections describe the MPP, including the accepted levels of autonomy used for the MPP, the technique for calculating the MPP, and the type of data needed to drive the MPP.

A. MPP Autonomy Levels

The MPP starts from a pre-defined autonomy level. One of the major weaknesses of the contextual autonomy metrics presented in Section II is that autonomy level was a dynamic value that required field-testing data to calculate and left substantial room for interpretation. The MPP starts from an approach similar to the NCAP that fixes the UMS's autonomy level. This approach provides several benefits. First and foremost, it fulfills the goal of assessing mission performance as a function of autonomy level. Second, these predefined autonomy levels provide the users with a better understanding of the UMS's capabilities rather than an abstract number. Lastly, this approach deals with the fact that for a given UMS, the autonomy level may vary between missions and environments. For example, a UMS may operate with some autonomy in urban environments but be fully teleoperated in off-road environments while having the same overall level of mission performance in each environment.

The MPP defines five levels of autonomy as follows:

1) Radio-control - the operator is provided with a method of controlling the actuators of the vehicle directly. Sensory feedback is through human senses that are limited by visual range and noise.
2) Tele-operation - the operator is provided with a method of indirectly controlling the actuators on the vehicle, through control-by-wire or rates' control. He is also informed of the vehicle's status through communication subsystems and data visualization techniques, i.e., visual animated gauges, maps, arrows, or heads-up-displays.
3) Supervised Autonomy - the operator is provided with a method of controlling the vehicle's general behaviors. It is assumed the operator can maintain communications with the vehicle for task reallocation. This AL includes waypoint control, goal-based control, and scenario-based control.
4) Adaptive Autonomy - the operator is provided with a method for accepting the vehicle-initiated changes to the initial task, path, or goal. The vehicle is capable of suggesting, changing, or overriding previous operator commands, based on new situational awareness. It is up to the operator to manage the decision-making process in the UMS.
5) Higher Intelligence - the operator is provided with the vehicle's relevant information for decision making and tactical planning. The operator does not need access to full vehicle's sensor readings or navigation sensors, and instead focuses on the mission sensitive data collection.

B. MPP Input Data and Calculation

At its core, the MPP is similar to the previously proposed performance assessment frameworks. In particular, the MPP is an extended application of the basic ideas behind the NCAP that is built on the theoretical basis of the AFLUS. The MPP leverages the work already done in other efforts and reframes these ideas into a new framework that addresses mission-specific performance potential. Figure 1 shows a high-level overview of the MPP.

The MPP framework uses a similar data collection method as the NCAP. Then, questions related to the mission and environment are used to create "masks" to compute the final MPP score for the UMS. For example, if a mission requires a UGV to operate in soft-soil conditions, the MPP will automatically be set to zero for any UGV that cannot operate in these conditions regardless of its level of autonomy or performance in other areas. This is a major benefit of the MPP over previous methods.

Calculation of the MPP score requires three types of input data:

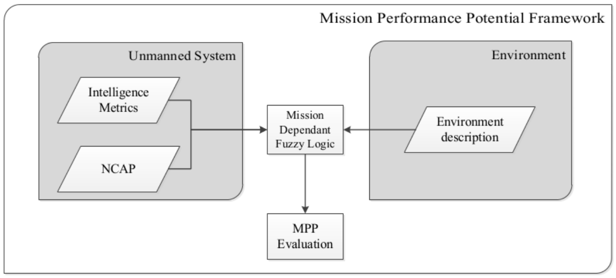

Fig. 1. The MPP framework. Intelligence metrics and UMS hardware metrics (the NCAP) are combined using mission-dependent fuzzy aggregation to provide a single MPP value.

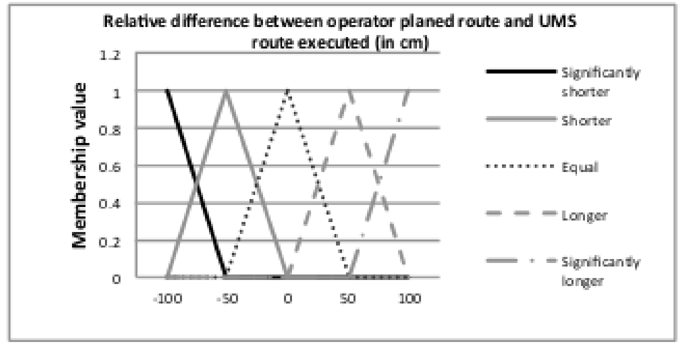

Fig. 2. Example mapping of a measured performance value onto a qualitative, fuzzy set.

1) Data about the system being estimated, i.e. the platform's physical parameters like weight, shape, dimensions, and sensing capabilities describing sensor types and their functional characteristics.
2) Data about the system's intelligence, namely the platform's decision making abilities including path planning, re-planning, obstacle avoidance, and other relevant qualities that demonstrate the system's active and reactive behaviors.
3) Data about the mission environment such as weather conditions, soil conditions, structured-ness (i.e. urban vs. cross-county), to name only a few.

Tables III and IV, found in the Appendix, provides a breakdown of the data, including the values, ranges, and types of information needed to drive the MPP calculation.

The main challenge behind the MPP calculation is the need for a reasoning procedure that allows the combination of input data that is different both in its nature and its value domains. As Tables III and IV show, data values fall within wide ranges and contain disparate types of information (binary, percentile, linguistic, etc.). The only feasible solution for MPP calculation is therefore the use of fuzzy inference techniques allowing the combination of different information types into a unified inference mechanism. A full discussion of fuzzy logic and fuzzy aggregation operators is well beyond the scope of this work, and a detailed review of these topics can be found in [10], [11], and [12]. As an example of the application of fuzzy logic for calculating the MPP, Figure 2 illustrates how the difference between operator planned path and UMS executed path for a route following behavior can be mapped into a qualitative performance metric.

Using fuzzy logic, the MPP aggregates all the necessary data related to the UMS system (hardware, software, and intelligence) into a final MPP score. The rules and "masks" mentioned above for the fuzzy aggregation are determined by the mission description. A brief description of some of the fuzzy aggregation methods used for the following example application of the MPP can be found in [13].

IV. Example MPP Calculation

In this section, the MPP will be calculated for an example UMS scenario: a UAV performing a target tracking mission. There is much work left to be done in developing and refining the MPP, particularly in defining the question tables and data needed to drive the MPP and the fuzzy logic rules used to calculate the MPP using these data. This simple example serves as only a first, small step towards applying the MPP tool to fielded UMS.

A. Unmanned Aerial Vehicle Mission Description

A UAV performs target detection and tracking of a ground-based target, in this case a moving vehicle/convoy. The UAV will take off under manual controls and then, after systems checks, go into automatic mode. It will then travel to a designated point and begin searching for the target. After acquiring the target, the UAV tracks and follows the target, following either behind or to the side of the target while maintaining altitude. When the target is lost, the UAV switches off of automatic control for the operators to either relocate the target or command the UAV to return to the base station.

B. MPP Data

The data that were used as input for the MPP calculation in presented in Table I. Table I represents the subset of data from Tables III and IV that apply to the given UMS and mission.

C. MPP Calculation and Comparison to Mission Performance

A field-test recreation of the UAV mission was performed on December 06, 2013 by Portuguese Air Force personnel at the Ota Air Force Base in Portugal. The UAV was controlled by three operators, an Operator, a sub-systems Operator, and a Pilot (for those tasks performed at an AL of 0 or 1). Four dedicated flights were performed with the same mission on the same day to provide, as much as possible, the same conditions for each flight. During testing, the temperature varied between 4^{o}C to 10^{o}C, cloud cover was roughly 50%, and winds varied between 12km/hr to 20km/hr gusts. The test environment consisted of approximately 40% urbanized/city terrain and 60% cross-country terrain.

The UAV operators where given a task breakdown for the mission as follows:

TABLE I

DATA USED IN THE MPP CALCULATION FOR THE EXAMPLE UAV AND MISSION.

Parameter	Value
UAV System and Platform Parameters	
Technology Readiness Level	6
Autonomy Level	Supervised Autonomy (3)
Weight, Height, Length, Span	14kg, 0.6m, 2.1m, 2.4m
Ground Clearance	0.1m
Wheels/Skid	wheels
# of wheels	3
VTOL	No
On-site launch/recovery	runway
Ground Control Station Parameters	
Mobility	fixed when operating
Size	(3x2.4x2.4)m
Weight	700kg
Command Latency	0.02s
Minimum turn radius	70m
Load Factor	-1g to -2g
Weather Limits	
Operational temperatures	-3^{o}C to 45^{o}C
Wind limitations	30 km/hr crosswind/45 km/hr gusts
Cloud cover (percent)	100%
Rain	0.2mm
Can operate at night	yes
Communications and Video Link	
Telemetry	yes
Frequency	2.4GHz
Update rate	25Hz
Line of sight required	no
Range	40km
Encryption	no
Real-time configuration	yes
Video link Frequency, Update Rate	1.31 GHz, 25Hz
Video link Range	40km
Video link encryption	no
Sensors	
GPS	yes
GPS Position Resolution	1.5m
GPS update rate	10Hz
Inertial Measurement Unit (IMU)	yes
IMU type	6 DOF
EO (camera)	yes
Camera articulation	+/- 180^o Pan; -5^o-100^o Tilt
Camera resolution	1.3 Megapixels
Camera geotagging	yes
Perception and Intelligence	
Mapping type	none
Onboard obstacle detection	no (marked by operator)
Obstacle avoidance	yes
Path planning	real-time 3D path planning
Path re-planning	no

1) Airborne: Take off and proceed with first checks; Transition to Automatic control;
2) Fly/route: Proceed to search area;
3) Observe/Reconnaissance/Identify: Observe, recognize and identify the target;
4) Follow: Track and follow the target for 10 minutes; if the target is lost, re-task with previous task;
5) Fly/route: After finishing the mission, return to base through predetermined flight path;
6) Land: Preform final checks and land.

In order to compare the MPP, which represents the predicted mission performance potential, with the true mission performance, a questionnaire was developed and given to the three UAV operators. Using the questionnaire, each mission task was qualitatively evaluated and scored in the range 0 to 9. The questionnaire and measured UAV mission performance ratings are shown in Table II below.

TABLE II

UAV OPERATOR MISSION PERFORMANCE RATINGS BROKEN DOWN BY TASK.

Parameter	Value
Task 1: Airborne	
Autonomy Level(s)	1
Relative time spent in AL(s)	100%
Evaluate the performance (0-9)	9,9,9,9
Task 2: Fly/Route	
Autonomy Level(s)	3
Relative time spent in AL(s)	100%
Evaluate the performance (0-9)	9,9,9,9
Task 3: Observe/Reconnaissance/Identify	
Autonomy Level(s)	2,3
Relative time spent in AL(s)	50%, 50%
Evaluate the performance (0-9)	7,7,5,5
Task 4: Follow	
Autonomy Level(s)	2,3
Relative time spent in AL(s)	50%, 50%
Evaluate the performance (0-9)	7,7,5,7
Task 5: Fly/Route	
Autonomy Level(s)	3
Relative time spent in AL(s)	100%
Evaluate the performance (0-9)	9,9,9,9
Task 6: Land	
Autonomy Level(s)	1
Relative time spent in AL(s)	100%
Evaluate the performance (0-9)	9,7,7,9

The MPP was calculated using the MatLab Fuzzy Logic Toolkit [14]. The data presented in Table I were aggregated using a fuzzy rule set and "masks" derived from the mission description. In essence, each of the data in Table I was given some weight, or importance, to overall mission success, which was mapped onto a membership value between 0 and 1 similar to process shown in Figure 2. Then membership values for each data where aggregated, and the final total membership function was de-fuzzified into a single value between 0 and 100, with 100 representing perfect performance and 0 representing absolute failure.

The calculated MPP for this particular UAV and mission scenario was 78. Therefore, the maximum possible performance for this asset for this mission is roughly 78/100. The reason the MPP predicts a maximum possible performance below the theoretical max of 100 is the imperfections in the UAV's sensors, other technical parameters such as maximum altitude and flight speed, and a low overall platform intelligence regarding the UAV's onboard reasoning algorithms. Comparing both assessments, the 88 UAV operator performance rating observed during live testing and the 78 calculated using the MPP tool shows that the calculated MPP and observed performance are close, meaning that the proposed MPP method is a valid approach for performance assessment and warrants future development.

V. Conclusions and Future Work

The goal of this research was to develop procedures for the assessment of system mission performance as a function of platform autonomy for unmanned land, sea, and air vehicles. To accomplish this task, a new performance assessment tool was developed to predict UMS performance for a given mission at a given autonomy level. This new performance assessment tool was named the Mission Performance Potential (MPP). The MPP was developed by first performing an in-depth review of many of the currently accepted metrics for UMS autonomy and performance.

The development of the MPP was necessary because the current methodologies used for autonomous performance assessment were insufficient, particularly in terms of defining a UMS's performance for its mission or range of missions. Many of the existing tools required extensive field testing to compute autonomy level or autonomous performance. Many of the existing tools also required well-defined metrics describing the UMS's environment and mission. Furthermore, while these tools measured autonomy level, they did not provide an answer for the impact of autonomy level on mission performance.

The MPP works by taking data related only to the UMS platform hardware, software, and intelligence and combines these data using fuzzy logic rules derived from the mission profile. The MPP starts from a pre-defined autonomy level and predicts the UMS performance for its mission at that level of autonomy. The MPP methodology removes the two major barriers preventing performance assessment of UMS: the need for field testing and the need for detailed, standardized environment and mission metrics. Furthermore, the MPP was actually implemented and calculated for an example UMS, moving the MPP from the theoretical world to the practical, a key step that is missing with other proposed methodologies and frameworks. The key benefits of the MPP over other existing frameworks can be summarized as:

1) The MPP can be calculated using only data related to the UMS platform and does not depend on field testing results.
2) The MPP does not compute an autonomy level but rather fixes the UMS Autonomy Level (AL).
3) The MPP allows decision makers and users to evaluate the performance of a UMS across varying ALs.
4) The MPP defines a potential for mission-specific performance, not an assessment of performance, i.e., it provides an idea of the maximum possible performance of a UMS system for a given mission, allowing better planning by users for which UMS to use for a certain mission and weather investment in higher autonomy for that UMS is worth pursuing.
5) The MPP value is calculated using fuzzy logic, and the specific rules for the fuzzy aggregation of the MPP are defined using the mission description.
6) The MPP allows cross-type comparisons between ground-, air-, and sea-based UMS.

Because the MPP predicts mission performance, it must be validated against full-scale, mission-level testing. Since the MPP can be computed in a number of ways using different data, checking the predicted MPP performance against the mission performance is necessary to determine how to compute the MPP. Future development of the MPP should be done in conjunction with UMS testing, competitions, and in-theater deployments. Once the tool has been validated, it will serve as a key enabler for increased UMS use and increased UMS autonomy.

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APPENDIX*

TABLE III

EXAMPLE DATA RELATED TO UMS HARDWARE AND SOFTWARE SYSTEMS NEEDED TO DRIVE THE MPP CALCULATIONS. THIS LIST IS NOT EXHAUSTIVE BY ANY MEANS, AND THE ESTIMATION APPROACH FOR MANY VALUES STILL NEEDS TO BE DEFINED.

Parameter	Description	Estimation Approach	Comments
UMS Platform Parameters			
weight, height, width, length, etc.	physical size of the UMS	single numeric values	Different missions will require different sized UMS.
Ground clearance	distance from the bottom of the UMS to the ground	single numeric value	Different missions will require different sized UMS.
Locomotion scheme	value list that includes the relevant locomotion schemas, i.e. skid-steered, Ackerman steered, fixed-wing, etc.	single value	The locomotion type can effect the MPP, for example a tracked vehicle will have a higher MPP for cross-country applications
Soft soil performance	minimum soil strength the system can operate over	single numeric value	Applicable to UGVs for determining suitability for cross-country missions
VTOL	vertical take off and landing functionality	yes/no	Applies to UAV applications
On-site launch/recovery; Catapult launch/recovery	type of launch and recovery used by the UMS	single value from list	Captures the launch and recovery mechanics of the UMS (primarily for UAV systems)
Control Station Parameters			
Command latency	time between command input and platform response	single numeric value	UMS with higher latency often have lower mission performance.
Maneuvers	UMS response to commands	multiple values	Currently this parameter is qualitative and subjective to operator opinion.
Weather Limits and Environmental Concerns			
Temperature	minimum and maximum operational temperatures	range of values	NA.
Wind	maximum wind speed in which the UMS can operate	range of values	Applies mainly to UAV systems.
Visibility	Minimum operational visual range due to fog, clouds, rain, vegetation, etc.	numeric values	Applies mainly to UAV systems.
Rain	maximum rainfall in in which the UMS can operate	single numeric value	NA.
Communications and Video Link			
Range	max. range from control station	single numeric value	NA.
Line of Sight	Does the UMS require LoS to operate	yes/no	NA.
Real-time configuration	does the control station allow real-time configuration of the UMS	no/some/yes	This parameter is currently qualitative and subjective.
Frequency	Transmission rate between the UMS and the control station	single numeric value	NA.
Standards	Does the control station comply with any standards (i.e., JAUS)	yes/no	NA.
Encryption	are the data broadcast between the UMS and control station encrypted	yes/no	NA.
Sensors			
Range (EO sensors)	maximum range of the sensor	single numeric value	In general, a LIDAR with a greater sensing range will provide a better overall UMS mission performance.
Resolution (EO sensors)	maximum resolution (picture size for cameras, point spread for LIDAR, etc.)	single numeric value	In general, a LIDAR or camera with a finer resolution range will provide a better overall UMS mission performance.
Field of view (EO sensors)	Angle of view (vertical and horizontal) for cameras and LIDAR	numeric range	In general, a LIDAR or camera with a greater FOV will provide a better overall UMS mission performance.
Accuracy	Maximum measuring error, i.e., for GPS or IMU: location accuracy or drift rate; for camera or LIDAR: mixed pixel effects, etc.	various numeric values	Accuracy can be measured in many ways, and the impact of sensor accuracy on mission performance varies.
Frequency	Update frequency for the sensor	single numeric value	NA.
Perception and Intelligence			
Mapping type	Defines the map building approach used	value list	Currently this is a qualitative variable describing the general mapping approach, i.e., SLAM, LIDAR segmentation, stereo-camera, etc.
Map Accuracy	Measure of the map's "goodness"	numeric value	Many metrics for map quality have been proposed, and it remains to be determined which metrics should be used.
Map resolution	The scale/resolution of the map	single numeric value	NA.

TABLE IV

Example data related to UMS hardware and software systems needed to drive the MPP calculations. This list is not exhaustive by any means, and the estimation approach for many values still needs to be defined (continued).

Parameter	Description	Estimation Approach	Comments
Obstacle detection type	Defines the obstacle detection approach used	value list	Currently this is a qualitative variable describing the general obstacle detection approach, i.e., image classifiers, LIDAR segmentation, etc.
Obstacle size (min and max)	The minimum and maximum size of detectable obstacles	numeric values	NA
Obstacle detection range	The minimum and maximum distance at which obstacles can be detected	numeric values	NA
Obstacle behavior prediction	Can the UMS detect dynamic obstacles and predict their behaviors?	value list	Some UMS missions will require the UMS to interact with dynamic objects.
Obstacle avoidance	Does the UMS react to obstacles to avoid them?	yes/no	NA
Path planner	Defines the type of path planner used (if any), i.e., A*	value list	NA
Path following	Metric assesses how closely the planned path is followed	numeric value	As with mapping, many metrics have been proposed to quantitatively measure how well a UMS follows its planned path.
Path re-planning	Can the UMS re-plan its path due to changing mission parameters?	yes/no	This is currently a qualitative variable describing the UMS' ability to re-plan routes.
Other intelligence	Countless other intelligence algorithms can be defined depending on the UMS and mission, such as target detection algorithms, and values and variables will have to be defined.	varies	NA.
Interaction with the Environment			
Gripper/Arm	Parameters related to the UMS' ability to effect its environment via arms and grippers	value list	This is currently a qualitative/quantitative variable. Many robotic arm and gripper attachments for UMS have been fielded, and the effectiveness of these devices can be measured in a number of ways.
Deployable payloads	Various payloads the UMS carries and deploys throughout its mission, for example a mule-type UGV that transports supplies to squads in the field	value list	This parameter describes what payloads the UMS carries (number of items, total weight, etc.) and the UMS' ability to deploy these items as part of its mission.
Weapons	Does the UMS have weapon systems?	value list	Some UMS, primarily UAVs, have been weaponized as part of their mission.