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Defining Operational Design Domain for Autonomous Systems: A Domain-Agnostic and Risk-Based Approach

Morayo Adedjouma¹, Bernard Botella¹, Javier Ibanez-Guzman^{2,3}

Kevin Mantissa³, Chauk-Mean Proum^{3,4}, Asma Smaoui¹

¹ Université Paris-Saclay, CEA List, France, ²Renault, France, ³IRT SystemX, France, ⁴Naval Group
morayo.adedjouma@cea.fr; bernard.botella@cea.fr; javier.ibanez-guzman@renault.com;
kevin.mantissa@@irt-systemx.fr; chauk-mean.proum@naval-group.com; asma.smaoui@cea.fr

Abstract—The integration of Artificial Intelligence (AI) into industrial systems with high levels of automation has introduced significant uncertainty and complexity. In particular, work by the automotive industry, on autonomous vehicles has led to the emergence of the Operational Design Domain (ODD) concept, which delineates the expected operating domain of such vehicles, departing from conventional automotive Use Case-based approaches. However, this ODD’s automotive-centric approach has hindered its broader application, lacking the comprehensive guidance on the system engineering methodologies required for its definition. This paper presents a domain-agnostic definition of ODD, grounded in established system frameworks and emphasizing a systemic risk-based engineering to make it applicable to multiple domains. A case study from the maritime domain illustrates the benefits and applicability of the proposed methodology. By providing a systematic framework, this research facilitates the adoption of ODD principles beyond the automotive sector, fostering the development of AI-based products and services across diverse industrial domains. The ODD represents a key aspect of systems engineering for autonomous systems, integrating considerations of technology, environment, regulation, and user expectations.

Index Terms—Operational Design Domain, Autonomous System, Systems engineering, AI system

I. INTRODUCTION

In recent years, air, land, and maritime (both surface and underwater) mobile platforms have witnessed a significant surge in their automation, propelled by advancements in sensor technologies and software capabilities. Notably, the automotive sector has seen a paradigm shift with the integration of increasingly sophisticated Advanced Driver Assistance Systems (ADAS), delegating various driving tasks from human operators to computerized systems. This evolution lays the groundwork for the ongoing development of autonomous vehicles (AVs), where computers assume full control of driving functions. The adoption of data-driven methods, particularly those based on machine learning (ML) and deep neural networks (DNNs), has notably facilitated the deployment of advanced perception systems onboard vehicles, unlocking a multitude of possibilities for diverse vehicle applications.

However, this technological advancement has introduced a layer of complexity to already intricate systems responsible

for controlling safety-critical functions. The widespread incorporation of Artificial Intelligence (AI), particularly in ML-based approaches, presents challenges in system analysis and certification. The inherent uncertainty associated with ML-derived data, resulting models, and the unpredictable behavior of other agents within the operational domain exacerbates the complexity of these systems, necessitating the integration of methods and tools from systems engineering disciplines. Therefore, ensuring the safety and security of such systems has become an urgent imperative, mandating rigorous verification and testing across a spectrum of scenarios and environmental conditions. Thus, it becomes urgent to define the operating conditions under which the system will operate and ensure only within this perimeter the system’s safety. The formulation of the Operational Design Domain (ODD) principles is centered around these fundamental principles [1].

The concept of Operational Design Domain originated in the automotive industry and was formulated as part of the SAE J3016 standard [2]. It has been taken up since then in different standards [3], [4]. According to the ISO 34503 standard [4], “*the ODD defines the operating conditions under which an automated driving system (ADS) is designed to operate safely*”. Other industries like avionics, where numerous AI-based systems exist, have tried to appropriate the ODD concept. However, it was difficult to identify common points and differences with the original concept [5], [6]. The ODD automotive-centric nature focused on road networks and operating conditions has hindered its broader application, lacking a comprehensive guidance on system engineering methods required for its application. This paper addresses this gap by presenting a domain-agnostic definition of ODD, grounded in established frameworks and emphasizing a systemic risk-based engineering approach.

The remainder of the paper is organised as follows. Section II presents the related work. Section III details our systems oriented ODD definition and approach. Section IV includes an industrial use case from the maritime domain as an application example. Finally, Section V concludes the paper and provides an insight into future work.

II. RELATED WORK

Most ODD definitions focus on descriptions of parts of the operational domain without specifying how it can be defined and to which level of granularity. Few approaches structure the ODD definitions as process-based, taxonomy-ontology formulations, or data-driven. For instance, Gyllenhammar et al., propose a framework where use cases in early development phases help classify and quantify operating conditions to be compiled into the ODD [7]. This preliminary ODD is further refined based on safety requirements during product development [8]. The Autonomous Vehicles Safety Consortium (AVSC) adopts a bottom-up approach for ODD specification, by identifying road networks, then environmental conditions, and operational constraints to describe the ODD in terms of permissive and non-permissive characteristics [9]. Taxonomy and ontology-based approaches are preferred in automotive domain as in [10], [2], [4], [11], [12], and [13]. They offer hierarchical structures to specify the ODD with generic categories, while ensuring completeness by clustering entities and relations into layers such as physical and digital infrastructure, environmental conditions and road users. [14], [15]. These approaches benefit from the existence of several well-defined driving related taxonomies. However, they often lack justification for choosing the ODD conditions, and provide little insight into the relationship between the system design constraints and the ODD specification, limiting their applicability beyond the automotive domain.

Alternatively, data-driven approaches characterise the ODD through iterative data analysis, tailoring data requirements across design levels from an aligned ODD taxonomy and ontology at the vehicle level [6], [16]. This approach enables the definition of different ODD at each development level, to incrementally cover the data-driven characteristics of machine learning (ML) components. The focus is mainly on sensor inputs rather than intended functions at the vehicle level which may also include non ML-based components.

By contrast, we see the ODD as a voluntary restriction of the operational domain within which the expected nominal functioning of an AI-based system is ensured. Therefore, it should be described as a set of foreseeable and measurable operating conditions within which the AI-based system must operate. We propose a process-oriented ODD definition that aims to define the scope of the ODD and content for AI-based systems, using a risk-based approach that encompasses a taxonomy definition, and includes justifications for trustworthy ODD assurance. The approach is domain-agnostic, and adaptable to diverse AI-based system development contexts, addressing limitations of current domain-specific approaches.

III. ODD DEFINITION APPROACH

Our methodology for defining the ODD definition process followed an empirical research approach, and subsequently has been challenged and enriched through industrial assessments on several applications from various domains, includ-

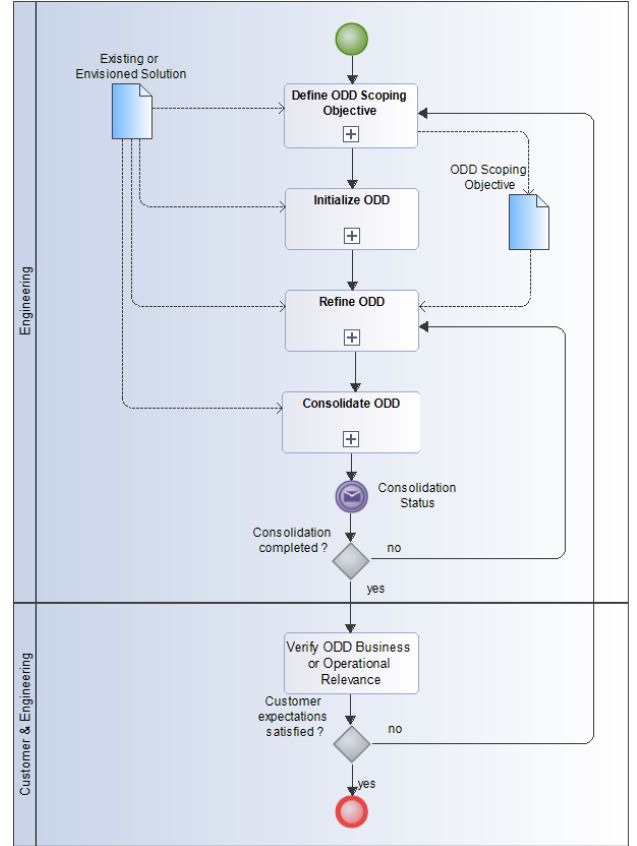


Fig. 1. Overall ODD definition process

ing Unmanned Aerial Vehicles (UAV) [17], manufacturing [18], robotic [19], automated driving systems [20] and naval applications [21]. The approach builds upon taxonomy and analysis of reference systems to define the attributes to be included within the ODD description of a given AI-based system. Figure 1 presents our ODD 5-step definition approach: 1) ODD scoping objective definition; 2) ODD initialization; 3) ODD refinement, 4) ODD consolidation, 5) ODD business or operational relevance verification. Steps 1 to 4 must be conducted by the multi-skills engineering team with the specification of an existing or an envisioned system solution as input. The specification must include the operational context description, the system requirements, the architecture and design information, known constraints on recommended or required technologies/components from reference systems, and relevant applicable standards and regulations. The last step is conducted by the engineering team in collaboration with the customer or his representative. It aims to verify that the consolidated ODD satisfies the customer needs or that it represents a satisfying trade-off for its expectations. Otherwise, it is required to re-adjust the ODD scoping objective and re-perform the ODD definition process accordingly. Steps 1 to 4 are detailed in the following subsections.

A. ODD scoping Objective

The need to define the ODD of an AI-based system may pursue different purposes. For a preexisting solution, the ODD serves to define the scope for its qualification. For an envisioned solution, which is typically based on a prototype or reference system, the ODD serves to identify rooms for improvement to satisfy the customer expectations. The ODD scoping objective must define the expected level of automation and expected level of performance of the AI-based system that needs to be achieved within the ODD. The level of automation relies on the ability of the system to achieve a set of goals under a set of uncertainties in the system and its environment, with identified and limited intervention from a human operator [22]. Each industrial domain is likely to have its own classification of the automation levels for related systems. For the automotive domain, the SAE J3016 standard defines six levels of vehicle automation ranging from 0 (No driving automation) to 5 (Full driving automation) [2]. In the railway industry, the automation of train operation is guided by the Grade of Automation (GoA), from GoA0 (no automation) up to GoA4 in which the train is automatically controlled without any staff on board, as defined by the standard IEC 62290-1 [23]. Similar taxonomies of automation system levels or degrees of autonomy exist in other domains, e.g. in aviation [24], manufacturing [25], maritime [26], among others. If a domain does not provide a standardized taxonomy, concerned stakeholders may define their own classification scale for a given application. The expected level of performance is interdependent on the level of automation: a given level of automation may require some levels of performance while some levels of performance may enable a level of automation.

In the case of an envisioned solution, the choice of these levels may lead to possible updates of the AI-based system solution by proposing or conversely excluding some functionalities or ODD attributes. For instance, a new driving automation system that is SAE Level 3 (conditional automation, with a fallback-ready driver expected to take over upon request) could use a similar application that is SAE Level 2 (feature supporting an active driver) as a reference system. However, the gap in design intent from level 2 to level 3 (with the driver intervening only in case of fallback) could lead to reducing some performances (automation performed at lower speeds) or restricting the ODD (exclusion of tunnels from the ODD due to a lack of maturity in available technologies, for a Traffic Jam Chauffeur). This illustrates the need to thoroughly review the impacts of an evolution in specification and design on the operating conditions of a newly developed system.

B. ODD initialization

The ODD initialization is inspired by existing taxonomy-based approaches. This step aims to capture all ODD attributes from the customer expectations, i.e. the customer needs and requirements, and those ODD attributes imposed by the existing or envisioned solution as well. A decomposition of the attributes and their characterization via values are defined as

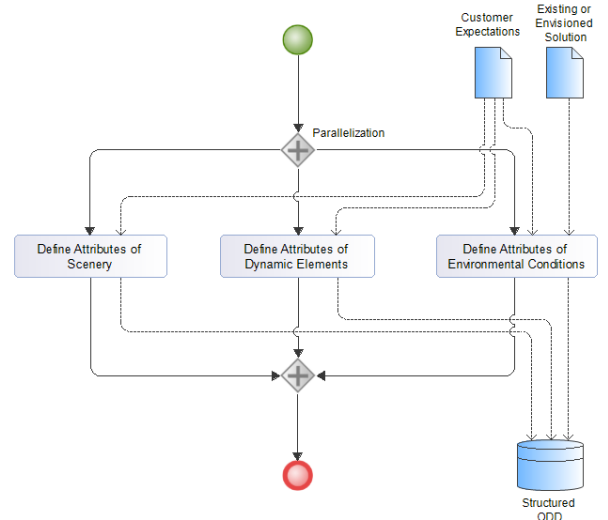


Fig. 2. ODD initialization process

needed. As illustrated in Figure 2, we adopt the hierarchical structure defined in the ISO 34503 standard [4] to organize the ODD attributes because it fits well for different applications - that we analyze - without a specific domain coloration.

- The *Scenery* category gathers the scene or static elements surrounding the system of interest, e.g., road structure or drivable area for an autonomous car.
- The *Dynamic Element* category gathers the moving elements within the scene, e.g., other drones or flying animals for a drone system.
- The *Environmental Condition* category gathers weather conditions including visibility and physical/infrastructure related environmental conditions of the system, e.g., illumination and vibration for a production system.

At the end of the ODD initialization, one must ensure that any elicited ODD element has an attached rationale to corresponding customer expectations. The rationale capturing the necessary argument, supported by underlying evidence, must be capitalized and compiled with the intent to justify the specification of the ODD attributes and attribute values.

C. ODD refinement

Figure 3 details the activities of the ODD refinement process. The refinement follows an analytical and risk-based approach, similar to system engineering practices to refine the ODD description previously initialized. The refinement of the ODD attributes relies on the analysis of situations, influence factors, and technical background retrieved from experience with similar or reference systems. First, the relevance of existing situations and influence factors is analyzed for the existing or envisioned solution to highlight constraints on the elicited ODD attributes and values, or discover new ones. The preliminary initialized ODD attributes are further analyzed to identify potential new influence factors and situations that pertain to the current considered system context. The influence factors help to refine the ODD to meet the ODD scoping

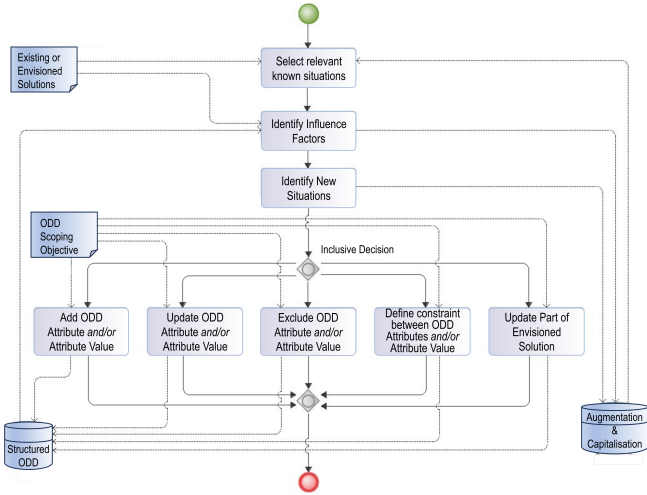


Fig. 3. ODD refinement process

objective by either: 1) updating, excluding ODD attributes and/or the initialized attribute values, or adding new ODD attributes and/or their value; 2) defining constraints between ODD attributes and/or attribute values; 3) updating the specifications of envisioned solution. All situations, associated influence factors, and refined ODD attributes discovered during this step must be compiled for assurance justification of the ODD description and later use for new systems.

D. ODD consolidation

The consolidation process objective is twofold. Firstly, the ODD attributes and associated values from the "Structured ODD" database are retrieved to identify potential redundant or overlapping elements. The identified attributes or attribute values are updated to obtain a complete but concise ODD. It consists of defining the optimum limits for the ODD attributes consistent with the operational goal of the system feature. This gathering also helps to reduce the number of relevant ODD attributes while maintaining the current limits. Secondly, the resulting ODD is checked against sectorial requirements and regulation requirements corresponding to the system of interest. For instance, in the case of the SAE Level 3 Drive Pilot system for Mercedes [27], the current ODD is limited to specific roads in Germany and 2 states of the United States, due to legal requirements and the reliance on geofencing technologies enabling the function. It is worth noting that these requirements should have already been considered in the definition of the existing or envisioned solution for the system of interest. A consolidation status report must be specified as a result of this process for assurance justification.

IV. INDUSTRIAL APPLICATION

A. Context

We have experienced various parts of our ODD definition approach on diverse applications, e.g., in automotive, manufacturing and naval domains, to judge its effectiveness as efficient and domain-agnostic. To illustrate the domain-agnostic aspect

and the combination of taxonomy-based, analytical and risk-based facets of our ODD definition approach, we present in this section an excerpt of the resulting ODD from the initialization and refinement steps for the LCMA (Lutte Contre les Menaces Asymétriques) [28], a Naval Group's system. The LCMA is a decision support system for the asymmetric warfare of a surface ship. The system is based on panoramic video surveillance for automatically detecting and identifying different threats. It aims at improving the decision-making responsiveness of the operator and replacing the operator in certain cases. The ODD for LCMA is intended to be used as a way to prepare its subsequent qualification.

B. ODD definition

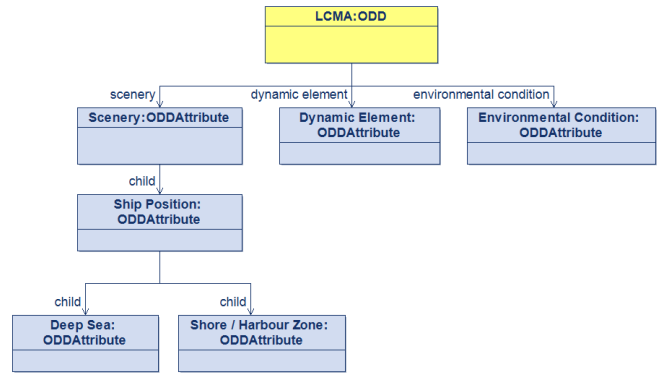


Fig. 4. Excerpt of LCMA ODD initialization - Scenery

The ODD initialization captures the ODD attributes covering the customer expectations and the solution constraints, organized into three different categories: *Scenery*, *Dynamic Elements*, and *Environmental Conditions*. Each category includes child attributes recursively. Each leaf attribute is likely an attribute to define the appropriate measurable value. Relevant scenery attributes are related to the *Ship Position* which can be in the *Deep Sea* or at *Shore Zone / Harbour Zone* as illustrated in Figure 4.

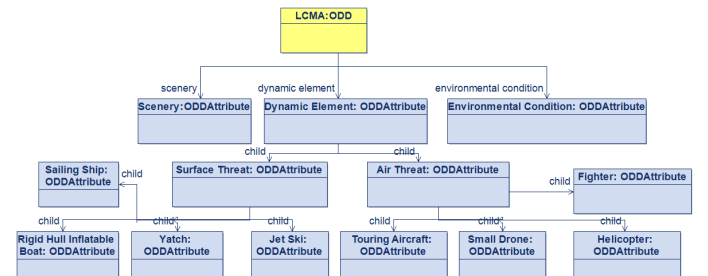


Fig. 5. Excerpt of LCMA ODD initialization - Dynamic Elements

As dynamic elements, we capture all expected surface and air elements considered as potential threats, as depicted in Figure 5. *Surface Threat* includes, e.g., *Sailing Ship*, *Yacht*, *Rigid Hull Inflatable Boat (RHIB)*, and *Jet Ski*. *Air Threat* includes, e.g., *Drone*, *Touring Aircraft*, *Fighter*, and *Helicopter*.

Environmental conditions cover natural environment elements such as *Weather*, *Sea State*, and also system solution

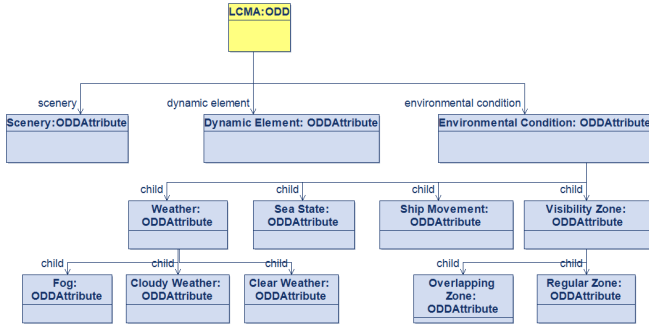


Fig. 6. Excerpt of LCMA ODD initialization - Environmental Conditions

environment element like *Visibility Zone* as illustrated in Figure 6. A *Regular Zone* has a visibility provided by a single camera image while an *Overlapping Zone* has a visibility provided by an image combined from multiple cameras.

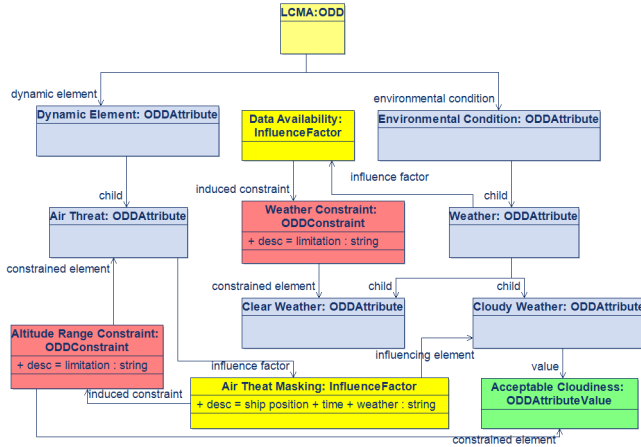


Fig. 7. Excerpt of LCMA ODD refinement - 1

Then, the ODD refinement focuses on the analysis of the ODD attributes previously identified. As the LCMA is a novel system, there is no known situation. However, the situation concept has been added to our approach from other use cases analysis. Figure 7 illustrates an excerpt of the refined ODD with some influence factors (in yellow) and ODD constraints (in red). We identify influence factors based on the ODD attributes, which may lead to the induction of constraints stemming from these influence factors. For example, the *Data Availability* influence factor related to the *Weather* attribute induces a *Weather Constraint* which in turn limits the covered weather conditions to *Clear Weather*. An influence factor from a given ODD attribute may depend on another ODD attribute. For example, the *Air Threat Masking* influence factor related to the *Air Threat* attribute depends also on the *Cloudy Weather* attribute. Hence, an induced *Altitude Range Constraint* limits the *Acceptable Cloudiness* attribute value (in green) of the *Cloudy Weather* attribute.

In the refinement step, additional attributes may also be identified. In Figure 8, the *Dazzle* influence factor related to the *Visibility Zone* attribute depends on the additional *Sun Position* attribute. The induced *Dazzle Constraint* excludes a *Regular*

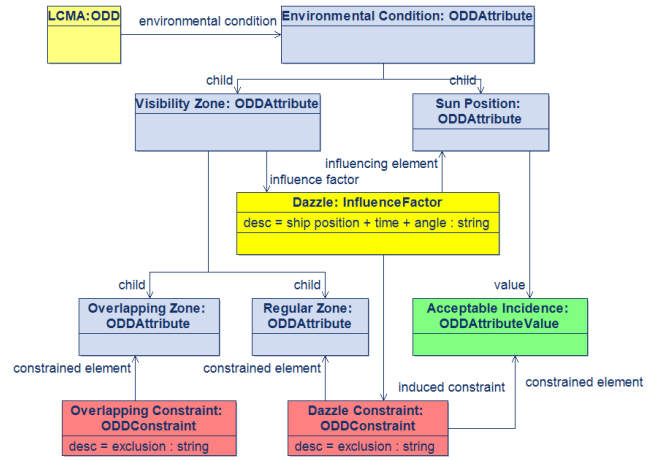


Fig. 8. Excerpt of LCMA ODD refinement - 2

Zone if the *Acceptable Incidence*, an attribute value of the *Sun Position* attribute, is not met. A constraint may also apply to an attribute without having an identified influence factor. For example, the *Overlapping Constraint* excludes an *Overlapping Zone*.

V. CONCLUSIONS

The proliferation of AI-based systems within complex systems has introduced significant verification challenges. Traditional methods struggle to ensure these systems are safe and trustworthy for deployment. This paper addresses this gap by proposing a systematic, top-down approach to defining the Operational Design Domain (ODD) for AI systems. Our approach leverages taxonomies and existing reference systems, promoting a deep understanding of the domain and the technical solutions necessary for successful implementation. This contrasts with existing data-driven methods that may overlook crucial domain knowledge. Furthermore, we recognize the potential limitations of solely relying on a top-down approach, particularly during the crucial prototyping phase. To address this, we propose a complementary bottom-up approach that analyses the AI models themselves and the data used to train them. This process begins by characterizing the system's perception capabilities, the conditions encountered during data acquisition, and the types of situations it might encounter. Sensitivity studies following this analysis can establish the precise domain of operation where the AI model can perform reliably, even beyond its initial training conditions.

This paper lays the groundwork for a comprehensive ODD definition process. Future works will focus on seamlessly integrating the proposed bottom-up approach into the existing top-down methodology. Additionally, we are currently developing a tool to formalize an ODD using Domain Specific Language (DSL) based on ISO34503 ODD taxonomy [4] that can be used for its validation.

Finally, we are developing a methodology based on assurance cases to rigorously evaluate ODD quality around three key categories: effectiveness, clarity, and usability. Effectiveness that encompasses completeness, accuracy, and operability

aims at ensuring that the ODD accurately defines the conditions under which the system should and could operate. Clarity that includes as sub properties concision, understandability, and explainability, emphasizes that the ODD description should be clear, comprehensive, and easily understandable for stakeholders. Usability encompasses verifiability, traceability, and measurability, and addresses the usability of the ODD across various engineering activities. This assurance case based methodology will ensure the ODD accurately reflects the operational domain and aligns with the system’s expected capabilities. By establishing a robust and comprehensive ODD definition process, we can ensure the safe and reliable deployment of AI-based systems within complex environments.

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REFERENCES

- [1] M. A. Mehlhorn, A. Richter, and Y. A. Shardt, "Ruling the operational boundaries: A survey on operational design domains of autonomous driving systems," *IFAC-PapersOnLine*, vol. 56, no. 2, pp. 2202–2213, 2023, 22nd IFAC World Congress. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S2405896323015318>
- [2] SAE Mobilus, "SAE J3016 Taxonomy and Definitions for Terms Related to Driving Automation Systems for On-Road Motor Vehicles," 2021.
- [3] British Standard Institution, "PAS 1883 - Operational Design Domain (ODD) taxonomy for an automated driving system – Specification," 2020.
- [4] ISO 34503, "Road Vehicles - Test scenarios for automated driving systems - Specification for operational design domain," International Organization for Standardization, Geneva, CH, Standard, Aug. 2023.
- [5] G-34 Artificial Intelligence in Aviation, *Artificial Intelligence in Aeronautical Systems: Statement of Concerns*, apr 2021.
- [6] SAE WG 11/ G-34 Artificial Intelligence in Aviation, *Process Standard for Development and Certification/Approval of Aeronautical Safety-Related Products Implementing AI*, 06 2023.
- [7] Gyllenhammar *et al.*, "Towards an Operational Design Domain That Supports the Safety Argumentation of an Automated Driving System," in *10th ERTS European Congress*, Toulouse, France, Jan. 2020.
- [8] I. Colwell, B. Phan, S. Saleem, R. Salay, and K. Czarnecki, "An automated vehicle safety concept based on runtime restriction of the operational design domain," in *2018 IEEE Intelligent Vehicles Symposium (IV)*, 2018, pp. 1910–1917.
- [9] SAE Industry Technologies Consortia - Automated Vehicle Safety Consortium, *AVSC Best Practice for Describing an Operational Design Domain: Conceptual Framework and Lexicon*, 04 2020.
- [10] ASAM e.V, "OpenODD Concept paper," 2021.
- [11] NHTSA *et al.*, *Federal automated vehicles policy: Accelerating the next revolution in roadway safety*. US Department of Transportation, 2016.
- [12] K. Czarnecki, "Operational design domain for automated driving systems: Taxonomy of basic terms," *Waterloo Intelligent Systems Engineering (WISE) Lab, University of Waterloo, Canada*, 2018.
- [13] G. Ollier, D. Razafindrabe, M. Adedjouma, S. Gerasimou, and C. Mraidha, "Using operational design domain in hazard identification for automated systems," in *18th European Dependable Computing Conference, EDCC 2022, Zaragoza, Spain, September 12-15, 2022*. IEEE, 2022, pp. 109–112.
- [14] J. D. Vreeswijk, A. Wijbenga, and J. Schindler, "Cooperative Automated Driving for managing Transition Areas and the Operational Design Domain (ODD)," in *8th Transport Research Arena (TRA), Helsinki, Finland*. IEEE, 04 2020.
- [15] M. Scholtes, L. Westhofen, L. R. Turner, K. Lotto, M. Schuldes, H. Weber, N. Wagener, C. Neurohr, M. H. Bollmann, F. Kortke, J. Hiller, M. Hoss, J. Bock, and L. Eckstein, "6-Layer Model for a Structured Description and Categorization of Urban Traffic and Environment," pp. 59 131–59 147, Jan. 2021.
- [16] R. Zhang, A. Albrecht, J. Kausch, H. J. Putzer, T. Geipel, and P. Halady, "Dde process: A requirements engineering approach for machine learning in automated driving," in *2021 IEEE 29th International Requirements Engineering Conference (RE)*, 2021, pp. 269–279.
- [17] G. Ollier, F. Arnez, M. Adedjouma, R. Lallement, S. Gerasimou, and C. Mraidha, "Towards an ontological methodology for dynamic dependability management of unmanned aerial vehicles," in *Proceedings of the DroneSE and RAPIDO: System Engineering for constrained embedded systems, RAPIDO, Toulouse, France, January 17-18, 2023*. ACM, 2023, pp. 12–19.
- [18] A. Bosca *et al.*, "Industrial use-cases: Specifications, tools, data and models – the confiance.ai program," 2023.
- [19] G. Ollier, M. Adedjouma, S. Gerasimou, and C. Mraidha, "An ontological approach for the dependability analysis of automated systems," in *2023 26th Euromicro Conference on Digital System Design (DSD)*, 2023, pp. 593–601.
- [20] L. Mendiboure, M. L. Benzagouta, D. Gruyer, T. Sylla, M. Adedjouma, and A. Hedhli, "Operational design domain for automated driving systems: Taxonomy definition and application," in *IEEE Intelligent Vehicles Symposium, IV 2023, Anchorage, AK, USA, June 4-7, 2023*. IEEE, 2023, pp. 1–6.
- [21] P. Akinin *et al.*, "Confiance.ai Days 2024. Booklet of articles & posters," Mar 2024, conférence: Confiance.ai Days, March 2024, (France).
- [22] P. Antsaklis, "Autonomy and metrics of autonomy," *Annual Reviews in Control*, vol. 49, pp. 15–26, 2020.
- [23] International Electrotechnical Commission, "Railway applications – Urban guided transport management and command/control systems – Part 1: System principles and fundamental concepts," 2014.
- [24] E. Anderson, T. Fannin, and B. Nelson, "Levels of aviation autonomy," in *2018 IEEE/AIAA 37th Digital Avionics Systems Conference (DASC)*, 2018, pp. 1–8.
- [25] J. Frohm, V. Lindström, M. Winroth, and J. Stahre, "Levels of automation in manufacturing," *Ergonomia - International Journal of Ergonomics and Human Factors*, vol. 30, pp. 181–207, 01 2008.
- [26] International Maritime Organization, "Autonomous shipping." [Online]. Available: www.imo.org/en/MediaCentre/HotTopics/Pages/Autonomous-shipping.aspx
- [27] Mercedes-Benz Group, "Introducing Drive Pilot: An Automated Driving System for the Highway." [Online]. Available: <https://group.mercedes-benz.com/dokumente/innovation/sonstiges/2023-03-06-vssa-mercedes-benz-drive-pilot.pdf>
- [28] Mer et Marine, "Naval Group : L'innovation au cœur de la stratégie." [Online]. Available: <https://www.meretmarine.com/fr/construction-navale/naval-group-l-innovation-au-coeur-de-la-strategie>