Slutrapport till Vinnova

Diarienummer

2021-05178

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PROJEKTUPPGIFTER OCH RESULTAT

Diarienummer
2021-05178

Projekttitel
VaViM - Validering av virtuella modeller för simulering av autonoma fordonssystem

Projektledare
Stefan Thorn

Koordinerande projektpart (Koordinator)
559285-4219

Volvo Autonomous Solutions AB

Arendal

Volvo Autonomous Solutions AB

Vinnovas handläggare
Eric Wallgren

Administratör på Vinnova
Lena Dalsmyr

Startdatum
2022-02-01

Slutdatum
2022-08-31

Startdatum för aktuell period
2022-02-01

Slutdatum för aktuell period
2022-08-31

Skicka in senast
2022-10-11

Vinnova bidrag totalt
864 000 kr

Projektresultat för Vinnovas bedömning

Projektsammanfattning - Utfall *

I arbetspaket 1 har en state-of-the-art (SOTA) av validering av virtuella modeller för simulering av självkörande fordonssystem har genomförts (se bifogat dokument "VaViM_SOTA.pdf"). Totalt har 87 vetenskapliga publikationer, standards och guidelines reviewats.
Baserat på SOTAn har prioriterade forskningsfrågor för fortsatta studier identifierats i arbetspaket 2. I arbetspaket 3 har ett konceptuellt verktyg för att visualisera värdet av en vald simuleringsstrategi skapats. Resultaten från dessa arbetspaket har summerats i en presentation av VaViM på Drive Sweden Forum 2022 (se bifogat dokument "VaViM_Drive_Sweden_2022.pdf"), och ligger till grund för arbetet i arbetspaket 4 med ett utkast till en ny projektansökan.

628 / 1500 tecken

Mål för projektet - uppfyllelse *

Målet med denna förstudie var att identifiera SOTA och högprioriterade forskningsfrågor inom metoder för validering av de modeller som krävs för virtuell V&V av självkörande fordonssystem inom inhägnat område, samt att formulera en gemensam projektansökan med identifierade nyckelaktörer för fortsatta studier.

SOTAn identifierade två viktiga forskningsgap som behöver fyllas: (1) Det finns idag inga generellt accepterade utvärderingskriteria eller standardiserade testprocedurer för validering av virtuella sensormodeller, (2) Det saknas kunskap om hur värdet (nyttiggörandet vs. kostnad) för en vald simuleringsstrategi skall utvärderas.
Utifrån dessa gap har 3 prioriterade forskningsfrågor formulerats: (1) Vad är värdet av en vald simuleringsstrategi? (2) Hur skall sambandet mellan en virtuell modells noggrannhet, nyttiggörande och kostnad bäst beskrivas? (3) Hur skall nya modellkapabilitieter bäst introduceras i en simuleringsmodell?
En feasibility-studie har genomförts där vi har testat ett konceptuellt verktyg som visualiserar värdet av en vald simuleringsstrategi. Detta verktyg vill vi utveckla vidare i framtida studier, i linje med de identifierade forskningsfrågorna nämnda ovan.
Ett utkast till en ny projektansökan har formulerats, och kontakt med intresserade partners har initierats. Resultaten från VaViM kommer att ligga till grund för det fortsatta arbetet med att skriva en projektansökan för fortsatta studier tillsammans med andra externa partners som har intresse i dessa forskningsfrågor.

1319 / 1500 tecken

PROJEKTREFERAT FÖR PUBLICERING

Projektreferat för publicering på www.vinnova.se och som en del av öppen data.

Jag är medveten om att nedanstående uppgifter kommer att publiceras efter granskning och eventuell redigering av Vinnova *: Ja

Syfte och mål - uppfyllelse *

Denna förstudie har identifierat state-of-the-art (SOTA) och forskningsfrågor inom metoder för validering av virtuella modeller som används vid simulering av självkörande fordonssystem. Vidare har ett konceptuellt verktyg för att visualisera värdet av en vald simuleringsstrategi konstruerats och testats. Ett utkast till en ny projektansökan har formulerats och uppkoppling mot intresserade partners har startat. Resultaten kommer att ligga till grund för det fortsatta arbetet med att formulera en gemensam projektansökan för fortsatta studier med intresserade partners.

498 / 500 tecken

Syfte och mål - uppfyllelse - på engelska *

This feasibility study has identified state-of-the-art (SOTA) and research questions in methods for validating virtual models used in the simulation of self-driving vehicle systems. Furthermore, a conceptual tool for visualizing the value of a chosen simulation strategy has been constructed and tested. A draft of a new project application has been formulated and contact with interested partners has been initiated. The results will be the basis for the continued work to formulate a joint project application for further studies with interested partners.

476 / 500 tecken

Resultat och förväntade effekter - utfall *

Förstudien resulterade i material (SOTA rapport, forskningsfrågor samt utkast till en ny projektansökan) som möjliggör formulerandet av fortsatta studier med andra nyckelaktörer.
Den långsiktiga målsättningen är att skapa objektiva mått på tillförlitligheten av simuleringar av självkörande fordonssystem. Ett arbetssätt där validerade modeller och verkliga tester används sida vid sida möjliggör en effektiv och predikterbar verifiering av produktens kvalitet och säkerhet under dess hela livscykel; förstudie, utveckling, driftsättande, underhåll & optimeringar.

495 / 500 tecken

Resultat och förväntade effekter - utfall - på engelska *

The pre-study resulted in material (SOTA report, research questions and a draft to a new project application) that enables the formulation of further studies with other key players.
The long-term objective is to create objective measures of the reliability of simulations of self-driving vehicle systems. A working method where validated models and real tests are used side by side enables an efficient and predictable verification of the product's quality and safety during its entire life cycle; feasibility study, development, commissioning, maintenance & optimizations.

491 / 500 tecken

Upplägg och genomförande - analys *

1. SOTA; Undersökning av den senaste forskningen på validering av simuleringsmodeller inom autonoma transporter och relevanta angränsande områden.
2. Forskningsfrågor; GAP-analys och definiering av viktiga forskningsfrågor för framtida studier.
3. Feasibility-studie; Modelleringsinsats resulterande i ett konceptuellt verktyg för att visualisera värdet av en vald simuleringsstrategi.
4. Utkast till nytt projektförslag; uppkoppling mot nya partners har startat med syfte att formulera en projektansökan för fortsatta studier.

463 / 500 tecken

Upplägg och genomförande - analys - på engelska *

1. SOTA; Survey of recent research on validation of simulation models in autonomous transportation and relevant adjacent areas.
2. Research questions; GAP analysis and definition of important research questions for future studies.
3. Feasibility study; Modeling effort resulting in a conceptual tool aiming to visualize the value of a chosen simulation strategy.
4. Draft new project proposal; connection to new partners has started with the aim of formulating a project application for further studies.

430 / 500 tecken

Länkar till externa webbsidor

Finns det en webbsida för projektet, klicka på knappen "Lägg till länk" nedan för att skriva in en sökväg.

URL

0 / 250 tecken

Beskrivning

0 / 100 tecken

SÄRSKILDA VILLKOR

Särskilt villkor

1. Projektet ska vara representerat av minst en projektpart vid de konferenser och andra aktiviteter som anordnas inom det strategiska innovationsprogrammet för Drive Sweden.
2. Följande villkor ersätter § 7.3 i de allmänna villkoren. Vid information om projektet och vid varje offentliggörande av projektresultat ska det anges att arbetet utförts inom det strategiska innovationsprogrammet för Drive Sweden, en gemensam satsning av Vinnova, Formas och Energimyndigheten. Med offentliggörande avses t.ex. publicering oavsett medium och muntliga presentationer.
3. Forskningsinstitut inom RISE-koncernen får, när de deltar i sin icke-ekonomiska verksamhet, göra påslag för indirekta kostnader enligt den fullkostnadsprincip som de tillämpar och som godkänts av Vinnova.
4. Projektet ska delge programkontoret för Drive Sweden ett referat av projektet som kan publiceras på hemsidan för det strategiska innovationsprogrammet för Drive Sweden http://www.drivesweden.net/. Referatet ska kunna spridas och publiceras fritt och får således inte innehålla konfidentiella eller på annat sätt känsliga uppgifter. På samma sätt ska ett referat av projektresultaten i samband med slutrapportering skickas till programkontoret för publicering på det programmets hemsida.

För den händelse samtliga godkännanden inte kommit in till Vinnova vid i beslutet angiven tid, kommer Vinnova besluta om att rätten till bidrag upphör och Koordinatorn blir återbetalningsskyldig avseende dittills utbetalt belopp."

Kommentarer

0 / 1500 tecken

Anvisningar och rekommendationer

Projektet ingår inom det Strategiska innovationsprogrammet Drive Sweden och projektet ska samverka med programkontoret för programmet i genomförandet. Projektet ska rapportera och beakta synpunkter från det strategiska innovationsprogrammet för Drive Sweden vid minst två tillfällen i överenskommelse med programmet. Ett publikt referat av Start- och Slutrapport ska skickas till Drive Swedens programkontor för publicering till programoffice@drivesweden.net

UPPARBETADE KOSTNADER

Nedan ska upparbetade, faktiska projektkostnader fyllas i för redovisningsperioden.

Kostnaderna ska fyllas i för den koordinerande projektparten (koordinatorn) och övriga projektparter. Om redovisningsperioden går över ett årsskifte ber vi dig fylla i kostnaderna i två kolumner då vi behöver veta fördelningen per kalenderår.

De förifyllda siffrorna i kolumnen "Budget" är hämtade från vyn "Projektparter, budget och finansiering" för aktuellt projekt.

Totalt för hela projektet

Totalt

	Upparbetade kostnader	Ack. kostnader	Budget	Återstår jfr med budget	
	2022-02-01 2022-08-31	**2022-02-01 2022-08-31**	**2022-02-01 2022-08-31**	**kr**	**%**
Personalkostnader	1 704 423	1 704 423	1 758 000	53 577	3.0%
Utrustning, mark, byggnader	0	0	60 000	60 000	100.0%
Konsultkostnader, licenser m.m	30 920	30 920	50 000	19 080	38.2%
Övriga direkta kostnader inkl. resor	108 510	108 510	292 000	183 490	62.8%
Indirekta kostnader	0	0	0	0	0.0%
Totala kostnader	**1 843 853**	**1 843 853**	**2 160 000**	**316 147**	**14.6%**

Koordinerande projektpart (koordinator)

Volvo Autonomous Solutions AB

Volvo Autonomous Solutions AB (559285-4219)

	Upparbetade kostnader	Ack. kostnader	Budget	Återstår jfr med budget	
	2022-02-01 2022-08-31	**2022-02-01 2022-08-31**	**2022-02-01 2022-08-31**	**kr**	**%**
Personalkostnader	617 659	617 659	864 533	246 874	28.6%
Utrustning, mark, byggnader	0	0	60 000	60 000	100.0%
Konsultkostnader, licenser m.m	0	0	10 000	10 000	100.0%
Övriga direkta kostnader inkl. resor	0	0	0	0	0.0%
Indirekta kostnader	0	0	0	0	0.0%
Totala kostnader	**617 659**	**617 659**	**934 533**	**316 874**	**33.9%**

Projektparter

Blekinge Tekniska Högskola

Blekinge Tekniska Högskola (202100-4011)

	Upparbetade kostnader	Ack. kostnader	Budget	Återstår jfr med budget	
	2022-02-01 2022-08-31	**2022-02-01 2022-08-31**	**2022-02-01 2022-08-31**	**kr**	**%**
Personalkostnader	663 297	663 297	470 000	-193 297	-41.1%
Utrustning, mark, byggnader	0	0	0	0	0.0%
Konsultkostnader, licenser m.m	30 920	30 920	40 000	9 080	22.7%
Övriga direkta kostnader inkl. resor	108 510	108 510	292 000	183 490	62.8%
Indirekta kostnader	0	0	0	0	0.0%
Totala kostnader	**802 727**	**802 727**	**802 000**	**-727**	**-0.1%**

Volvo Business Services International AB

Volvo Autonomous Solutions AB - Lundby (556539-9853)

	Upparbetade kostnader	Ack. kostnader	Budget	Återstår jfr med budget	
	2022-02-01 2022-08-31	**2022-02-01 2022-08-31**	**2022-02-01 2022-08-31**	**kr**	**%**
Personalkostnader	423 467	423 467	423 467	0	0.0%
Utrustning, mark, byggnader	0	0	0	0	0.0%
Konsultkostnader, licenser m.m	0	0	0	0	0.0%
Övriga direkta kostnader inkl. resor	0	0	0	0	0.0%
Indirekta kostnader	0	0	0	0	0.0%
Totala kostnader	**423 467**	**423 467**	**423 467**	**0**	**0.0%**

Återbetalningskrav eller kommande utbetalning

Det slutliga bidraget som en bidragsmottagare har rätt till är det lägsta av *Max stödnivå* × *Rapporterade kostnader* eller *Max bidrag*. Max stödnivå och Max bidrag framgår av vårt beslut. Rapporterade kostnader (ackumulerade kostnader) är de kostnader som rapporterats in av projektet via lägesrapporter och denna slutrapport. Tabellen nedan visar **preliminärt** återbetalningskrav eller vad som är kvar att betala ut.

Återbetalningskrav eller kommande utbetalning

Projektparter	Max bidrag	Max stödnivå	Budget	Rapporterade kostnader	Slutligt bidrag	Återkrav
Volvo Autonomous Solutions AB	174 800	19%	934 533	617 659	117 356	57 444
Blekinge Tekniska Högskola	610 000	77%	802 000	802 727	610 000	0
Volvo Business Services International AB	79 200	19%	423 467	423 467	79 200	0
Totalt	**864 000**	**-**	**2 160 000**	**1 843 853**	**806 556**	**57 444**
Belopp att betala tillbaka via Koordinatorn*						**57 444**

*Återbetalning ska alltid göras via koordinatorn. Inbetalningen görs till Vinnova bg 5051-5816 senast 30 dagar efter godkänd slutrapport. Ange projektets diarienummer som referens vid inbetalningen. Information om slutligt återbetalningsbelopp kommer när slutrapporten granskats och godkänts. Koordinatorn ansvarar för att informera berörda bidragsmottagare.

Obs! Andra regler för återbetalning kan gälla för ditt projekt t.ex. om beslutet för finansiering fattades 2014 eller tidigare, kontakta då din handläggare.

KOMPLETTERANDE FRÅGOR

Vinnova vill gärna ha din uppfattning om hur väl följande frågor stämmer överens med vad du tycker. Svarsalternativen är graderade från 1 till 10, där 10 är högsta betyg och 1 det lägsta. Markera det alternativ som stämmer bäst överens med vad du tycker.
Då Vinnova ser över rapporteringen kan det upplevas att ni får svara på likartade frågor. Vi ber om överseende med detta.

1. Hur väl motsvarar projektresultatet förväntningarna vid projektstart? *

9

2. Hur enkelt har det varit att ansöka och rapportera i Vinnovas Intressentportal? *

10

3. Hur väl har Vinnovas vägledning och stöd fungerat under projektets gång? *

10

4. Hur nöjd är du med Vinnova som myndighet i sin helhet? *

10

5. Eventuella övriga kommentarer

0 / 500 tecken

6. Hur stor del av projektarbetet har utförts av män i %. *

70

BILAGOR

Här kan du ladda upp bilagor.

För ett stort antal av våra beslut finns särskilda krav på rapportering. Dessa framgår i så fall av beslutsmeddelandets särskilda villkor. Mallar till läges- och slutrapportering för utlysningar med särskilda rapporteringskrav finns på
Rapportmallar

Revisorsintyg *

Om en bidragsmottagares maximala bidragsbelopp enligt beslutet uppgår till 3 miljoner kronor eller mer ska revisorsintyg från kvalificerad revisor avseende bidragsmottagaren bifogas slutrapporten. För kommun, landsting och statliga myndigheter accepteras också revisorsintyg från kommunal yrkesrevisor eller internrevisor. Kostnader för revisorsintyg med upp till 30 000 kronor kan tas upp i slutrapporten även om fakturan inte kommit.

Universitet och högskolor är undantagna från skyldigheten att inkomma med revisorsintyg såvida inte annat framgår av beslut eller särskilda villkor.

Revisorsintyg krävs inte för någon projektpart.

Mall för revisorsintyg samt Instruktion för revisorns granskning av bidragsprojekt finns här:
https://www.vinnova.se/sok-finansiering/regler-for-finansiering/allmanna-villkor/

Revisorsintyg

Övriga bilagor

Övriga bilagor_1.pdf

Övriga bilagor_2.pdf

FÖRHANDSGRANSKA OCH SKICKA IN

Inskickad av

Förnamn

Stefan

Efternamn

Thorn

E-postadress

stefan.thorn@volvo.com

Uppföljningsfrågor

1. Har projektet lett till ökade FoU- eller andra innovationsinvesteringar? *

- ○ Ja
- ◉ Nej

b. Nej, inga ökade FoU- eller andra innovationsinvesteringar har gjorts eftersom... *

- ○ Det är för tidigt för att ta ett sådant beslut.
- ◉ Det inte har varit syftet med projektet.
- ○ Annat.

2. Har projektet resulterat i nyanställningar?
(flera val möjliga)

- [ ] Ja, projektet har lett till nyanställningar inom projektet.
- [ ] Ja, projektet har lett till nyanställningar utanför projektet.
- [x] Nej, inga nyanställningar har gjorts.
- [ ] Vet inte.

3. Har projektet lett till nya eller utvecklade samarbeten av betydelse för FoU- och innovationsverksamhet? *

- ◉ Ja
- ○ Nej

a. Ja, projektet har resulterat i...
(flera val möjliga)

- [x] Helt nya samarbeten.
- [ ] Fördjupning och/eller förlängning av redan etablerade samarbeten.

b. Samarbete har inletts och/eller fördjupats med:
(flera val möjliga)

- [x] Aktörer som ingått som formella projektpartners.
- [x] Aktörer som inte varit formell del av projektet.
- [x] Aktörer i Sverige.
- [ ] Aktörer utanför Sverige.
- [ ] Annat.

c. De nya eller fördjupade samarbetena har:
(flera val möjliga)

- [ ] Avslutats i och med projektets avslut.

- [x] Fortsätter i nya aktiviteter.
- [ ] Annat.

4. Har projektet lett till lic- och doktorsavhandlingar, vetenskapliga artiklar eller konferensartiklar? *

- ( ) Ja
- (x) Nej

b. Nej, projektet har inte resulterat i några vetenskapliga publikationer eftersom… *

- ( ) Det inte är relevant för detta projekt.
- (x) Det planeras längre fram.

5. Har projektet lett till andra publikationer? *

- ( ) Ja
- (x) Nej

c. Nej, projektet har inte resulterat i några publikationer eftersom… *

- ( ) Det inte är relevant för detta projekt.
- (x) Det planeras längre fram.

6. Har projektet bidragit till ansökningar om – eller godkända – patent eller immaterialrättsskydd? *

- ( ) Ja
- (x) Nej

7. Har projektet resulterat i eller bidragit till nya eller väsentligt förbättrade produkter (varor), tjänster, tekniska processer eller produktionsprocesser? *

Observera att frågan även inkluderar tidiga utvecklingsstadier innan produkt (vara) eller tjänst är färdig för lansering.

- ( ) Ja
- (x) Nej

8. Har projektet resulterat i nya eller väsentligt förbättrade affärsmodeller eller strategier? *

- ( ) Ja
- (x) Nej

9. Har projektet resulterat i intäkter? *

- ( ) Ja, projektet har resulterat i intäkter för en eller flera projektparter.
- (x) Nej, och det var inte heller målet.
- ( ) Nej, inte ännu.

10. Har projektet resulterat i utveckling av policy, regelverk eller metoder i offentlig verksamhet eller politik? *

- [ ] Ja
- [x] Nej

11. Har eller kommer projektet att leda till följdprojekt? *

- [x] Ja
- [ ] Nej

a. Det/de nya projektet/projekten har följande status:
(flera val möjliga)

- [x] Planerat/planerade men utan formellt beslut.
- [ ] Formellt beslutat/beslutade men inte igångsatta.
- [ ] Formellt beslutade och igångsatta.

b. Det/de nya projektet/projekten kommer att finansieras på följande sätt:
(flera val möjliga)

- [x] Av ingående projektparter.
- [ ] Av Vinnova i samma program.
- [x] Av Vinnova i annat program.
- [ ] Av andra offentliga finansiärer eller stiftelser.
- [ ] Med riskkapital via privata investerare.
- [ ] Med riskkapital via offentliga fonder/investerare.
- [ ] Av EU:s program.
- [ ] Genom annan internationell kanal.
- [ ] Ingen finansiering behövs.
- [ ] Vet inte.
- [ ] Annat.

c. Följdprojektets syfte är att resultat från det slutrapporterade projektet ska...
(flera val möjliga)

- [x] Valideras med hjälp av tester (piloter, fältförsök, prototyper, demonstrationer).
- [x] Integreras i mer avancerade utvecklingsprojekt eller mer tillämpningsorienterade FoU-projekt.
- [x] Integreras i nya forskningsprojekt.
- [ ] Integreras i utbildningar och kurser.
- [ ] Förpackas för informations- /kommunikation och spridningsverksamhet.
- [ ] Införas, överföras och/eller integreras i policysammanhang (reglering, styrmedel, standardisering, policy- och strategiarbete mm).
- [ ] Annat.

12. Har resultat från projektet använts i utbildnings- eller undervisningssammanhang (förutom workshop och/eller konferens)? *

- [ ] Ja
- [x] Nej

13. Ange de tre viktigaste insatserna för kunskapsspridning som har gjorts inom ramen för projektet. Max antal

tecken 800. *

- Presentation av VaViM projektresultat på Drive Sweden Forum 2022. - Återkommande workshops med forskare och doktorander på Blekinge Tekniska Högskola. - Publicering av kommande artiklar: Bertoni, M., Thorn, S. (2023) A Value Driven Design application for virtual vehicle validation and verification. In Proceedings of the 24th International Conference on Engineering Design (ICED'23), Bordeaux, France, July 24-27. Larsson, T., Thorn, S., Machchhar, R., (2023) Digital Twins for virtual vehicle validation and verification in development phase (2023). In Proceedings of the CIRP Design Conference 2023 (CIRP 2023), Sydney, Australia, May 17-19, 2023.

655 / 800

14. Har projektet bidragit till mobilitet av deltagare i projektet? Med mobilitet menas att projektdeltagare har jobbat/forskat i en annan organisation än den där de har sin huvudanställning. *

- ○ Ja
- ● Nej

15. Har projektet resulterat i genomförande av internationella aktiviteter? Till internationella aktiviteter räknas aktiviteter som syftat till att sprida kunskap eller information internationellt, samarbeten utanför Sverige eller dylikt. *

- ○ Ja
- ● Nej

VOLVO

VAVIM

Validation of Virtual Models – a pre study with SOTA analysis

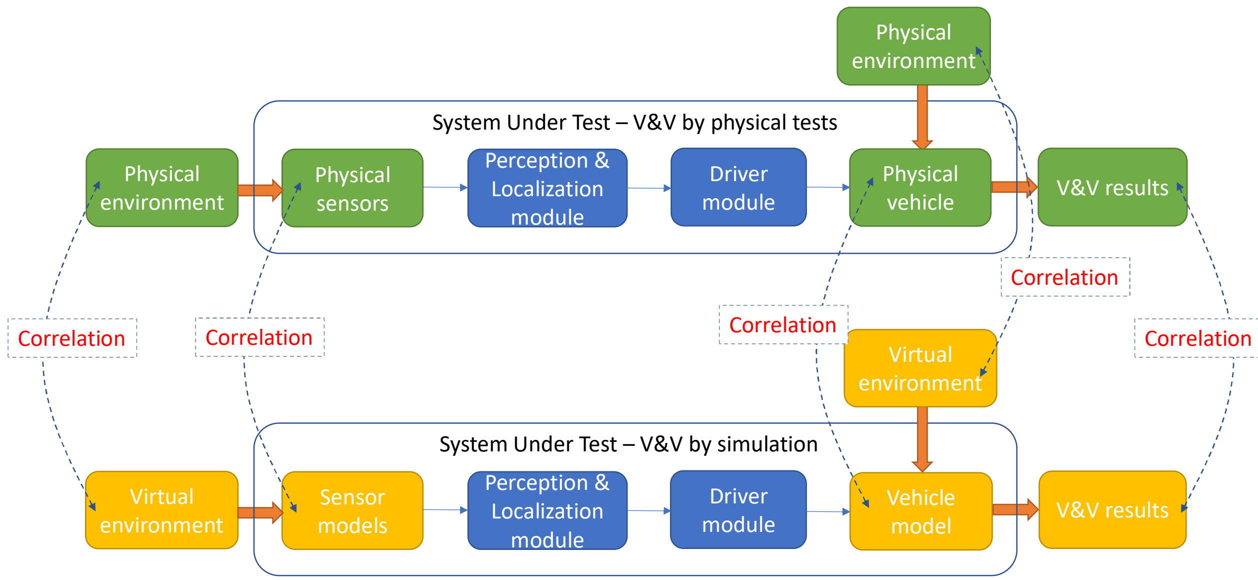
Marco Bertoni, Blekinge Institute of Technology

Stefan Thorn, Volvo Autonomous Solutions

Within the strategic innovation program for Drive Sweden, with support from: VINNOVA Sweden's Innovation Agency

BACKGROUND

- In order to achieve scalability and robustness, tests of self-driving vehicle systems need to be largely performed virtually
- Reliable virtual tests require validated models on sensors, vehicles and environment where the systems are to operate;



GOALS / WORK PACKAGES

- WP1: Analyze the state-of-the-art (SOTA),
- WP2: Identify prioritized research questions,

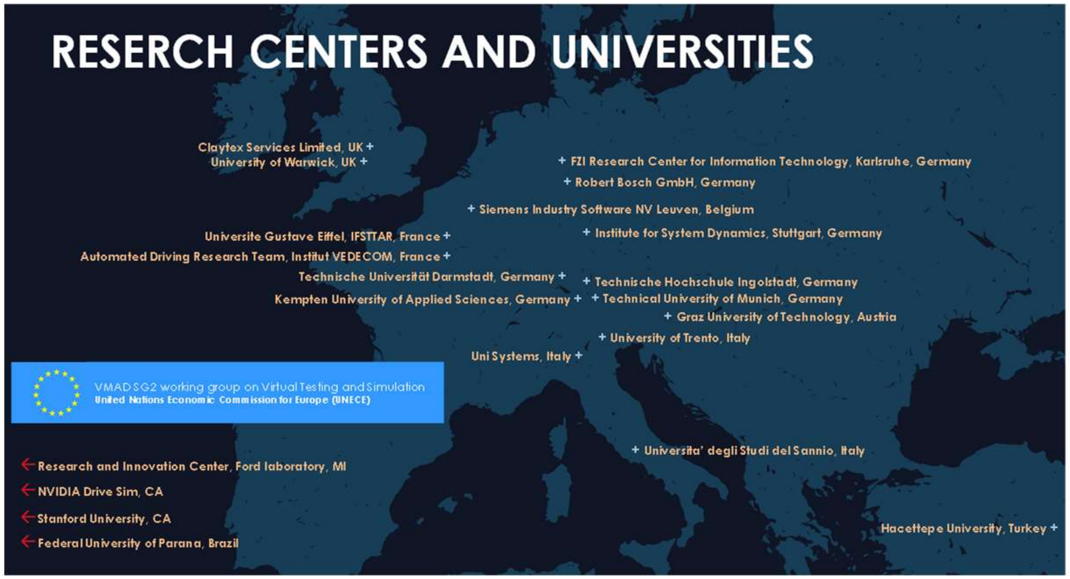
related to validation of models used in virtual tests of autonomous vehicle systems

- WP3: Perform a feasibility study with demonstration of a model validation approach
- WP4: Formulate a draft project proposal for future studies

VOLVO

WP1 – SOTA ANALYSIS

- Focus:
  - Interaction between environmental models and sensor models / vehicle models
  - Methods to obtain measures of the correlation with the physical equivalents
- Outcome:
  - Review of 87 research publications between 2001-2022, from 15+ research centers, groups and universities;



WP1 – SOTA ANALYSIS

- On a high level, the autonomous vehicle shall perform the tasks sense, plan and act;
  - Sense: sensors provide information about the environment, in which the vehicle moves, to the planning unit
  - Plan: based on sensor inputs, the planning unit calculates the action of the vehicle
  - Act: considering the result of the planning unit, the ego- vehicle moves in the environment accordingly.
- There are well-developed virtual models for the latter two tasks: plan and act.
- Models and model validation methodologies for the sense task are relatively immature (e.g.: Schlager et al. 2020; Donà and Ciuffo 2022; Magozi et al. 2022).

Schlager, B., Muckenhuber, S., Schmidt, S., Holzer, H., Rott, R., Maier, F. M., et al. (2020). State-of-the-art sensor models for virtual testing of advanced driver assistance systems/autonomous driving functions. SAE International Journal of Connected and Automated Vehicles, 3(12-03-03-0018), 233-261.

Donà, R., & Ciuffo, B. (2022). Virtual testing of Automated Driving Systems. A survey on Validation Methods. IEEE Access.

Magosi, Z. F., Wellershaus, C., Tihanyi, V. R., Luley, P., & Eichberger, A. (2022). Evaluation Methodology for Physical Radar Perception Sensor Models Based on On-Road Measurements for the Testing and Validation of Automated Driving. Energies, 15(7), 2545.

WP1 – SOTA ANALYSIS

- Three levels of sensor model fidelity (Schlager et al. 2020):

Low-fidelity

Low-fidelity "black-box" sensor models are based on geometrical aspects and by definition are only able to **detect objects that are inside the Field of view** (FOV) and that are not occluded by any other object. They do not consider the influence of different environmental conditions, material properties, or sensor-specific effects.

Medium-fidelity

Medium-fidelity "grey-box" sensor models share the basic working principle of low-fidelity models. Nonetheless, they introduce the possibility of **modelling false positives and false negatives** rates, the effect of traffic objects' shape and texture on the detection, and environmental effects such as atmospheric degradation.

High-fidelity

High-fidelity "white-box" sensor try to replicate the **physical phenomena** regulating the interaction between the sensor and the external environment in simulation.

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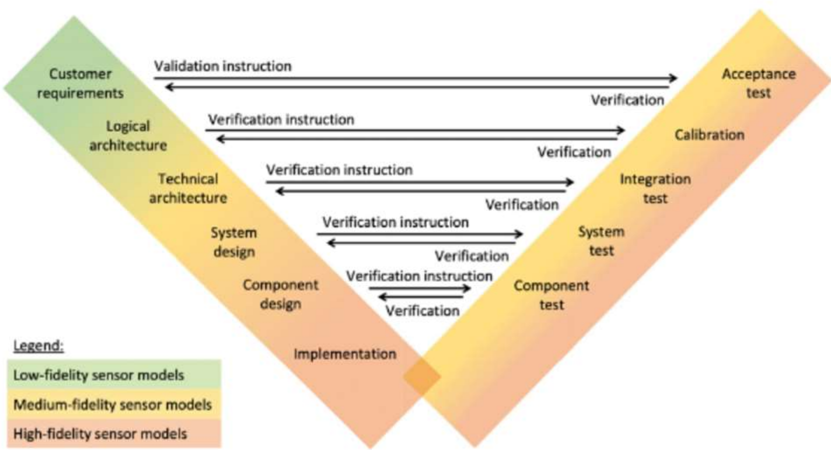
WP1 – SOTA ANALYSIS

- Suggested fidelity levels at different stages of the development process:



(Source: Schlager et al., 2020)

- List of papers addressing sensor modeling and model validation techniques:

	Radar	Lidar	Camera
Low fidelity	Hanke et al. (2015) Muckenhuber et al. (2019) Stolz and Nestlinger (2018)		
Medium fidelity	Bernsteiner et al. (2015) Buhren and Yang (2006, 2007a, 2007b, 2007c, 2007d,) Cao (2015, 2017), Danielsson (2010) Hammarstrand et al. (2012a, 2012b) Hirsenkorn et al. (2015) Mesow (2006) Schuler (2007) Schuler et al. (2008) Wheeler et al. (2017)	Hirsenkorn et al. (2015) Li et al. (2016, 2020)	Hirsenkorn et al. (2015)
High fidelity	Hirsenkorn et al. (2017) Maier et al. (2018) Holder et al. (2019) Peinecke et al. (2008)	Bechtold and Hofle (2016) Brown, Blevins, and Schott (2019a, 2019b) Doria (2019a, 2019b) Fang et al. (2020), Goodin et al. (2009) Gschwandtner (2013) Gschwandtner et al. (2011) Hanke et al. (2017) OBrien and Fouche (2005) Peinecke et al. (2008), Rossmann et al. (2012), Su et al. (2019) Wang (2015) Wang et al. (2012) Woods (2019a, 2019b)	Carlson et al. (2019a, 2019b) Goodin et al. (2009) Schneider and Saad (2018) Wittpahl et al. (2018)

WP1 – SOTA ANALYSIS

- Pros and cons of different fidelity levels:

	Low fidelity	Medium fidelity	High fidelity
Operating principles	Geometrical aspects	Physical aspects, detection probabilities	Rendering (rasterization, ray tracing, etc.)
Input	Object lists	Object lists	3D scene (meshs)
Output	Object lists	Object lists or raw data	Raw data
Pros	Low computational power needed	Trade-off between computational power and realistic output, a lot of effects can be considered	Most realistic output
Cons	High abstraction level, no realistic output	Lots of training data may be required	High computational power needed
V-model phases	First specification phases	Specification phases in the middle and integration phases	Component specification, implementation and integration phases
Design question	What point(s) or shape represents objects and which need to be in the line of sight for detection?	What point(s) or shape represents objects and which need to be in the line of sight for detection? What effects are considered?	What is the detection threshold? Which effects, material properties, and weather conditions are considered?

WP1 – SOTA ANALYSIS

CONCLUSIONS:

- There are well-developed virtual models for the plan and act tasks
- Models and model validation methodologies for the sense task are relatively immature
- Several papers are addressing initiatives to close the sense gap

REMAINING GAPS:

1. *No generally accepted **evaluation criteria** to validate a virtual sensor model, nor **unified testing procedure***
2. *Knowledge lacking on how to **evaluate the value** (benefit vs. cost) of a selected modeling approach*

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WP2 – RESEARCH QUESTIONS

- Three high level research questions were identified:

STRATEGICAL ISSUES

DECISION SUPPORT SYSTEM

What type of decision support system is essential?

TACTICAL ISSUES

FIDELITY

What is fidelity? What is the unit of fidelity? What is the use of that number? High-medium-low fidelity- What does it mean? Real site vs. Digital twin fidelity? Can we parametrise uncertainty (e.g., friction vs. temperature)? Trade-off between fidelity and computational requirements? What is the value (highest trade-off) of fidelity? What is good enough? Does it help to have 79% fidelity? To do what? For what decision? What are we validating in simulations? Capabilities of the actual tuning?

OPERATIONAL ISSUES

VIRTUAL ENVIRONMENT

How different environmental parameter affect different sensors/models? (Vibrations, temperature, various levels of occlusion/foliage, gravel road, Lidars, vehicle models, GNSS)

RQ1: What is the 'value' of a selected virtual simulation approach?

RQ1.1 | RQ1.2

RQ2: What are the relationships between fidelity, value and cost for a virtual model capability?

RQ2.1 | RQ2.2 | RQ2.3

RQ3: How shall new model capabilities best be introduced in the virtual simulation?

RQ3.1 | RQ3.2 | RQ3.3

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WP2 – RESEARCH QUESTIONS

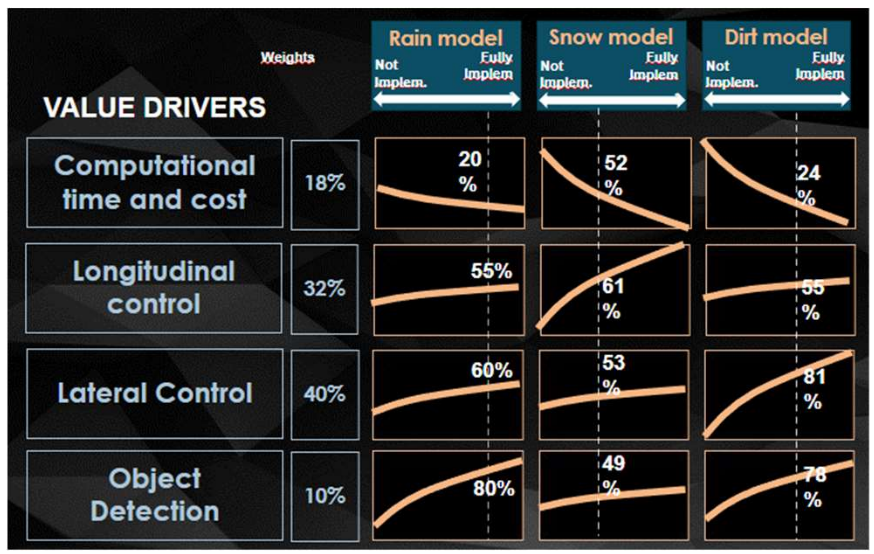
STRATEGICAL ISSUES

RQ1: What is the 'value' of a selected virtual simulation approach?

RQ1.1: How to define a Value Creation Strategy (list of prioritized value dimensions)?

RQ1.2: How to calculate the 'total value' associated to a solution design decision?

Example:



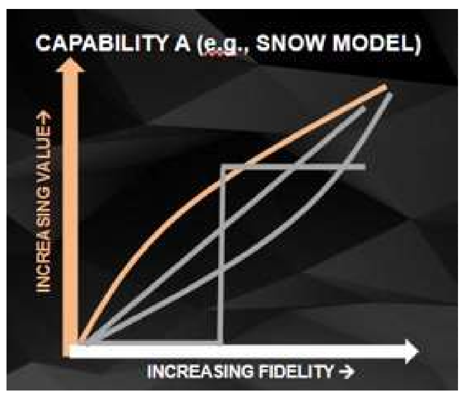
WP2 – RESEARCH QUESTIONS

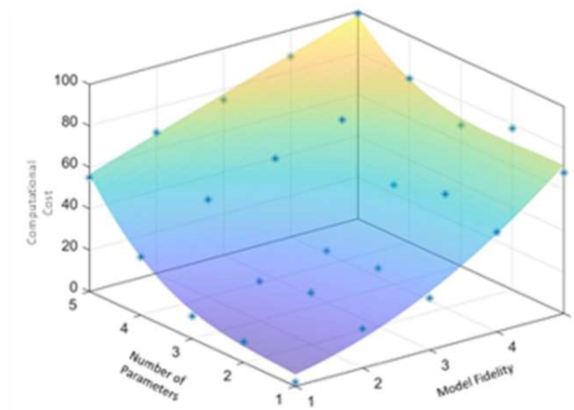
TACTICAL ISSUES

RQ2: What are the relationships between fidelity, value and cost for a virtual model capability?

- *RQ2.1: Which metrics do best describe the level of model fidelity?*
- *RQ2.2: How does 'value' increase with increased model fidelity?*
- *RQ2.3: How does 'cost' increase with increased model fidelity?*

Examples:





WP2 – RESEARCH QUESTIONS

OPERATIONAL ISSUES

RQ3: How shall new model capabilities best be introduced in the virtual simulation?

- *RQ3.1: Which model capabilities brings the most value?*
- *RQ3.2: Which of them should be introduced as model improvements and how?*
- *RQ3.3: Which of them should be introduced as error/uncertainty models and how?*

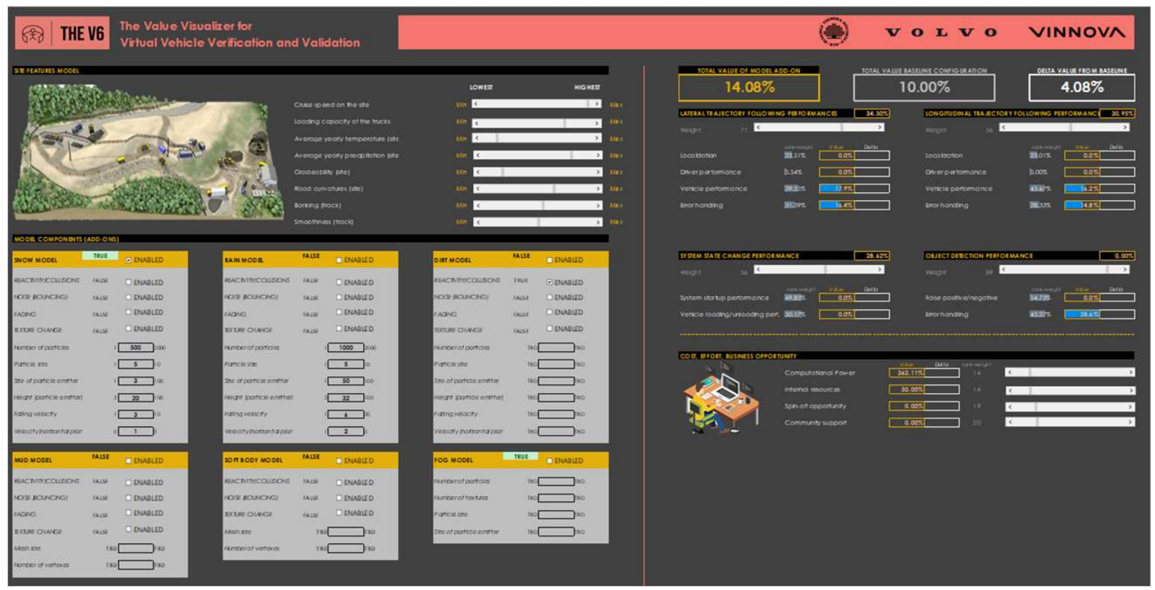
Examples:

WP3 – FEASIBILITY STUDY

Concept tool to visualize the value of a selected modeling approach

Aim:

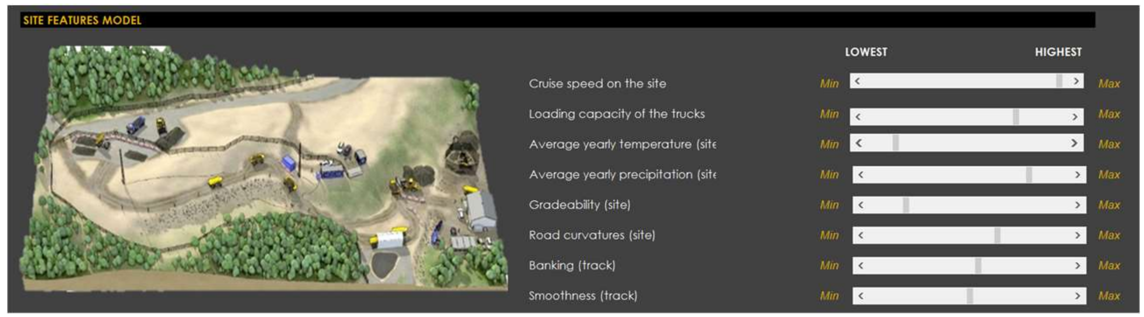
- Which model capabilities and fidelity levels (e.g., sensor model ability to detect snow) add most value to the goals of the simulation?

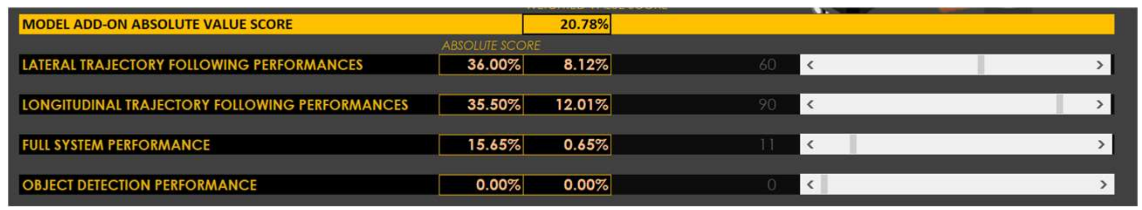


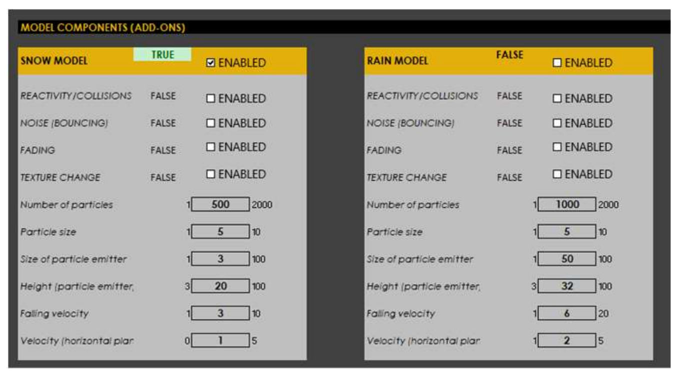
WP3 – FEASIBILITY STUDY

Inputs:

- Site features: Characteristics of the operational design domain
- Value drivers: phenomena that are important to be covered by the simulation
- Model components: Selection of modeling capabilities to be evaluated







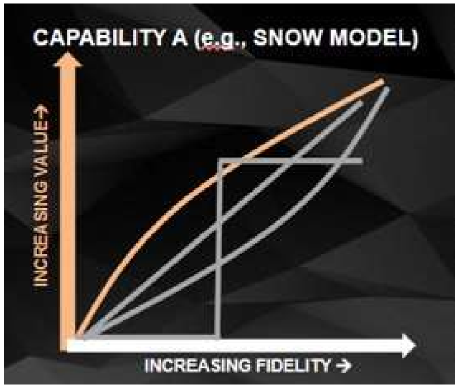
WP3 – FEASIBILITY STUDY

Output:

- Qualitative rather than quantitative evaluation;

  – Which model components give <u>most</u> added value to the simulation setup?

- Modeling knowledge is indicated with a maturity index (1-5);
  – How much can you trust your value adding results?
  – Where are the important knowledge gaps?



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WP4 – PROJECT PROPOSAL

Status

- Draft project proposal addressing:
  - research questions identified in WP2
  - concept tool demonstrated in WP3
- Will now reach out for partner interests for future collaborations

- Contact: stefan.thorn@volvo.com

VOLVO

VALIDATION METHODS FOR AUTONOMOUS DRIVING SYSTEMS

Version 0.3, 220919

Versioning history

V0.1	*Initial draft based on Donà, R., & Ciuffo, B. (2022). Virtual testing of Automated Driving Systems. A survey on Validation Methods. IEEE Access.* [*https://ieeexplore.ieee.org/stamp/stamp.jsp?arnumber=9718588*](https://ieeexplore.ieee.org/stamp/stamp.jsp?arnumber=9718588)
V0.2	*Added text to section 3.1 based on the work of (Schlager et al. 2020). Added section 3.2. New text is added to section 4.1 Radar validation (Hajri et al. 2017, Magozi et al. 2022, Jasinski et al. 2022) and section 4.3 Camera validation (Genser et al. 2021, Kamel et al. 2021). The list of research centers has been updated. The Reference section has been updated.*
V0.3	*Changed section 4.4 to section 5. And added text mainly based on the reviews - (Guo et al., 2018, Guo et al., 2019) along with some insights from (Donà and Ciuffo, 2022) and (Danquah et al., 2022). Some generic theory is covered from the book by (Schramm et al., 2016). Some former text this section has been updated. Reference list updated.*

1 INTRODUCTION

This section reviews the validation strategies related to virtual models in general) and to virtual testing toolchains for autonomous vehicles (in particular).

1.1 Generic validation framework for virtual models

One of the first attempts to build up a generic validation framework for virtual models was carried out by ***Carson (2002)***. According to the author, the validation should be made up of a **three steps procedure**:

1) face validity (i.e., answering the question: ''is the model returning reasonable results?'').
2) test the model over a range of input parameters (''stress test'').
3) comparison of the model's predictions with physical data whenever possible, in particular:
    a. collection of input data from real-world experiments.
    b. re-execution of the simulation model with the collected input.
    c. performance comparison with respect to the real-world.
    d. use statistical techniques to create confidence intervals in case multiple datasets are available.

In ***Oberkampf and Trucano (2008)***, a **three-steps validation approach** (Figure 1) is proposed where the virtual model is first compared against the real one in terms of predicted output. Secondly, an interpolation/extrapolation analysis over the required domain is carried out. Thirdly, the prediction uncertainty is characterized. A model with similar purposes is presented by ***Sargent in 2013***.

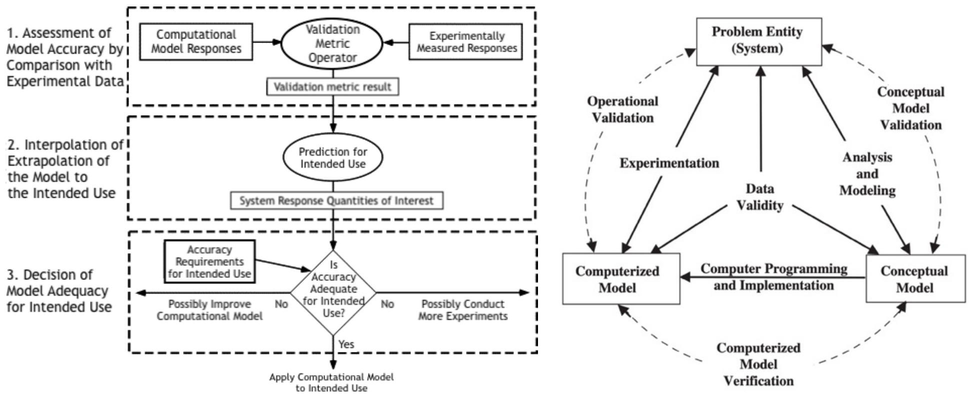

Figure 1: Validation workflow from Oberkampf and Trucano (2008)(left) and Sargent (2013)(right)

1.2 Credibility analysis

In order to partially account for the limitations, **a credibility analysis** is typically carried out in parallel to the validation he credibility investigation aims at enhancing the confidence in the developed virtual toolchain (***Carson 2002***).

A common framework for the credibility analysis of virtual models was developed at NASA and released publicly (***Nasa 2019***). Similarly, a credibility framework is currently being discussed at the UN/ECE level1 for ADS applications.

1.3 Validation strategies for virtual testing toolchains

In March 2022, ***Donà and Ciuffo (2022)*** (Uni Systems) performed a survey the state-of- the-art approaches adopted to validate both complete ADS virtual testing toolchains and simulation sub models involved in the virtual experiments.

The **validation process**, in general, aims at determining the <u>*capability*</u> of a *product* to fulfil its *purpose* and expectations for the required <u>*application*</u>. In contrast to the *verification* task, the process of validation takes place upon the completion of the product to ensure that the ''correct'' product was built. The **verification**, instead, is mainly concerned with the <u>*correct implementation*</u> of the conceptual (or mathematical) model into the actual product.

The validation of a virtual model (product) can be defined as a procedure aimed at establishing the model's accuracy (capability) in representing the real-world (purpose) from the perspective of the intended use (application).

The validation of a virtual testing environment can be decomposed into two methodologies:

- <u>*integrated system*</u>, where the overall simulation toolchain is tuned to replicate a distinct manoeuvre, and
- <u>*sub models-based*</u>, where each ingredient of the simulation pipeline is individually validated with respect to its physical counterpart.

Hybrid solutions combining both integrated system and sub model-based validation in a cascade fashion are also foreseen as explained in. However, no practical application of such an approach is available in the literature yet.

1.4 Simulation environments' setups

Five main environment setups for simulation and validation purposes are seen:

- **Model-in-the-Loop:** (MiL) full toolchain simulation on a general computing system.
- **Software-in-the-Loop:** (SiL) full toolchain simulation using compiled code.
- **Hardware-in-the-Loop:** (HiL) hybrid solution combining simulated models with real hardware components.
- **Vehicle-Hardware-in-the-Loop:** (VEHiL)hybrid approach combining a real vehicle placed on a chassis dynamometer while environmental information is provided by either data injection or sensor stimulation.
- **Vehicle-in-the-Loop:** (ViL) the vehicle can drive on a proving ground; however, virtual sensor information is still provided by the simulation environment via either signal injection or sensors stimulation.

2 VALIDATION OF THE INTEGRATED SYSTEM

Overall, the VeHIL was found to return significantly better fidelity than the MiL (***Dona et al. 2022***).

- On the positive side, the VeHIL methodology does not foresee the validation of each simulation sub model making up the virtual testing environment, thus reducing the validation effort. The focus is instead on providing high correlation with real-world data on a global level for the specific KPIs considered.
- On the downside, the VeHIL philosophy provides little information on how the toolchain is going to extrapolate outside the validation domain, which affects the credibility of the developed solution.

From a sensitivity perspective, it is also particularly hard for VeHIL to judge how small deficiencies in reconstructing the virtual scenarios propagate throughout the toolchain given the role played by the agents in the simulation, which can either dampen or amplify the discrepancies.

3 VALIDATION OF VIRTUAL SUBMODELS

The validation of the testing environment can alternatively be carried out by validating each individual simulation model making up the toolchain. The methodology is based on the functional decomposition of the virtual testing toolchain into sub models that replicate the physical counterpart (***ISO 2021***, ***Dueser and Gutenkuns 2021***).

A widespread approach is to adopt the decomposition shown in Figure 2(***Dona et al. 2022***).

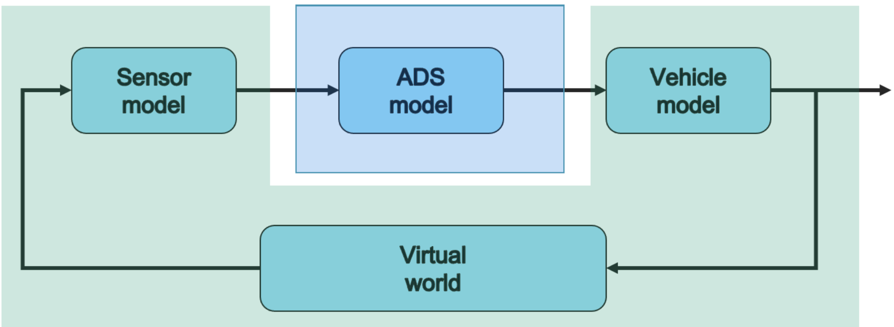

Figure 2: Sub-modules-based modelling framework for ADS simulation (Dona et al. 2022).

The toolchain is functionally divided into 4 main blocks: the sensors models, the vehicle model, the virtual world model and the ADS implementation.

3.1 Opportunities to model sensors

In Advanced Driver Assistance Systems/Autonomous Driving (ADAS/AD) a simplified vehicle shall perform the tasks' sense, plan, and act:

- Sense: sensors provide information about the environment, in which the vehicle moves, to the planning unit.
- Plan: based on sensor inputs, the planning unit calculates the action of the vehicle.
- Act: considering the result of the planning unit, the ego- vehicle moves in the environment accordingly.

According to ***Schlager et al. (2020)*** (Graz University of Technology) there are already well-developed models for the latter two tasks: plan and act. Also sensor models for the development of ADAS/AD functions are already developed and used by state-of-the-art environment simulation software.

However, there is still a significant deviation between the output of real sensors and the output of sensor models since sensor effects and sensor errors are often not considered. To reduce this deviation, sensor effects and sensor errors have to be investigated and modeled in further research and development.

Schlager et al. (2020) (Graz University of Technology) provides an overview of the properties of low-, medium-, and high-fidelity sensor models (Table 2). These can be described as the following:

- **low-fidelity**, also known a ''black-box'' models or ''object list''. Low-fidelity models retrieve the traffic objects' list and status directly from the simulation environment kernel. This modelling paradigm does not afford statistical aspects related to the perception, such as false positives/negatives rate. However, low fidelity models might account for basic sensor effects such as the Field of View (FoV) and occlusions to filter the whole object list;

- **medium-fidelity,** also known as ''grey-box'' (***Cao et al. 2015***) or ''phenomenological/data-driven'' according to the classification presented in ***Rosenberger et al. (2019)***. They share the basic working principle of low-fidelity models. Nonetheless, they introduce the possibility of modelling false positives and false negatives rates, the effect of traffic objects' shape and texture on the detection, and environmental effects such as atmospheric degradation.
- **high-fidelity,** also known as ''white-box'' or ''physics- based''. They try to replicate the physical phenomena regulating the interaction between the sensor and the external environment in simulation. Typically, advanced computer graphics techniques are adopted, such as raytracing and rasterization to render the 3D simulation environment.

Schlager et al. (2020) (Graz University of Technology) provides also an overview of the state-of-the-art sensor models classified into low-, medium-, and high-fidelity and into the specific sensor type that is modelled (radar, lidar, and camera) (Table 1).

Table 1: Overview of state-of-the-art radar, lidar, and camera sensor models for virtual testing of ADAS/AD functions.

<table>
<tr><th></th><th>Radar</th><th>Lidar</th><th>Camera</th></tr>
<tr><td>Low fidelity</td><td colspan="3">Hanke et al. (2015)
Muckenhuber et al. (2019)
Stolz and Nestlinger (2018)</td></tr>
<tr><td>Medium fidelity</td><td>Bernsteiner et al. (2015)
Buhren and Yang (2006, 2007a, 2007b, 2007c, 2007d,)
Cao (2015, 2017),
Danielsson (2010)
Hammarstrand et al. (2012a, 2012b)
Hirsenkorn et al. (2015)
Mesow (2006)
Schuler (2007)
Schuler et al. (2008)
Wheeler et al. (2017)</td><td>Hirsenkorn et al. (2015)
Li et al. (2016, 2020)</td><td>Hirsenkorn et al. (2015)</td></tr>
<tr><td>High fidelity</td><td>Hirsenkorn et al. (2017)
Maier et al. (2018)
Holder et al. (2019)
Peinecke et al. (2008)</td><td>Bechtold and Hofle (2016)
Brown, Blevins, and Schott (2019a, 2019b)
Doria (2019a, 2019b)
Fang et al. (2020),
Goodin et al. (2009)
Gschwandtner (2013)
Gschwandtner et al. (2011)
Hanke et al. (2017)
OBrien and Fouche (2005)
Peinecke et al. (2008),
Rossmann et al. (2012),
Su et al. (2019)
Wang (2015)
Wang et al. (2012)
Woods (2019a, 2019b)</td><td>Carlson et al. (2019a, 2019b)
Goodin et al. (2009)
Schneider and Saad (2018)
Wittpahl et al. (2018)</td></tr>
</table>

The authors further present a V-model that describes the virtual integration of ADAS/AD functions The descending branch on the left side of the V-model represents the specification phases of a a sensor system whereas the ascending branch on the right side of the V-model represents the integration phases. The higher the phase on the left side of the V-model the less detailed is the according phase. This means that specification phases at the top of the V-model require less detailed models (Figure 3).

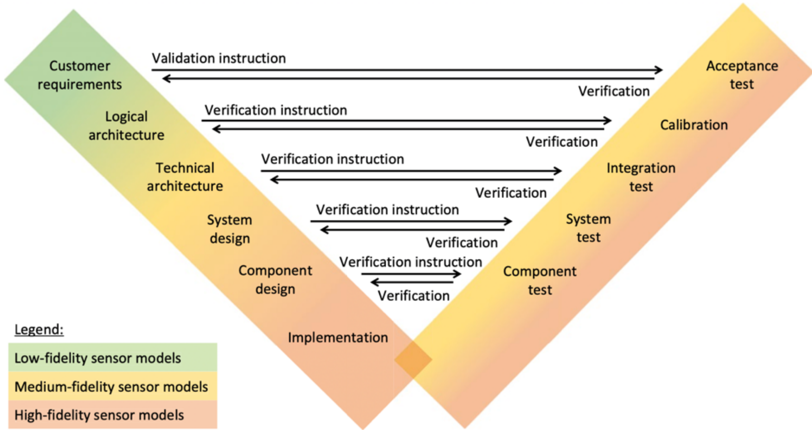

Figure 3: V-model mapped against sensor modelling types

3.2 Operating principles for virtual sensors

As presented by ***Schlager et al. (2020)*** (Graz University of Technology), sensor models take inputs from the environment simulation.

Table 2: Properties of virtual sensor models

	Low fidelity	Medium fidelity	High fidelity
Operating principles	Geometrical aspects	Physical aspects, detection probabilities	Rendering (rasterization, ray tracing, etc.)
Input	Object lists	Object lists	3D scene (meshs)
Output	Object lists	Object lists or raw data	Raw data
Pros	Low computational power needed	Trade-off between computational power and realistic output, a lot of effects can be considered	Most realistic output
Cons	High abstraction level, no realistic output	Lots of training data may be required	High computational power needed
V-model phases	First specification phases	Specification phases in the middle and integration phases	Component specification, implementation and integration phases
Design question	What point(s) or shape represents objects and which need to be in the line of sight for detection?	What point(s) or shape represents objects and which need to be in the line of sight for detection? What effects are considered?	What is the detection threshold? Which effects, material properties, and weather conditions are considered?

Outputs of sensor models within this classification are either object lists or raw data (radar data cubes, point clouds, or images). In the case of raw data as an output, object detection has to be added separately in order to extract the objects of the environment for further processing in the ADAS/AD function under test (Figure 4).

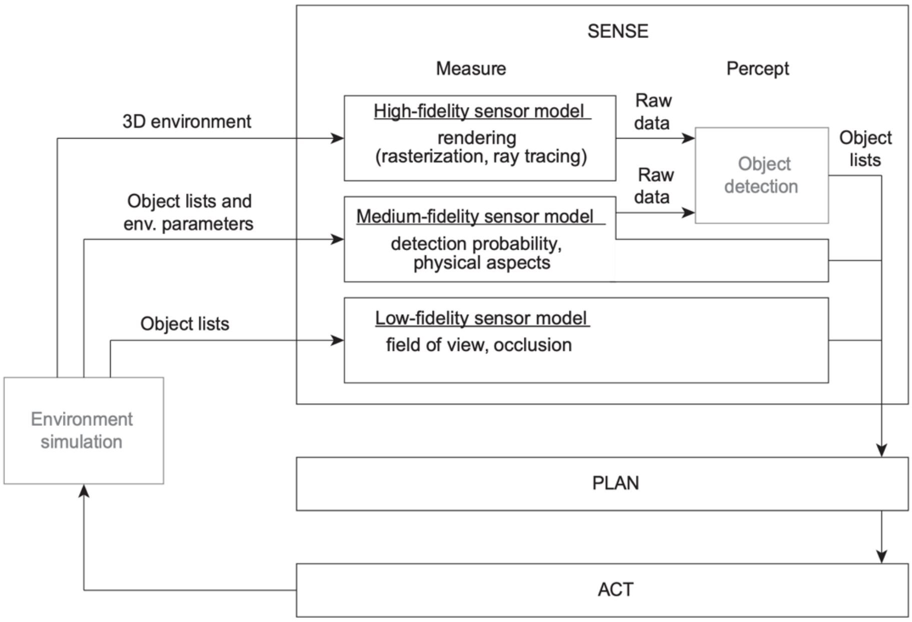

Figure 4: Classification of sensor models based on a combination of attributes as well as input and output data formats into low-, medium-, and high-fidelity sensor models.

Low-fidelity sensor models are based on geometrical aspects (constellation of objects in the environment in 2D or 3D) and use object lists as input and output data format (see Figure 3). The input object lists are denoted as "ground-truth" since the exact positions, poses, velocities, etc. of the objects are provided by the environment simulation. These objects lists are filtered according to the sensor-specific Field of View (FOV), which often has a conical outline but may also have a more complex outline (e.g., based on a radar antenna pattern). Low-fidelity sensor models are able to detect *objects that are inside the FOV and that are not occluded by any other object.* The definition of occlusion is part of the sensor model. They do not consider the influence of different environmental conditions, material properties, or sensor-specific effects.

Medium-fidelity sensor models consider the FOV, the detecion probability, and/or physical aspects. Compared to low-fidelity sensor models, *medium-fidelity sensor models usually model one of the perception sensors, either radar, lidar, or camera*. As input, medium-fidelity sensor models use ground-truth object lists (lists of actual objects in the environment). The ground-truth object lists are filtered according to the FOV and occlusions of objects by other objects, as described for low-fidelity sensor models. Besides medium-fidelity sensor models consider environmental parameters and additional object parameters like material properties.

High-fidelity sensor models utilize rendering techniques for the computation of raw data output from the 3D environment input, which is supplied by the environment simulation software. Compared to low- and medium-fidelity sensor models, which have ground-truth object lists as input, high-fidelity sensor models take the *whole 3D environment as an input*. Rendering techniques are extensively used for the implementation of high-fidelity sensor models. There are mainly two types of rendering techniques used for state-of-the-art high-fidelity sensor models: rasterization and ray tracing.

- Rasterization includes the projection of the 3D scene onto a 2D plane and the quantization onto a 2D image consisting of pixels.
- Raytracing consists of forward ray tracing where virtual rays are sent out by the transmitter and backward ray tracing where virtual rays are sent out by the receiver.

Ray casting is a more basic type of ray tracing, where only the intersections with the first surface are considered for rendering. Ray paths beyond reflection are left out. Ray casting is by far less expensive in computation than advanced ray-tracing methods. A further method of high-fidelity sensor models based on ray tracing is photon mapping, which is based on forward and backward ray tracing.

3.3 Information level at which carrying out the calculation

- **objects detection level:** the highest-level information provided by the sensors' models, *e.g.*, class and size of the object. This option is the only available when adopting the lowest fidelity virtual sensor models which cannot provide pixel-level detailed information.

- **occupancy grid:** (OG) intermediate level sensor information which refers to the probability of a pixel to be occupied by an obstacle.
- **raw data:** lowest level sensor information extracted before any tracking/classification algorithm is employed. It needs static obstacles (*e.g.*, buildings, fences, ...) to be digitized and included in the simulation environment for the pixel-level comparability of the results.

3.4 Investigation strategy for sensors

- **explicit open-loop simulations (E-OL):** where only the sensors' output is obtained via the re-simulation of a previously recorded driving scenario and the validation is carried out on the point cloud level;
- **implicit open-loop simulations (I-OL):** where only the sensors' output is obtained via the re-simulation of a previously recorded driving scenario and the validation is carried out after clustering and tracking;
- **closed-loop simulations (CL):** where the actual virtual sensors generated information is fed to the ADS and the ego-vehicle motion is part of the validation process.

Currently, no realistic correlation thresholds have been established to accept the models, and, secondly, no consolidated modelling framework has been adopted.

4 SENSORS VALIDATION

Donà and Ciuffo (2022) (🇮🇹 Uni Systems) argue that sensor models are still immature, and the modeling validation methodologies are still immature. **Magozi et al. (2022)** (🇦🇹 Graz University of Technology, 🇭🇺 Budapest University of Technology and Economics) recently added that, in spite of the huge amount of development and research ongoing in providing virtual sensors, there is no accepted method today for the proof of realism and prognosis quality for sensor models.

Currently, no standard modeling framework has been adopted, no validation framework has been standardized both in terms of KPIs and via setting realistic correlation thresholds. The most critical aspects are noise figures, Radar Cross-Sections (RCS), and real-world weather parametrization/replication.

4.1 Radars

No generally accepted evaluation criteria to validate a virtual sensor model, nor unified testing procedure (***Holder et al. 2018*** - 🇩🇪 Technische Universität Darmstadt, 🇦🇹 Graz University of Technology, 🇷🇴 Siemens FZI Research Center).

The replication of such phenomena in the virtual world is better accomplished using white-box modelling approaches.

The solution of the governing equations of a RADAR in real-time is an extremely challenging demand, simply not a viable option for most commercial automotive simulation environments and modelling assumptions must be introduced.

The most widespread solution to partially replicate the physics behind the RADAR is to adopt the **ray tracing framework**. Ray tracing is still a computationally intensive and requires a detailed 3D representation of the obstacles' geometry.

Dosovitskiy et al. (2017) compared real sensor data vs. synthetic ones generated using the open-source CARLA simulator. The RADAR Cross Section (RCS) model and long-distance obstacles were found to be the main responsible for the dissimilarity with respect to the experimental data.

Hajri et al. (2017) (🇫🇷 Automated Driving Research Team, Institut VEDECOM, France) propose a method for automatically generating sets of ground truth data to support advances in the field of obstacle detection and tracking.

Holder et al. (2018) (🇩🇪 Technische Universität Darmstadt, 🇦🇹 Graz University of Technology, 🇷🇴 Siemens FZI Research Center) found path propagation, separability, and sensitivity to the RCS as the major modelling challenges.

Ngo et al. (2021) (🇩🇪 University of Stuttgart and Bosch) trained a neural network to predict whether a point cloud is real or simulated.

Magozi et al. (2022) (🇦🇹 Graz University of Technology, 🇭🇺 Budapest University of Technology and Economics) proposes the Digital Ground Truth–Sensor Model Validation (DGT-SMV), a validation method based on the re-simulation of actual test drives to allow for a direct comparison between the simulated and recorded sensor output. The authors apply a sensor model provided by IPG CarMaker that imitates the physical wave propagation by an optical ray-tracing approach. This sensor includes the major effects of wave propagation, e.g., Multipath/repeated path propagation. Relative Doppler shift. Road clutter. False positive/negative detections of targets. The contribution shows the behaviour and the differences of the sensor model compared to the Ground Truth and the real sensor.

Jasinski et al. (2022) (🇵🇱AGH University of Science and Technology) recently propose an end-to-end methodology for validating generic radar sensor models based in a 4-step process: (1) coordinate systems definition, (2) data description, including ground truth and radar measurements, (3) re-simulation, which is about generating synthetic radar detections (point cloud) by feeding the GRSM with recorded labels and feeding the simulated detections to radar tracking algorithm, and (4) comparison and fine-tuning. In order to validate virtual radar sensors, the approach calculates the noise probability distributions of the real and synthetic data (Xreal and Xsynth), measuring how close these are to each other using Wasserstein distance.

4.2 Lidars

From a modelling perspective, there is little difference in the virtual models for RADARs with respect to lidars, given the similar working principles as they both rely on similar modelling technique.

Ray tracing can thus be safely exploited for white-box modelling approaches. Their modelling effectiveness using ray tracing is considerably higher with respect to RADARs thanks to the higher frequency range where they operate which reduces interference ***(Cao et al. 2015)*** (Technische Universität Darmstadt)

Schaermann et al. (2017) (Technical University of Munich and BMW) validated a ray tracing-based LiDAR model both explicitly and implicitly using Pearson correlation.

Rosenberger et al. (2019) (Technische Universität Darmstadt) found temporal scan order, noise figures, and the received signal's intensity as the most prominent effects for the sake of defining requirements for Lidar's virtual replication using high-fidelity model.

Hanke et al. (2017) (Technical University of Munich) and ***Rosenberg et al. (2020)*** (Technische Universität Darmstadt) validated the virtual model against both a real LiDAR's output and the ground-truth information derived from Real Time Kinematic (RTK) device by comparing the RMSE of the target vehicle trajectory.

4.3 Cameras

Passive sensing devices such as cameras require **ad-hoc modelling techniques** to craft high-fidelity models. The validation of virtual camera models must take into consideration the following phenomena according to ***Donà and Ciuffo (2022)*** (Uni Systems):

- Lens distortion: optical aberration due to projection
- Vignette: darkening of the screen border.
- Grain jitter: white noise injection.
- Bloom: presence of fringes around bright areas
- Auto exposure: image gamma adaption to darker or brighter areas.
- Lens flares: reflection of bright objects on the lens.
- Depth of field: blurring of objects near or very far away of the camera.
- Exposure time: shutter opening duration.

Kamel et al. (2021) (NVIDIA Drive Sim) presents two methodologies supporting the thorough validation of a simulated camera, the first one based on (1) the individual analysis of each component of the model (Figure 5), and the second one based on (2) a top-down verification that the camera data produced by a simulator accurately represents the real camera data in practice, for instance, by comparing the performance of perception models trained on real or synthetic images.

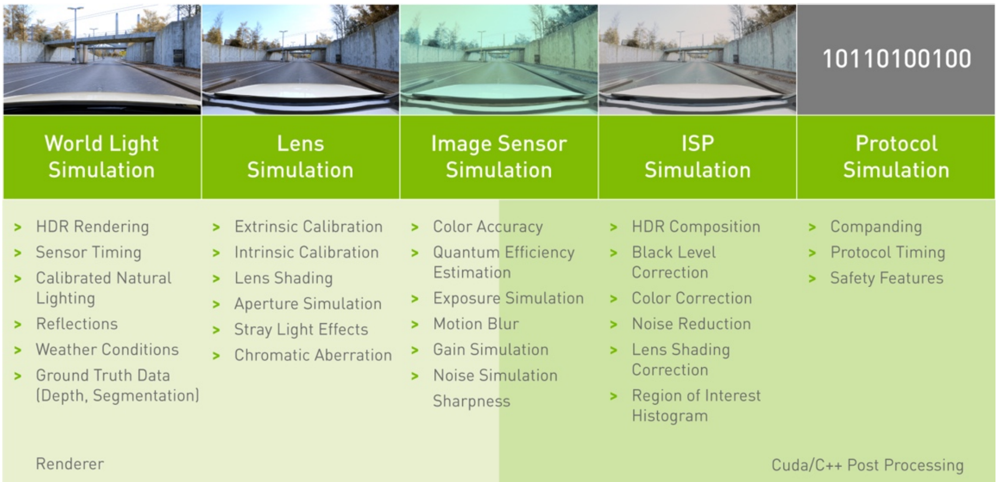

Figure 5: Individual camera components validation model (Source: https://developer-blogs.nvidia.com/wp-content/uploads/2021/12/image1-2.jpg)

With regards to (1), the work focuses on camera calibration (extrinsic and intrinsic parameters) and colour accuracy. The camera models chosen comes from the NVIDIA DRIVE Hyperion sensor suite.

Intrinsic camera calibration deals with the lens geometry and considers (1) the distance in pixels to the distortion center, (2) the coefficients of the distortion function and (3) the resulting projection angle in radians, to characterise the lens distortion characteristics. The process (Figure 6, left) is composed of 4 steps:

- Perform intrinsic camera calibration: Mounted cameras on a vehicle or test stand capture video of a checkerboard chart moving through each camera's field of view at varying distances and degrees of tilt.

- Produce simulated checkerboard calibration images: The real camera lens calibration data are used to re-create each camera in DRIVE Sim. The real checkerboard images are re-created in the simulation from the estimated chart positions and orientations output by the calibration tools.
- Produce intrinsic calibration from synthetic images: synthetic images are inputted into DriveWorks calibration tools to produce new polynomial coefficients.
- Compute max theta distortion from real to simulated lens: For each lens,the geometry defined by the calibration from real images to the geometry defined by the calibration from the simulated images.

Extrinsic camera calibration (Figure 6, center) is composed of three steps:

- Perform extrinsic camera calibration: Mounted cameras on a vehicle or test stand capture images of multiple calibration patterns located in the environment to calculate the exact position and orientation of the camera and the calibration charts in 3D space.
- Re-create scene in simulation: Using extrinsic parameters from real calibration and ground truth, the cameras and charts are spawned in simulation at the same relative positions and orientations as in the real lab. The system generates synthetic images from each of the simulated cameras.
- Produce extrinsic calibration from synthetic images and compare to real calibration: Synthetic images are inputted into the calibration tools to output the position and orientation of all cameras and charts in the scene. The 3D differences between extrinsic parameters derived from real vs. synthetic calibration images is then calculated.

The Color image accuracy assessment (Figure 6, right) is based on a 4-step process

- Capture image of ColorChecker chart in test chamber with a camera placed at a known height and distance from the chart.
- Re-create image in simulation using the calibrated chart values to render the test scene
- Extract mean brightness and RGB values for each patch:
- Compare white-balanced brightness and RGB values

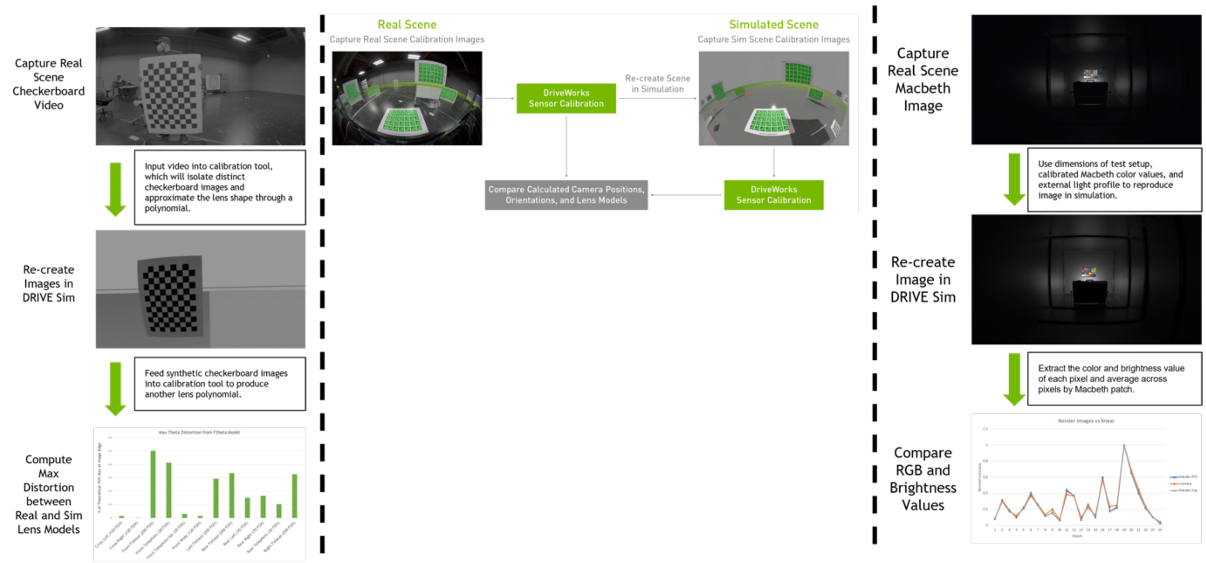

Figure 6: Intrinsic (left) and Extrinsic (center) camera calibration processes, Color image accuracy assessment (right).

Gruyer et al. (2012) (🇫🇷 Universite Gustave Eiffel) proposed a preliminary validation activity using static reference scenarios. Here an optical module and a CCD sensor creates an RGB representation of the simulation engine rendered frame.

Höber et al. (2020) (🇦🇹 Graz University of Technology) validated a phenomenological camera model against real-world data and an ideal sensor model using a frequency-based approach.

Reway et al. (2020) (🇩🇪 Technische Hochschule Ingolstadt and 🇧🇷 Federal University of Parana) presented a Simulation-to-Reality Gap index, an overarching validation metrics for camera models implemented in the simulation environments. Difficulties of replicating the real-world noise levels and the limited capabilities of reproducing the weather conditions, which affect how the Deep Neural Network (DNN)-based object tracking modules perform are the main limitations reported.

Genser et al. (2021) (🇦🇹 Graz University of Technology) propose novel approach that combines kernel density estimation with regression modelling to validate position measurements errors. The approach is applied to validate virtual camera sensors. The model was quality-tested in a real-world scenario (Hungarian motorways) and compared to reference measurements, leading to a pointwise position error of 9.60% in the lateral and 1.57% in the longitudinal direction.

5 VEHICLE MODELLING AND VALIDATION

A vehicle model is needed to answer several questions, such as:

- What is the capability of the vehicle in terms of fuel economy, gradeability, etc.?
- What is the acceleration/deceleration profile? What is the stopping distance?
- Will the vehicle rollover?
- Do the stability controls perform adequately?
- …

There is no "one" universal model that can address or answer all these questions simultaneously. Different modeling techniques need to be employed based on the requirement. An expectation from a model is to confer the capability to understand the response to stimuli of the entire vehicle as a system or many of its subsystems when simulated. These responses are usually regarded as the "states". When these states are a function of time, they are called "dynamic states". There are three differentiable methods modeling to represent dynamics states of a vehicle (Schramm et al., 2016), 1) mathematical models, 2) physical models (like CAD, FEM, etc.), and 3) a combination of the two. However, the focus will be mathematical methods for modeling and validation.

Kinematics: about the geometric description of motion in space (e.g., based on different reference frames and coordinate systems). It uses mathematical equations to describe movement without the use of forces or torques.

Dynamics: about the laws of the causes of motion (e.g., the effects of forces/moments in Newton's laws). Dynamics refers to changes in physical systems over time. Simply speaking, it is the study of vehicle motion, e.g., how a vehicle's forward movement changes in response to driver inputs, propulsion system outputs, ambient conditions, air/surface/water conditions, etc.

Kinematics vs Dynamics: Vehicle dynamic state estimation using kinematics-based models mainly involves numerical integration from sensors or establishing a kinematic estimator according to the configuration. However, noise accumulates when integrating over a long period, resulting in a large estimation error (Guo et al., 2018). Therefore, kinematics-based methods have become less common in recent years. However, many aspects of vehicle dynamics are derived from vehicle kinematics.

5.1 Reference Frame for State Representation

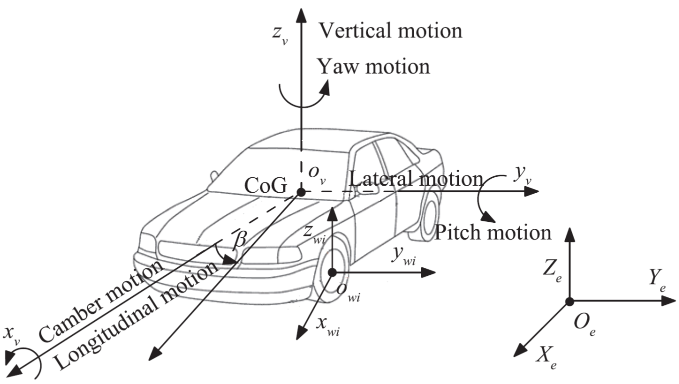

Figure 7: A vehicle reference frame, from (Guo et al., 2018)

Vehicle performance is affected by many factors, broadly classified into six categories, such as, vehicle, weather, traffic, roadway, travel, and driver-related factors (Liu et al., 2016). Several models and methods exist to modelling and simulating vehicle. One way to categorize is based on degrees of freedom (DoF). Intuitively, as the DoF in the model increases, so does the state estimation accuracy and the complexity of the model.

- 1DoF model (Longitudinal)
- 2DoF model (Lateral + Yaw)
- 3DoF model (Longitudinal + Lateral + Yaw)

- 7DoF model (Longitudinal + Lateral + Yaw + 4xRotwheel)
- 8DoF model (Longitudinal + Lateral + Yaw + Roll + 4xRotwheel)
- 14DoF model (Longitudinal + Lateral + Vertical + Yaw + Roll + Pitch + 4xRotwheel + 4xVertwheel)
- 19 or more DoF model (complete model)

These DoFs are typically achieved by a combination of vehicle body, tires, and suspension system. DoFs can be reduced by assigning them a predefined value or by user input.

As an example, here is the list of input variables:

- Normalized acceleration pedal position $0 < P_f < 1$
- Normalized brake pedal position $0 < P_b < 1$
- Gear selected
- Steering wheel angle

A brief description of common body and tire models is as follows:

5.2 Body Model

Some of the common track models based (Schramm et al., 2016, Guo et al., 2018, Donà and Ciuffo, 2022) are described below:

Longitudinal Model

The longitudinal model concentrates on the force or torque in the longitudinal direction while ignoring the lateral dynamics. The element of interest is longitudinal force on wheel (or power at wheel) that enables the calculating velocity as a function of time. The dynamic behavior of the system is hidden in the longitudinal expression where longitudinal force on wheel can be a function of normal tire-force, tire-road friction, longitudinal slip, wheel side-slip angle, etc.

Linear Single-Track Model

Commonly known as bicycle model. They have a series of simplifications such as velocity of the vehicle's center of gravity is constant, lifting, rolling, and pitching motion will be neglected, vehicle's mass is assumed to be concentrated at the center of gravity, wheel-load distribution between front and rear axle is assumed to be constant and the longitudinal forces on the tires, resulting from the assumption of a constant longitudinal velocity is neglected. Mainly used for an insight into the typical self-steering (eigen-) behavior of a vehicle.

Nonlinear Single-Track Model

Still, it is the bicycle model, but the longitudinal velocity is no longer assumed to be constant. It is the simplest model to simulate effects of dynamic velocity and could be useful to understand the vehicle behavior at larger steering angles or at higher lateral accelerations.

Linear Roll Model

Single track models can be complemented with a roll model to investigate effects resulting from different tire loading, for example, during cornering. The roll at chassis is a result of the forces, and components of the wheel suspension are still not be considered. Also, chassis is assumed to be a rigid body. Addition of this model is particularly helpful for the investigation to load fluctuations during cornering.

Twin Track Model

May also be referred to as double track model. Still, no kinematic wheel suspensions are modeled, i.e., the wheels are simply connected to the vehicle chassis by the spring and damper forces. Also, it shall be assumed that the center of the wheel can only move relative to the chassis and perpendicular to the road. This means that with this model it is not possible to investigate the influence of the camber or the influence of other spatial motions of the wheels. However, it is however sufficient for initial principal investigations or even for a basic vehicle simulator model

Twin Track Models with Suspensions

This model is an extension of the twin track models, where front and rear axle suspensions will be modeled. Now, the wheel can perform independent spatial motion. Naturally, more realistic steering behavior and roll dynamics of the vehicle can be simulated. Such a model can have 14 DoFs.

Complete Vehicle Model

Complete vehicle model includes mechanical as well as non-mechanical subsystems comprising components like wheel suspensions, drivetrains, wheels, and tires along with electronic elements, controllers, or ECUs to be modeled. Simulating complete vehicle model might look like "all problem - one solution", but that is seldomly true. Firstly, respective models need to be modified to suit the objective, and secondly, they require high computational effort. Nonetheless, such models are used to test safety critical features such as emergency braking, advanced driver assistance systems, or electronic stability programs or even systems that need a complete model of the vehicle such as comfort systems.

5.3 Tire Model

Some of the commonly used tire models based on (Pacejka, 2006, Schramm et al., 2016, Guo et al., 2019,) are described below:

Fiala model (Brush model)

The brush model relies on the assumption that the slip is caused by deformation of the rubber material between the tire carcass and the ground. The material is approximated as small brush elements attached to the carcass, which is assumed to be stiff. The carcass can still flex toward the hub, but it can neither stretch nor shrink. Every brush element can deform independently of the other (Svendenius and Wittenmark, 2003). In its simplest form, the brush model needs only two parameters, a cornering stiffness and a friction coefficient, to relate a slip angle, the difference between the orientation and direction of travel of a tire, to lateral force.

Pacejka tire model

One of the most widely used tire models is the so-called "Magic Formula Model" (Pacejka, 2005). Longitudinal and lateral slips are not constants but vary with normal load and longitudinal force. Hence, Pacejka is a better model than Fiala. It is a pure mathematical description of the input-output relationship of the tire-road contact under quasi-stationary conditions but requires operational data for curve fitting.

HSRI tire model

HSRI stands for "Highway Safety Research Institute" based in Michigan, and it was developed around 1974. The core of these model is that they can adapt to unsteady vehicle traveling simulations (Xu et al., 2018). Good comparison between Pacejka and HSRI can be found in (Carlson and Gerdes, 2005). There are many variations of the same in literature such as HSRI-NBS-I, HSRI-NBS-II, HSRI-NBS-III.

Tmeasy tire model

TMeasy is a semi-physical tire model for low frequency applications in vehicle dynamics (Hirschberg et al., 2007). It is yet another curve fitting tire model. One feature of TMeasy is the wide physical meaning of its smart parameter set, which allows to sustain the identification process even under uncertain conditions.

5.4 Validation

Three questions are stated to define complete vehicle validation (Bernard et al., 1994):

- Conceptual validity: Is the model appropriate for the vehicle of interest?
- Verification: Is the simulation based on equations that fully replicate the model?
- Data validity: Are the input parameters reasonable?

ISO (2016) provides provide specifications on how to virtualize and validate vehicle models for Electronic Stability Control (ESC) applications. More recently (***ISO 2022***) points out fidelity levels associated with the modelling approaches.

Three classes of modelling approaches, based on the fidelity level provided:

- **low-fidelity:** point-mass or kinematic models. Mainly used for controller synthesis and for simulations where detailed vehicle modelling is not required such as microscopic traffic studies.
- **medium-fidelity:** chassis models such as single-track, double-track, and lumped mass with linear or non- linear tires. Their range of application spans from the synthesis of model predictive controllers (***Falcone et al. 2007*** - Universita' degli Studi del Sannio and Ford Laboratory; ***Da Lio et al. 2020*** – University of Trento) to intermediate fidelity simulations involving the testing and prototyping of ADAS/ADS functionalities.
- **high-fidelity:** multibody models (***Blundell and Harty 2004***; ***Dempsey et al. 2015*** - Claytex Services Limited) including suspensions geometry, chassis compliance, engine mounting stiffness and damping characteristics, driveline dynamics, and tires contact points to provide the ultimate degree of faithfulness.

Some applications of different fidelity levels in the literature.

Fidelity	***Example***
Low fidelity:	(Fiori et al., 2016), (Kapania et al., 2016), (Theodosis and Gerdes, 2013), (Prokop, 2001), (Xie et al., 2021), (Falcone et al., 2008), (Ziegler et al., 2014), (Subosits and Gerdes, 2019)

Medium fidelity:	(Brach and Brach, 2000), (Wang et al., 2018), (Velenis and Tsiotras, 2005), (Rucco et al., 2012), (Olofsson et al., 2013), (Timings and Cole, 2013), (Tavernini et al., 2013),
High fidelity:	(Kelly and Sharp, 2010), (Perantoni and Limebeer, 2014), (Dal Bianco et al., 2019), (Xu et al., 2018)

Kutluay and Winner (2014) (🇩🇪 Technische Universität Darmstadt and 🇹🇷 Hacettepe University) provide a comprehensive review of modelling and validation methods for vehicle dynamics.

With regards to the design of simulation models to support the development of vehicular technology, they typically target a specific use case such as handling or riding studies, and each application is commonly backed by an ad-hoc devised validation procedure. Most of the works do not specify nor suggest correlation thresholds for validation. Mainly subjective criteria based on a qualitative evaluation a selection of charts is reported. Statistical analysis and confidence intervals definition for the validity of the simulation models are only rarely found.

Henning and Sawodny (2016) (🇩🇪 Institute for System Dynamics, Stuttgart) validated the virtual models with real-world trajectories to investigate the effect of order reduction on the fidelity delivered by the model. Simple model proves to be faithful at reproducing the steady-state response and manoeuvres which do not involve frequency components higher than 1 Hz.

Viehofand and Winner (2018) (🇩🇪 Technische Universität Darmstadt) proposed a framework to introduce the model's uncertainty analysis into the validation activity. Here the authors decouple the validity of the model structure from the actual parametrization to isolate the model's inherent uncertainty and increase the credibility of the developed simulation framework. An actual application is missing. Artificial actuators have also different frequencies that human drivers.

Subosits and Gerdes (2021) (🇺🇸 Stanford University) showed that simple models can predict surprisingly accurately the traveling velocity and path recorded on the dry road, whereas detailed modelling approaches were deemed necessary to predict transients at the beginning and the exit of curves, especially for the low-friction scenarios.

Danquah et al. (2020) (🇩🇪 Technical University of Munich) identified four key aspects originating the uncertainty in vehicle dynamics simulation. Yet no literature work can be found that fulfilled all the uncertainty sources.

- The reconstruction of the input signals used for executing the virtual test the virtual tests.
- The input model's parameters aleatoric and epistemic uncertainty.
- The parametrization of the model.
- The models' output.

(Donà and Ciuffo, 2022) (🇮🇹 Uni Systems) presented the following methods to determine the degree of discrepancy between the simulated model and the physical realization, thus containing it below a prescribed threshold level:

- **Graphical comparisons**: provide an intuitive and straightforward way to compare the results. Typical ways of visually representing data include 2/3D plots, histograms, and scatter charts.
- **Scalar quantities**: can derive from extracting a reference value from a time-history, for instance, by applying min or max operators.
- **Time-histories**: can give extensive information about the virtual model's fidelity but require extra care when carrying out the assessment with respect to the scalar quantities.
- **Statistical validation**: The fundamental problem around conventional validation is that important uncertainties are neglected, e.g., input parameters. New research in the field of statistical validation is being carried out to addresses this problem, by including those uncertainties in the validation process (Danquah et al., 2022).

5.5 Simulation Scheme

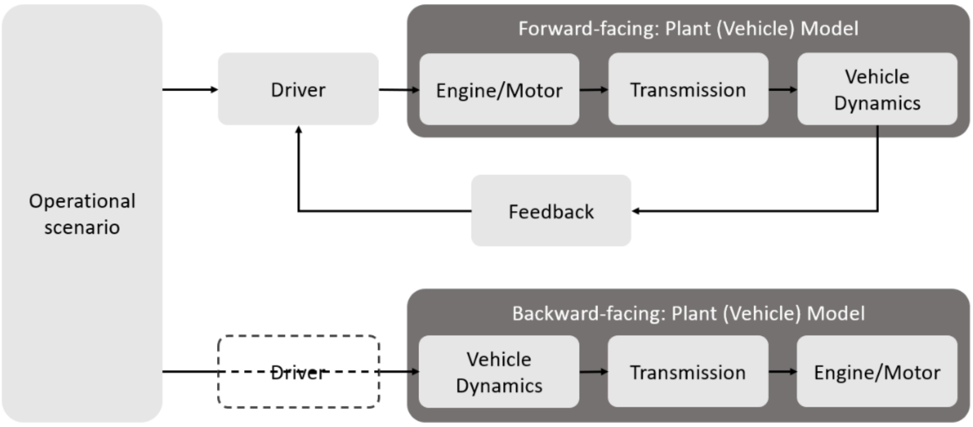

Figure 8: Simulation scheme: Forward vs Backward

There are two common methods for predicting energy usage in vehicles through mathematical simulation (Pettersson et al., 2020; Wipke et al., 1999):

- Backward scheme
- Forward scheme

In the **backward scheme**, a target speed is provided by the driving cycle or optimizer. The necessary propulsion force is computed from Newton's second law, and together with the vehicle speed, is propagated from the wheels, through the transmission, to the prime mover, where the necessary input power for the propulsion effort is computed. The approach is called backward because the data flows backwards. It is assumed that the target speed will be perfectly followed, thus vehicle speed is not a dynamic state. In the **forward scheme**, the driver controls the longitudinal vehicle interfaces, the accelerator, and the brake pedals, to achieve a certain vehicle speed. The driver model controls the vehicle to follow the input driving cycle and the vehicle speed is intrinsically a dynamic state.

On solving ordinary differential equations (ODEs) or differential-algebraic equations (DAEs), a thorough overview on **numerical methods** for static and dynamic problems, including software issues and a discussion which method fits best for which class of problems is can be found in (Arnold et al., 2011). Challenges beyond the mainstream of numerical mathematics: 1) modelling and simulation of contact problems in multibody dynamics, 2) real-time capable numerical simulation techniques in vehicle system dynamics and 3) modelling and time integration of multidisciplinary problems in system dynamics including co-simulation techniques (Arnold et al., 2011).

6 VIRTUAL WORLD MODELS

Validation approaches for these models are on their infancy, at maximum a few years old.

6.1 Road layout

The virtualization of the roads' layouts is well supported by the Association for Standardization of Autonomous and Measuring Systems ASAM (www.asam.net) modelling standards:

- OpenCRG: which standardizes local properties of the lane in terms, for instance, of asphalt granularity and potholes location;
- OpenDRIVE: which regulates the definition of the road geometry in terms of number of lanes, curvature radius, lane marking and slope/camber;
- OpenSCENARIO: institutes a standard way to model the behaviours of road users and traffic agents.

Although no explicit validation activities have been pursued for the listed modelling approaches, they are widely recognized as faithfully replicating road geometry for the sake of ADAS/ADS virtual testing in the actual simulation practice.

6.2 Traffic agents

The validation of traffic models is an open point in the literature given the intrinsic stochasticity of human behaviour, which makes it **fundamentally impossible** to obtain ground-truth information. Additionally, high-fidelity traffic models might even not be necessary in the case of scenario-based approaches where targets' trajectories are assigned beforehand.

6.3 Static objects

Currently, **no modelling standard exists** which aims at standardizing the modelling approaches for this class of components.

6.4 Collision models

ISO (2021) proposes three main approaches for collision models:

- **low-fidelity:** using relative velocity and heading angle to directly estimate damage of the collision;
- **medium-fidelity:** use the involved agent's kinematic to determine acceleration and classify the damage consequently;
- **high-fidelity:** use FEM to precisely compute forces exerted during the collision.

6.5 Weather

Replicating adverse weather conditions that darken cameras' output; absorb and scatter RADARs' pulses and back-scatter and reduce surface reflectivity in the case of LiDARs is today an extremely challenging task due to the need of providing sensor-grade realism.

Wang et al. (2004) present structural similarity (Figure 9) as a metrics to evaluate the quality of generated images.

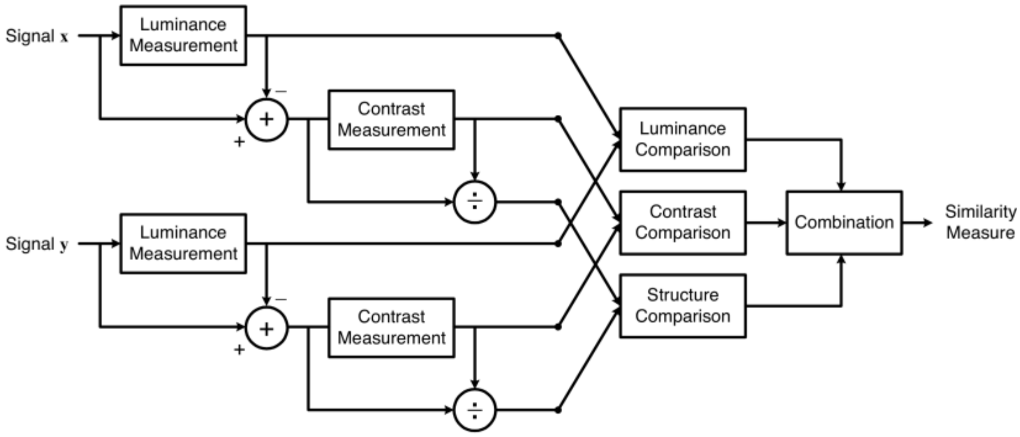

Figure 10: Diagram of the Structural Similarity (SSIM) measurement System (Wang et al. 2004)

Hasirlioglu and Riener (2018) (🇩🇪 Technische Hochschule Ingolstadt) uses **ray tracing** to model rain-induced noise for virtual cameras and an equivalent RCS for RADAR sensors.

7 RESEARCH CENTERS, GROUPS AND UNIVERSITIES

7.1 Working Groups

VMAD SG2 working group on Virtual Testing and Simulation

- Part of the United Nations Economic Commission for Europe (UNECE)

Lead Reseachers

- Barnaby Simkin (Artificial Intelligence, Automated Driving and Virtual Testing at NVIDIA)
- Tobias Duser (Head of Adas and Ad Virtual Testing Solutions)
- Gil Amid (Co-founder of Foretellix)
- Siddartha Khastgir (Head of Verification & Validation, Intelligent Vehicles)
- Espedito Rusciano (Dutch Vägverket)

7.2 Research Centres and universities

Technical University of Munich, Institute of Automotive, Germany

Technische Hochschule Ingolstadt - Center of Automotive Research on Integrated Safety Systems and Measurement Area (CARISSMA), Germany

Technische Universität Darmstadt Institute of Automotive Engineering, Germany

Institute for System Dynamics, Stuttgart, Germany

Kempten University of Applied Sciences, Germany

University of Stuttgart, High Performance Computing Center, Germany

FZI Research Center for Information Technology, Karlsruhe, Germany

Robert Bosch GmbH, Germany

Graz University of Technology, Austria

Budapest University of Technology and Economics

University of Warwick, UK

Claytex Services Limited, UK

Stanford University, CA

NVIDIA Drive Sim, CA

Research and Innovation Center, Ford laboratory, MI

Uni Systems, Italy

University of Trento, Italy

Universita' degli Studi del Sannio, Italy

AGH University of Science and Technology, Poland

Hacettepe University, Department of Mechanical Engineering, Turkey

Federal University of Parana, Brazil

Universite Gustave Eiffel, IFSTTAR, France

Automated Driving Research Team, Institut VEDECOM, France

Siemens Industry Software NV Leuven, Belgium

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