FEV

#81
SPECTRUM

Agentic AI advantage with FEV **P. 08**

FEV's TARA Copilot – Saving time, increasing quality **P. 14**

Bridging the gap with REEVs and long-range PHEVs **P. 36**

Next-gen generators for efficient hybrid architecture **P. 44**

Dear readers,

Artificial intelligence (AI) has evolved from a promising vision into a powerful enabler of modern engineering. What was once experimental is now shaping tangible solutions – accelerating processes, enhancing safety, and opening entirely new possibilities.

At FEV, we bring together decades of engineering expertise and cutting-edge AI technologies to deliver measurable value for our customers. Our approach is pragmatic: AI systems act as digital collaborators that learn, adapt, and support decision-making. With tools like FEV's TARA Copilot, we are already streamlining safety-related processes, while AI-driven simulations shorten development cycles and unlock innovative design pathways. Data-driven diagnostics further ensure reliability and efficiency across entire vehicle fleets.

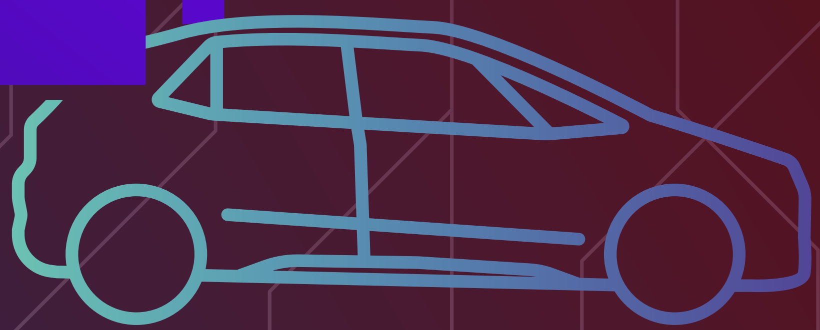
But innovation is not only digital. The path to climate-neutral mobility requires diverse and practical solutions. Range-extended electric vehicles (REEVs) and long-range plug-in hybrids (PHEVs) are proving to be strong transitional technologies. In this issue, we share insights on how to develop scalable battery platforms, define the right performance indicators, and design optimized generators and inverters for series-hybrid architectures. These advances turn today's challenges into tomorrow's competitive advantages.

I invite you to explore the following pages for inspiration and opportunities to collaborate. Together, we can drive smarter engineering and shape a cleaner, more resilient mobility ecosystem that excites and empowers people around the world.

Enjoy the read!

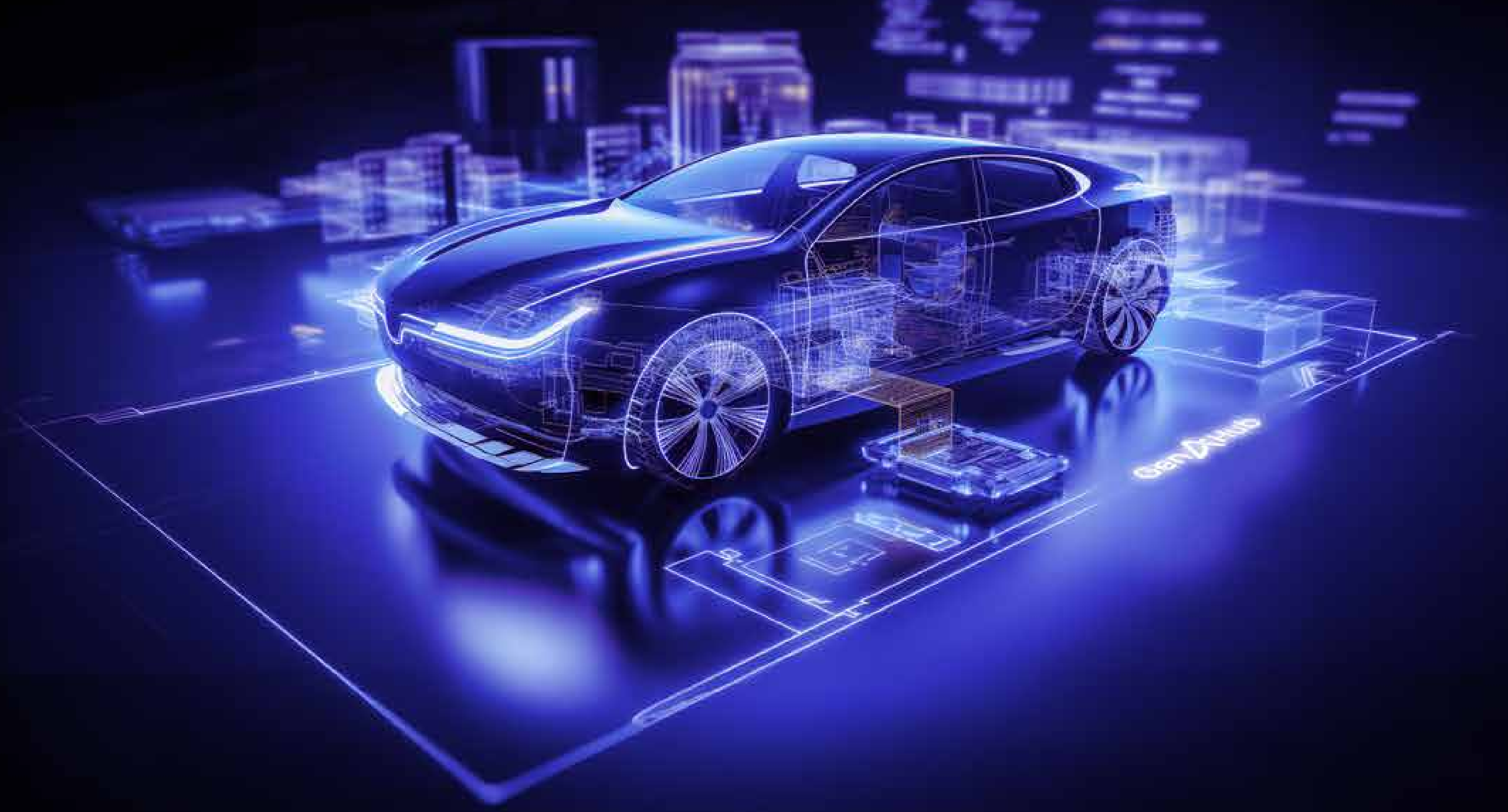
Dr. Patrick Hupperich
President and CEO
FEV Group

CONTENT



#1 Turning ***AI in mobility*** into success — How FEV makes the difference

»AI transformation is an immediate operational imperative.«



The automotive industry is undergoing not just incremental change, but structural disruption. New players are entering the market with entirely different principles — achieving development cycles up to 50% faster and product cost advantages of as much as 45%. In this environment, traditional product development timelines and cost structures are becoming unsustainable. The pressure to innovate faster and more efficiently is immense.

To meet this challenge, leadership teams are turning to Artificial Intelligence (AI). However, AI is not a cure-all. It is a powerful set of tools that, when applied with strategic precision, can drive profound efficiencies. For the automotive sector, this translates into tangible advantages: streamlining system design and requirements engineering, co-piloting functional safety and cybersecurity assessments, accelerating complex simulation and testing cycles, optimizing powertrain calibration, reducing manual validation efforts, and embedding intelligent functions directly into vehicles. The objective is not to simply adopt AI, but to incorporate it for a lasting competitive advantage.

Many in the industry have already launched AI initiatives. Yet too often, companies fall into what we call 'Pilotitis' — a proliferation of promising pilot projects that never scale. The reason is usually the same: a missing link between technology and measurable business value. That is why we strongly believe that a clear AI strategy, with defined business cases and top-management support, is a non-negotiable prerequisite for success. Progress is also frequently stalled by fragmented data landscapes and legacy IT architecture. Therefore, our approach prioritizes the creation of a robust data foundation, transforming disparate data silos into a strategic asset for AI development. Finally, the "make-or-buy" dilemma further complicates decisions as AI functions are rapidly integrated into off-the-shelf software. As a technology-agnostic partner, FEV provides a neutral, outside-in perspective to help clients navigate these choices with long-term architectural integrity in mind.

Success with AI in the automotive sector requires navigating this complexity. It demands a partner who speaks both languages fluently: AI and automotive. AI consultants may understand the algorithms but not the intricacies of powertrain calibration. Seasoned automotive engineers may understand the vehicle but not the nuances of machine learning model governance. At FEV, these disciplines converge. Our credibility is built on 45+ years of deep domain expertise across the vehicle development process. Our approach is therefore holistic and pragmatic, engaging at every level — from shadowing engineers in their daily workflows to identify high-impact opportunities, to co-creating enterprise-wide AI roadmaps and governance frameworks. With a strategic foundation in place, the next step is execution. FEV supports customers in bridging the gap between software solution providers and engineering teams to integrate AI solutions into their workflow. Furthermore, we have developed a software-as-a-service platform, the GenAI Hub, to provide our engineers with the necessary AI tools to offer our customers even more efficient and higher-quality engineering services. Through daily use, our AI tools have achieved a high level of robustness and development maturity, enabling FEV to offer them to our customers as ready-made solutions so that they can directly implement the advantages of AI in their processes. The GenAI Hub is built with automotive-grade security protocols, ensuring that all development and intellectual property handling meet the stringent requirements of the industry.

To move from this strategy to concrete practice, the upcoming articles in this series will take you inside this ecosystem. We will present several of our implemented AI use cases in detail. The AI transformation is not a distant vision – it is an immediate operational imperative.

Contact FEV to explore your AI roadmap.

BY
Johannes Jeub
jeub_j@fev.com
Kevin Heinen
heinen_k@fev.io
Dr. Dominik Lückmann
lueckmann@fev.com

#2
Turning ***agentic AI*** into a unique engineering advantage with FEV

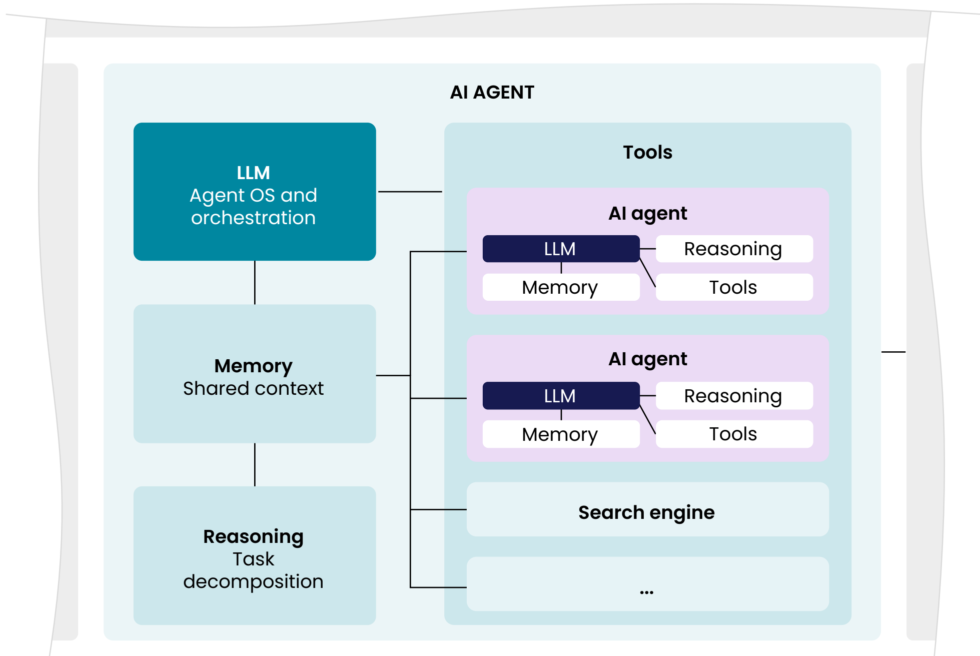
Engineering and automotive companies are facing more complex challenges and stricter rules than ever before. Standard AI tools often lack the flexibility and sophistication required to achieve the efficiency increase needed to meet these demands in real projects. FEV takes a new approach by bringing agentic AI — smart systems made up of teams of specialized digital agents — into practical use for engineers. This article shows how the company is adapting to the latest AI trends and developments, and how it applies these advances to its own tools. The approach is presented in the context of two examples: first, how agentic AI assists engineers in the field of function development, and second, how agents facilitate the comparison of regulations across diverse markets. Through these use cases, it is shown how agentic AI can simplify complex engineering work, improve reliability, and help teams ensure compliance. The goal is to demonstrate the benefits of FEV's agentic AI for modern engineering challenges.

Agentic AI at FEV

Recent breakthroughs in generative AI (GenAI) have resulted from increasingly large and powerful language models but also — more importantly — advances in model interactions and agent orchestration. Modern systems go beyond the simple, one-off responses of single language models, by using multi-agent systems (MAS) that break down complex queries, deploy domain-specific tools, and aggregate results into robust answers. This synergy enables next-generation capabilities and greater reliability compared to prior single-model approaches.
The real leap emerges when one moves from isolated AI agents to agentic AI architectures that enable collaboration, memory, and orchestration. While traditional AI agents follow a Sense–Plan–Act loop — perceiving their environment, analyzing it, and taking action — agentic AI extends this model into a multi-agent, context-aware ecosystem.

This evolution is not just incremental; it represents a dynamic shift in how AI systems operate:

- From single-task execution to coordinated, multi-agent collaboration
- From stateless reasoning to persistent, shared memory
- From isolated decision-making to orchestrated, system-level planning



1
An agentic AI framework where AI agents collaborate, share information via persistent memory, and provide services to one another.

FEV adapts these agentic AI principles directly to the engineering and automotive sectors. In practice, complex engineering queries are decomposed into a series of focused subtasks, each managed by specialized, dedicated agents. To tackle these subtasks, agents may utilize a variety of tools – such as document analysis engines, regulatory databases, and requirements checkers. Their outputs are integrated into a comprehensive and dependable answer.

One concrete example is FEV's "Completeness Check" service — a service to validate an arbitrary set of requirements for completeness. In this setup, the Reference Set Assembly Agent first creates a benchmark requirements set based on industry best practices. The Comparison Agent then evaluates the user's set against this benchmark. The Regulatory Completeness Agent verifies compliance with relevant standards. Finally, the Quality & Clarity Check Agent identifies unclear or missing items and proposes actionable improvements.

This modular multi-agent system is encapsulated as the Completeness Check Agent, which operates as a tool within the Requirements Review Agent. The Requirements Review Agent, in turn, is a component of the overarching MBSE Agent, ensuring that completeness checks are integrated into a broader model based systems engineering workflow.

Building agentic systems comes with unique complexities. Reliable communication between agents, consistent state sharing, and standardized interfaces are essential to keep processes smooth. There is also the risk that errors may accumulate or amplify as tasks move between agents. At the same time, permissions, compliance, and auditability must be carefully managed, particularly in distributed setups. FEV addresses these challenges through continuous monitoring, strong governance, and dedicated platform support to enable robust, dependable solutions. FEV's proprietary GenAI Hub is used monthly by hundreds of employees, feeding real-world data into continuous improvement. Feedback mechanisms and analytics track value, guiding rapid updates that enhance quality and usability. The result is a continuously evolving toolset that delivers measurable gains in engineering productivity and quality.

Agentic AI for automotive function development

In the context of automotive function development, FEV applies MAS to accelerate the transformation of software requirements into fully tested Simulink functions. The system is built around the following key roles:

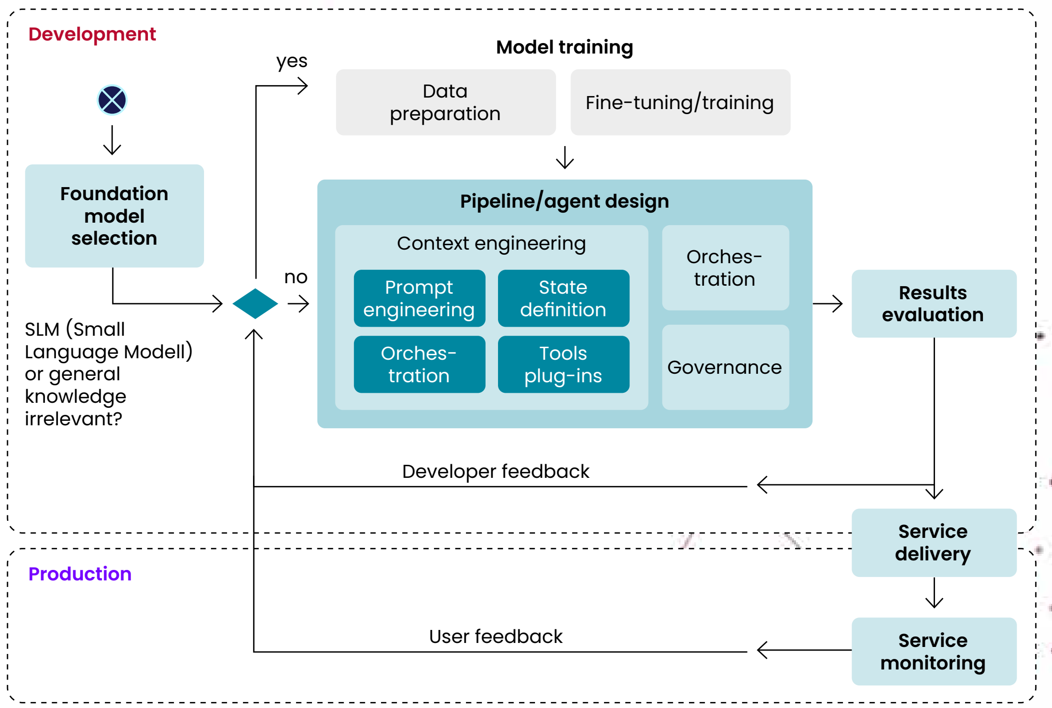
- Function Developer Agent: Translates formalized software requirements into initial Simulink models. It applies domain-specific rules, guidelines, and configurations to ensure consistency and correctness in the generated functions.
- Testing Agent: Derives requirement-based test specifications. These are passed to the Test Execution Agent, which runs the tests in MATLAB/Simulink, collects results, and identifies failures or unexpected behavior.
- Execution and correction loop: When tests fail or builds are unsuccessful, the system iteratively diagnoses issues, corrects the model or test logic, and re-runs the process until a valid, passing solution is reached.

To ensure reliability and reduce errors due to possible hallucinations or incorrect assumptions of LLMs, a human-in-the-loop mechanism is integrated at each stage. Developers can review, adjust, and approve outputs, maintaining engineering ownership and traceability.

This structured, agent-based workflow acts as a co-pilot for engineers, enhancing productivity while preserving decision-making authority. By combining generative AI with iterative refinement and human oversight, one can accelerate automotive function development while preserving safety, quality, and accountability.

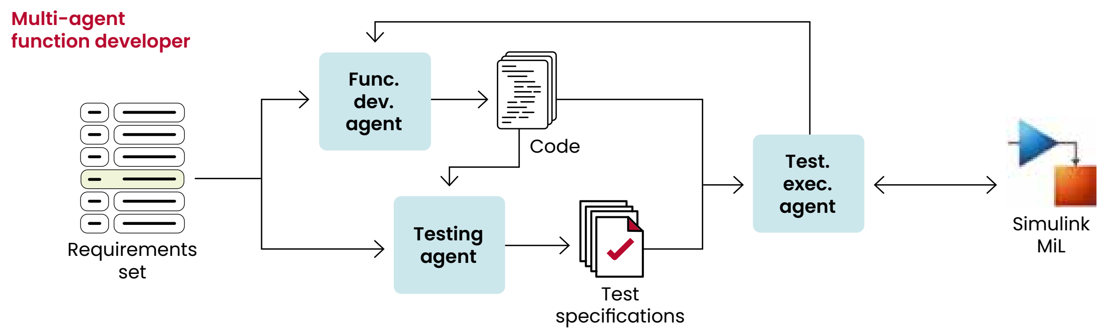
Regulatory gap analysis service

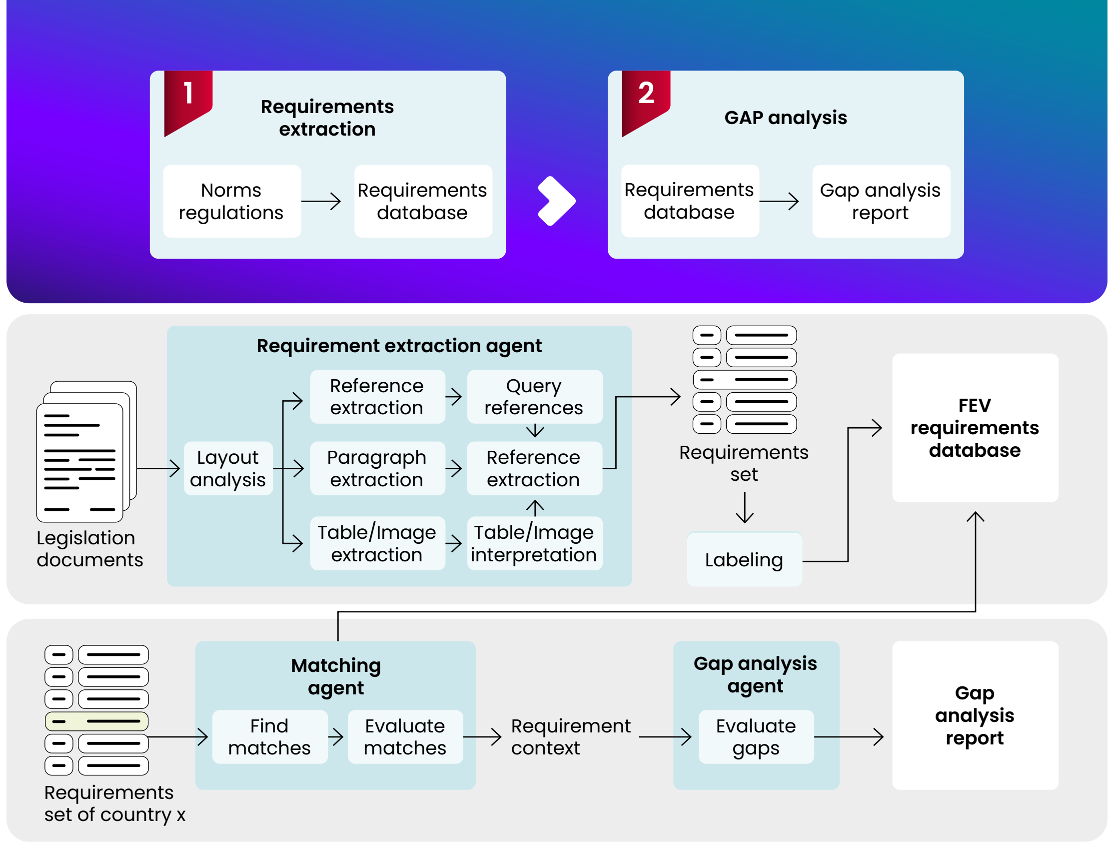
Another key application of FEV's agentic framework is the automated extraction of requirements from all types of regulatory documents. The target is to build a comprehensive regulatory requirements database spanning all relevant automotive systems and markets. This structured repository serves as a foundation for a wide range of downstream workflows, enabling system development agents to systematically verify compliance with legal requirements. Dedicated agents can then perform gap analyses, identifying omissions and overlaps across different requirement sets.



2
FEV's DevOps loop drives continuous service improvement by collecting, monitoring, and automatically incorporating user feedback.

3
FEV's multi-agent framework acting as function developer agent.





4
FEV's regulatory gap analysis service consisting of multiple individual agents extracting requirements from regulatory documents and identifying gaps in individual requirement sets.

The process begins by analyzing and interpreting the layout of regulatory documents, extracting both textual and non-textual requirements, covering images, tables, and cross-references. Agents not only parse these various elements, but also assess how visual information informs or modifies individual requirements. Extracted requirements are then enriched with critical metadata, such as applicable markets, system context, and regulatory scope, before being securely stored in a centralized, searchable company-wide database.

For gap analysis, specialized agents systematically compare regulatory requirements from different markets. By leveraging semantic search and advanced matching algorithms, each requirement is paired with its closest equivalents in the compared set. The system then evaluates these pairings to identify gaps, overlaps, and discrepancies, providing targeted insights for compliance engineers and decision makers.

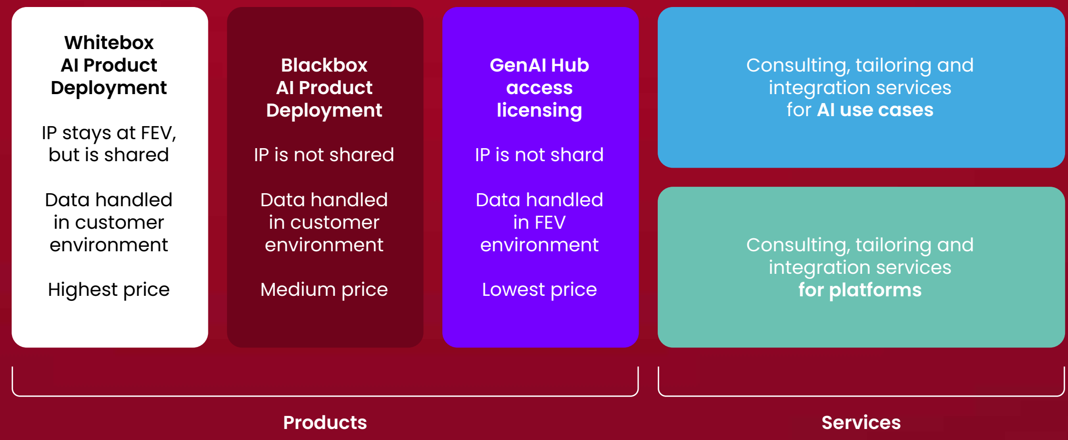
From AI vision to reality: Choosing the right path

In summary, the generative AI revolution is entering a new phase: one defined not just by bigger models but also by smart architecture. In engineering and automotive development, this shift is more than technical – it's transformational.

Traditional AI systems from some years ago, built around single-model responses, have reached their limits. The real leap forward comes from agentic AI: multi-agent systems that collaborate, remember, and reason in context. The impact is tangible: delivering lower costs, faster decisions, improved traceability, and greater confidence in outcomes. Now, the question is no longer whether to adopt agentic AI, but how.

Bringing advanced AI capabilities to customers is not just a matter of delivering code or deploying a model. At FEV, it is about aligning the right technology, deployment model, and integration approach with the specific needs, constraints, and ambitions of each client. The presented portfolio is designed to give engineering organizations maximum flexibility while ensuring performance, security, and compliance remain uncompromised.

To address the diverse customer requirements, FEV offers three distinct product paths. White-box AI product deployments give customers full transparency, with intellectual property shared and data processed entirely in their own environment. This option offers the highest level of control and is ideally suited for highly regulated or security-critical domains. Black-box deployments, where the intellectual property is retained by FEV but delivered as a turnkey solution within



5
FEV's products and services landscape in the field of AI/Generative AI.

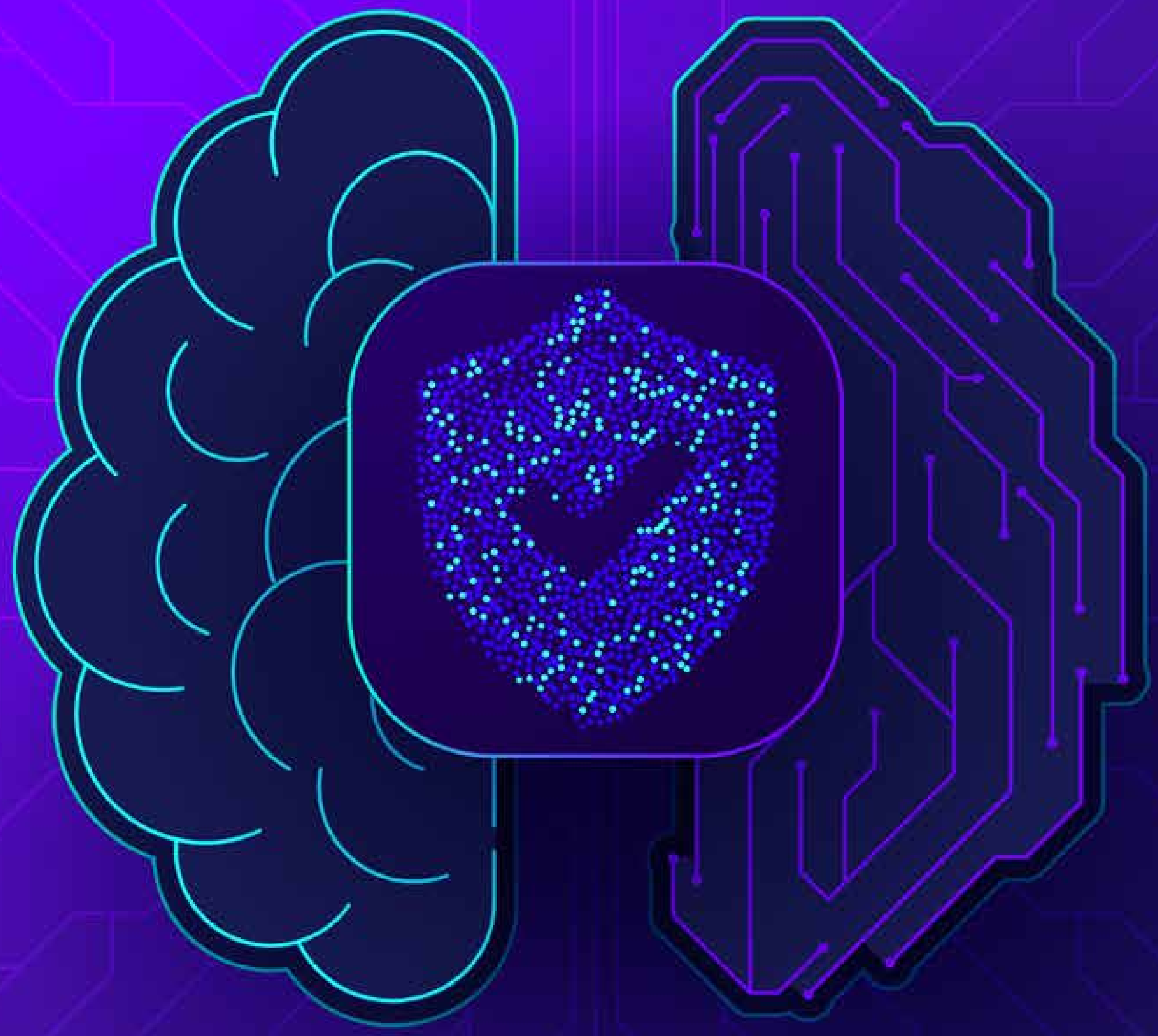
tomer's infrastructure while balancing speed with customization. Finally, for organizations seeking rapid adoption at the most competitive cost, FEV GenAI Hub access licensing provides cloud-hosted AI capabilities operated in FEV's secure environment.

Technology alone does not guarantee impact, which is why FEV's services focus on consulting, tailoring, and integration. For AI use cases, the company works directly with engineering teams to adapt solutions to their unique workflows, tools, and data structures. For platform-level integration, the engineering experts ensure that AI modules seamlessly interoperate with existing digital ecosystems, preserving both technical stability and organizational efficiency.

This combination of flexible product delivery and targeted services allows FEV to translate AI innovation into operational value for its customers. Whether they choose deep, in-house deployments or cloud-based access to the platform, they benefit from the same engineering rigor, domain expertise, and long-term commitment to success. In essence, FEV delivers AI as the company engineers systems: fit for purpose, built to last, and designed to perform in the real world.

BY
Lukas Schäfers
schaefers_luk@fev.com
Dr. Hendrik Ruppert
ruppert_h@fev.io
Kevin Heinen
heinen_k@fev.io
Abdelrahman Abdalla
ext_abdalla@fev.com
Dr. Rene Savelsberg
savelsberg@fev.com
Dr. Joschka Schaub
schaub@fev.com

#3 *FEV's TARA Copilot* - Saving customers time while increasing quality and consistency of results



The Threat Analysis and Risk Assessment (TARA) is a mandatory work product of the cybersecurity lifecycle defined by the standard ISO/SAE 21434 for road vehicles. TARA consists of seven activities, namely

1. Asset identification (including damage scenario identification)
2. Impact rating
3. Threat scenario identification
4. Attack path analysis
5. Attack feasibility rating
6. Risk determination
7. Risk treatment decision

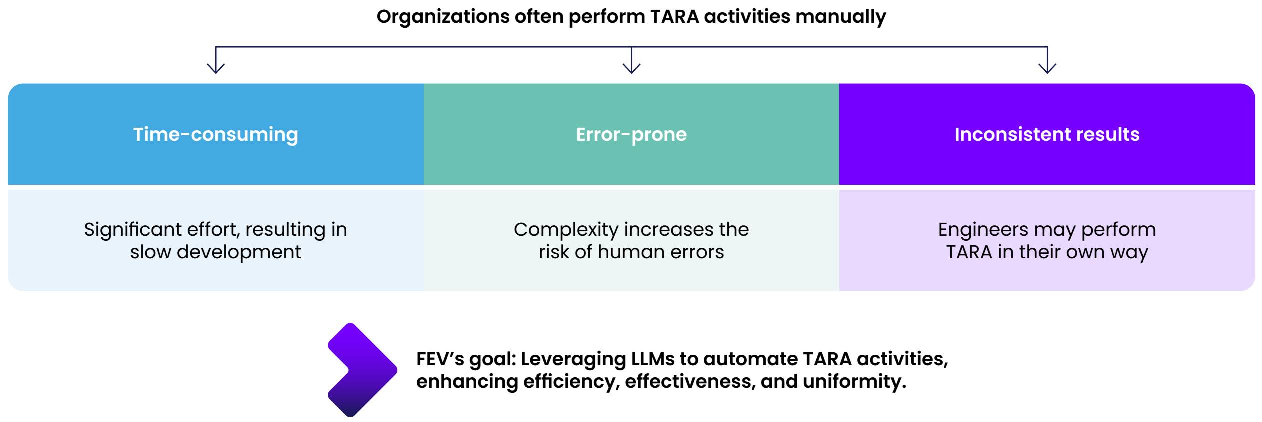
Typically, TARA activities are performed manually by cybersecurity engineers – a time-consuming task that may result in incomplete or incorrect results. Furthermore, the task of performing TARA depends on the individual viewpoint of the respective cybersecurity engineer, which is to a certain degree subjective. Therefore, TARAs which are performed by different engineers may vary significantly (Figure 1), potentially resulting in inconsistent results. Partial automation of the TARA process can solve these shortcomings, but it is important to define the right degree of automation to deliver TARA results of the highest quality. An AI-based full automation of a highly critical and compliance-related process like TARA requires careful oversight and validation by human experts. Therefore, FEV's concept of the "TARA Copilot" is defined as a support tool for the cybersecurity engineer. This person remains fully responsible for providing the inputs for the automation routine and reviewing the results of every step performed by the tool.

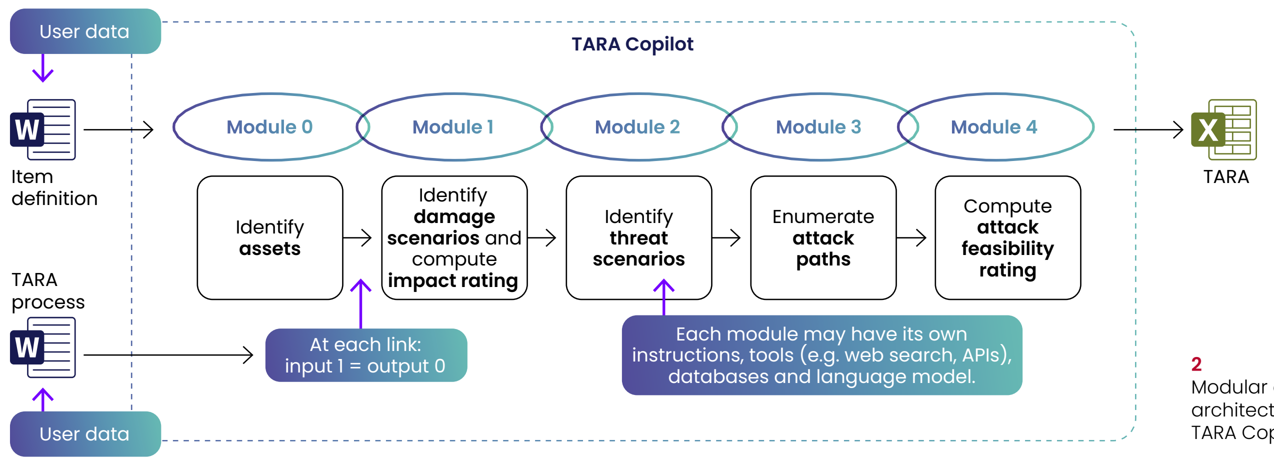
Modular chain architecture

An overview of the architecture of FEV TARA Copilot is shown in Figure 2. The system is designed using a modular chain architecture to automate TARA activities with the help of Large Language Models (LLMs). TARA Copilot automates the following activities: asset identification, damage scenario identification, threat scenario identification, attack path analysis, and attack feasibility rating.

Each activity is encapsulated as an independent module within the chain, forming the backbone of the modular system architecture. Every module leverages large language models to generate specific TARA outputs based on defined inputs, such as tailored instructions (for example, prompts) and, when required, external databases. The output of each module seamlessly feeds into the subsequent one. Case in point, the results from the asset identification are directly utilized in the damage scenario identification module.

1
Industry state of practice and challenges for TARA.





2
Modular chain architecture of TARA Copilot.

As an alternative to the execution of all modules, the implementation of TARA Copilot allows the user to start the tool from an intermediate step if results from previous steps are already available. If assets have been identified already and are available as an additional input, TARA Copilot for instance can start directly with the identification of damage scenarios.

To demonstrate the workflow of TARA Copilot, we have selected a Body Control Module responsible for the door locking/unlocking function, which is critical for cybersecurity.

The first module is called Module 0 and aims to identify cybersecurity-relevant assets. It starts with two inputs: the definition of the item under consideration (the BCM in our example) and instructions derived from FEV´s TARA process specification. These instructions are formulated in natural language. For example: "Derive a comprehensive list of assets based on the item functions, technical information, and the asset types provided." Both the instructions and item definition are then passed to TARA Copilot Flowise interface. This setup prompts the LLM to analyze the context (i.e., the inputs provided) and identify cybersecurity-relevant assets. Two of these assets are shown in Figure 4.

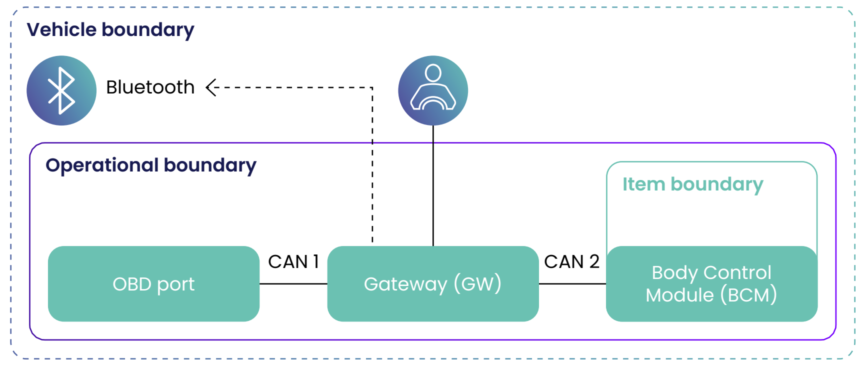
In Module 1, TARA Copilot shifts to describing damage scenarios and assigning impact ratings (safety, operational, financial, privacy). Inputs include the item definition, assets from Module 0, and instructions such as: "For damage scenarios related to item functions (e.g., communication interfaces), include the driving scenario as part of the damage scenario."

TARA Copilot computes the impact rating for each damage scenario, including a rationale explaining the choice of the impact rating. Similar to Module 0, the inputs are passed to TARA Copilot Flowise interface. Figure 5 illustrates one example of a damage scenario described by TARA Copilot. The impact ratings are omitted. Module 2 identifies threat scenarios.

Besides the item definition and the results of the previous modules, the so-called Threat Database is used as an additional input at this point. This Threat Database is designed to generate a more comprehensive set of threat scenarios than what a human could typically produce. To this end, FEV leveraged LLMs to create a database aligned with all threats defined in UNECE R155. Further sources for known threats can be used for additional inputs, such as customer databases (Figure 6).

FEV´s TARA process specification provides detailed definitions and descriptions of asset types (e.g., messages, software update), threat types (e.g., tampering, denial of services), and attack surfaces (e.g., wireless access interface by an external actor). Our experts systematically generated all possible combinations of asset types, threat types, and attack surfaces. LLMs were then used to validate which combinations correspond to legitimate threats from UNECE R155. For each valid combination, the LLM produced a detailed threat scenario description.

»FEV's TARA Copilot leads to time savings of approximately 50% and improvement of the quality and consistency of TARA results.«



3
Body Control Module (BCM) selected as item.

An example of a valid combination and its threat scenario description would be:

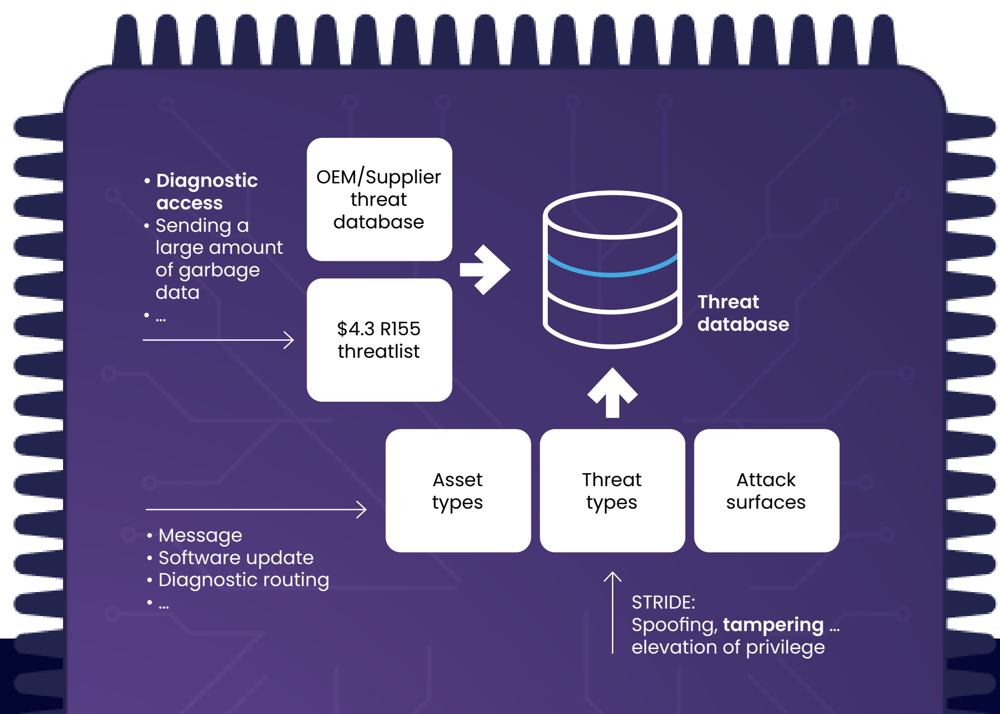
- **R155 threat:** Malicious diagnostic messages
- **Asset type:** Diagnostic routing
- **Threat type:** Tampering
- **Attack surface:** Physical access to the OBD port by an external actor
- **Threat scenario description:** An attacker uses the OBD port to inject malicious diagnostic messages, potentially leading to unauthorized access and manipulation of vehicle data.

Asset ID	Asset description	Asset type	Asset property	Involved ECU(s)	Rationale
BCM-ASSET-010	Door_Unlock_ Request – CAN 2: Door Unlock	Messages	Integrity	BCM, Gateway	Manipulation of unlock requests can lead to unauthorized access. Integrity ensures the message is genuine and unaltered.
BCM-ASSET-011	Door_Unlock_ Request – CAN 2: Door unlock	Messages	Available	BCM, Gateway	Unlock requests must be available to ensure vehicle access. Availability ensures the message can be processed when needed.

4
Exemplary assets identified by TARA Copilot for a BCM.

Asset ID	Asset description	Asset property	Damage scenario ID	Damage scenario description
BCM-ASSET-010	Door_Unlock_ Request – CAN 2: Door Unlock	Integrity	BCM-ASSET-010-DS-001	Driving scenario: The vehicle is parked in a public area. Damage scenario: An attacker manipulates the Door_ Unlock_Request message causing the doors to unlock unexpectedly.

5
An exemplary damage scenario identified by TARA Copilot for a BCM.



6
Threat Database.

Similar to other modules, the inputs are configured in TARA Copilot Flowise interface. Figure 7 illustrates one example of a threat scenario identified by TARA Copilot. Note that the ID of the threat scenario is omitted.

Module 3 enumerates attack paths taking into account instructions related to the following questions:

- How does the attacker reach the attack surface?
- How does the attacker proceed to reach the asset from the attack surface?
- How does the attacker proceed to violate the cybersecurity property of the asset?

Figure 8 illustrates one example of an attack path described by TARA Copilot.

In Module 4, attack feasibility ratings are computed based on instructions aligned with the attack potential-based approach recommended by ISO/SAE 21434. Figure 9 illustrates the attack feasibility rating computed for the attack path in Figure 8. The final attack feasibility rating (e.g., Low, High) is calculated automatically afterwards based on defined core factors (e.g., elapsed time, expertise). A feasibility rating concludes the automated steps, as both risk determination and risk treatment decision activities are outside the scope of TARA Copilot. The risk values are computed deterministically by using a risk matrix, which may be automated using formulas. The risk treatment decision is project-specific, as such decisions are often made based on a company-specific risk treatment decision policy.

After completing all calculations, TARA Copilot exports the results into FEV's TARA report, enabling the designated TARA owner to perform a systematic review. Review findings are transferred to updated inputs, and consecutive runs of TARA Copilot are conducted afterwards until the results are accepted by the TARA owner.

Asset ID	Asset description	Damage scenario description	Threat scenario description	Threat type	Attack surface	R155 reference
BCM-ASSET-010	Door_Unlock_ Request - CAN 2: Door Unlock	Driving scenario: The vehicle is parked in a public area. Damage scenario: An attacker manipulates the Door_Unlock_Request message causing the doors to unlock unexpectedly.	An attacker tampers with the Door_Unlock_Request message on the CAN bus while the vehicle is parked, leading to unauthorized access to the vehicle.	Tampering	Physical access to a CAN interface by an external actor	4.3.2/5.2

7
An exemplary threat scenario identified by TARA Copilot for a BCM.

Threat scenario ID	Threat scenario description	Attack path ID	Attack path description
BCM-ASSET-010-DS-001-TS-001	An attacker tampers with the Door_Unlock_Request message on the CAN bus while the vehicle is parked, leading to unauthorized access to the vehicle.	BCM-ASSET-010-DS-001-TS-001-PATH-001	1. Park the vehicle to obtain extended physical access to the CAN bus interface. 2. Connect to the CAN bus using standard CAN injector. 3. Use internal (restricted) documentation to analyze the proprietary Door_UnLock_Request message format. 4. Craft a modified message that instructs the BCM to unlock the door. 5. Inject the crafted message into the CAN bus to simulate the tampering scenario.

8
An exemplary attack path identified by TARA Copilot for a BCM.

Attack path ID	Elapsed time	Expertise	Knowledge of system	Window of opportunity	Equipment	Rationale
BCM-ASSET-010-DS-001-TS-001-PATH-001	<=1 week	Proficient	Restricted information	Easy	Standard	When the vehicle is parked, the attacker benefits from unlimited time to analyze and understand the proprietary message using internal documentation. The lower time pressure allows the use of standard equipment and proficiency-level expertise, with an easier window of opportunity compared to an attack during vehicle motion.

9
An exemplary attack feasibility rating computed by TARA Copilot for a BCM.

Conclusion

FEV's TARA Copilot has consistently demonstrated its effectiveness in a wide range of development projects, delivering measurable benefits in efficiency and quality alike. Its integration into the Threat Analysis and Risk Assessment (TARA) process has led to a remarkable reduction in overall effort – cutting the time required for finalization by approximately 50% and streamlining complex assessments without compromising rigor. Beyond time savings, TARA Copilot significantly improves the quality and consistency of TARA results. Automated support ensures standardized output and reduces human error, while intelligent guidance helps teams maintain alignment with cybersecurity best practices. Thorough reviews by the responsible TARA owner, along with precise inputs for the tool – namely the item definition and process instructions – remain essential to maintain high-quality outcomes.

Following its successful proof of concept, FEV is actively expanding the deployment of the TARA Copilot across its global cybersecurity organization. The tool is now also available to external customers, offering organizations a powerful solution to enhance cybersecurity risk assessments with greater speed, consistency, and confidence.

BY
Dr. Yuri Gil Dantas
dantas@fev.io
Dr. Bastian Holderbaum
holderbaum@fev.io
Lars Kamphausen
kamphausen@fev.io
Dr. Hendrik Ruppert
ruppert_h@fev.io

#4 Artificial intelligence in computer-aided engineering

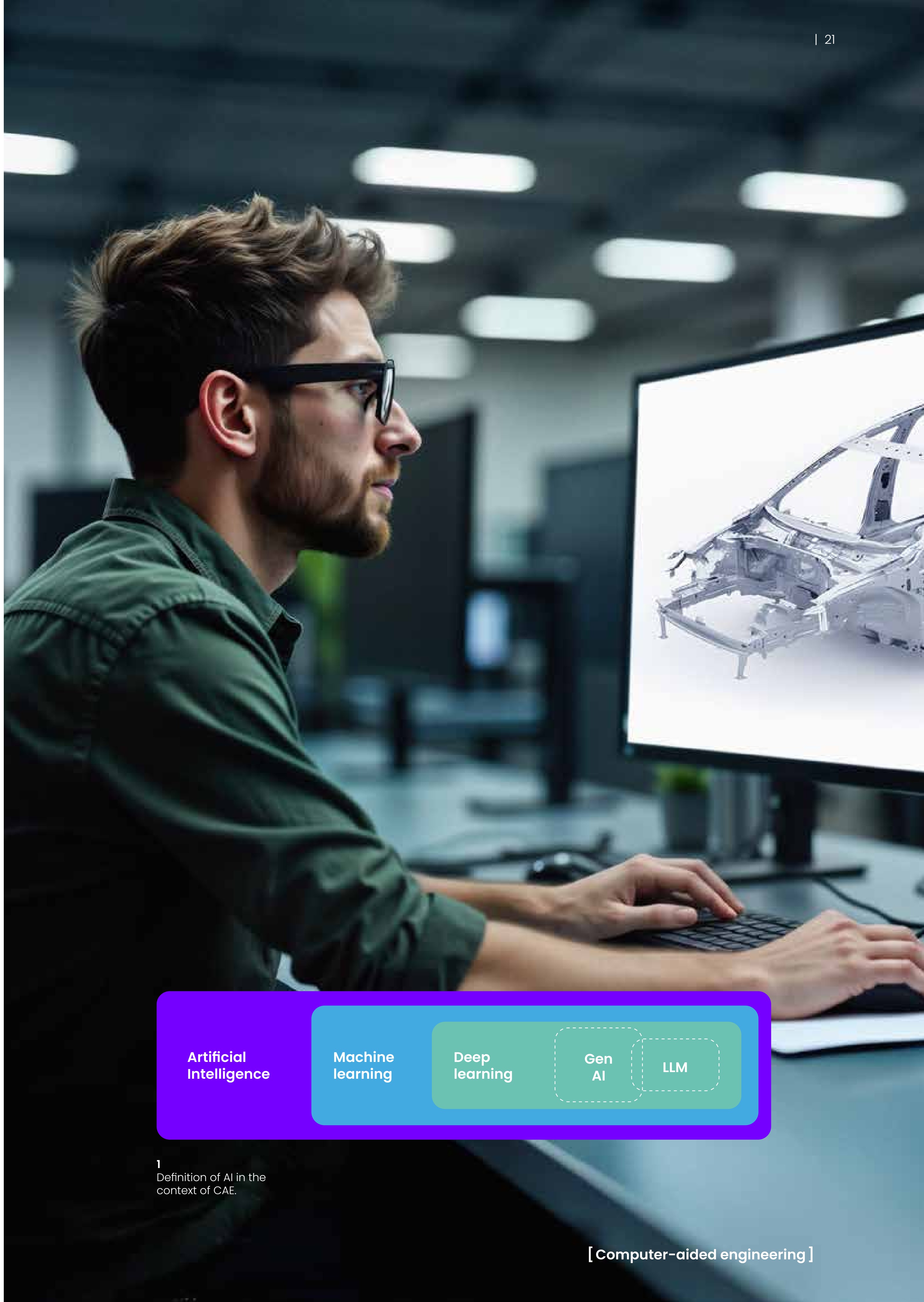
The surge in Artificial Intelligence (AI) development is profoundly impacting computer-aided engineering (CAE). Both traditional CAE methodologies and emerging approaches are experiencing a significant boost. Conventional CAE processes are being enhanced through better availability of high-performance computing resources or coupling to AI-driven optimization. Beyond these enhancements, entirely new methods are emerging, often termed "AI-driven CAE", alongside approaches such as "Explainable AI". These innovative approaches leverage AI to tackle complex engineering challenges that were previously intractable. Tools such as generative design and simulation acceleration may soon even allow real-time prediction.

It is crucial to clarify what is meant by "AI" in this context. While large language models (LLMs) have captured widespread attention, the application of AI in CAE extends far beyond conversational interfaces. Here, "AI" encompasses a broader spectrum of technologies, including machine learning and deep learning, see Figure 1.

The implications for product development cycles, especially time-to-market, are enormous. In an increasingly globalized and competitive market, the ability to rapidly design, test, and refine products is paramount. We are witnessing a clear divergence in development speeds, with certain regions, and their respective OEMs, demonstrating remarkable agility. Their adoption of modern CAE methodologies allows for significantly compressed development timelines compared to some traditional players. This provides a strategic advantage and underscores the urgent need for companies to integrate AI into their engineering workflows to remain competitive.

FEV is at the forefront of this revolution. With its deep expertise and cutting-edge tools, the company offers a comprehensive suite of CAE services that integrate the power of AI to address the most demanding engineering challenges across various industries.

This article provides a cross-section of three completely different AI-driven approaches: physics-informed neural networks (PINNs), Bayesian optimization (BO), and moving morphable component (MMC) topology optimization.



1
Definition of AI in the context of CAE.

Physics-informed neural networks

Physics-informed neural networks (PINNs) are a pioneering application of AI in simulations. As with conventional neural networks, a PINN is trained using data. The crux of PINNs is that during this training, the outputs are compared with the results of physical governing equations, such as conservation of mass and energy, or momentum in the form of the Navier-Stokes equations. This deviation is then incorporated into the loss function of the neural network, allowing for physics-based training of the network (Figure 2). The integration of the governing equations into the neural network not only enables accurate predictions of the system behavior, but also significantly reduces the required amount of training data.

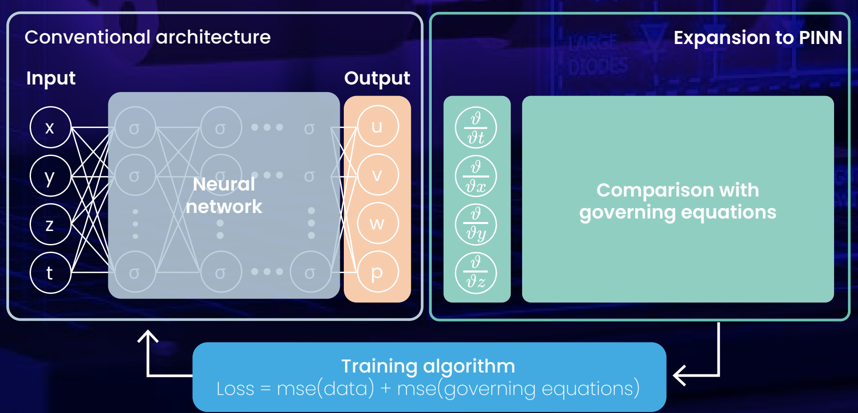
The biggest effort when working with PINNs or any neural network goes into the training process. Once such a network is trained, prediction of the trained model can be conducted in a matter of seconds.

Use Case: Design of bipolar plates for fuel cells

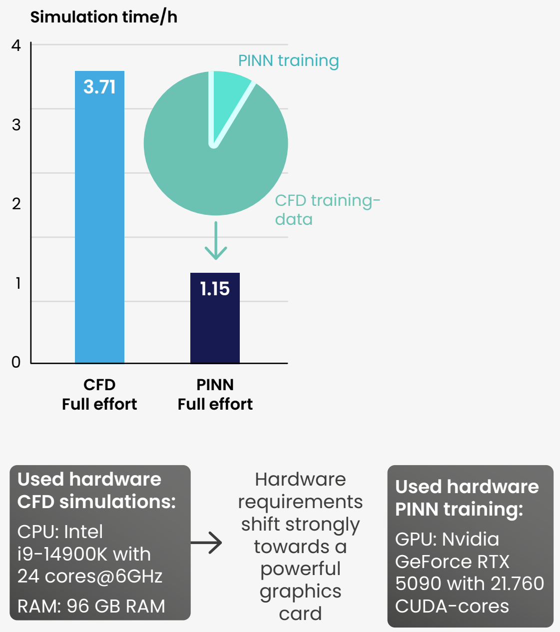
The design of the flow field of bipolar plates is a typical application for simulation and a crucial part of any fuel cell development. The targeted design of the flow field ensures a uniform supply of reactants to the cell, guarantees proper performance, and prevents premature deterioration. The design process involves an iterative loop of improvements to the CAD design and subsequent assessment through CFD simulation. However, the CFD simulation requires high resources, both in terms of computing time and costs. This is due to the various phenomena characterizing the flow. Diffusion through the gas diffusion layer (GDL) to the catalytic layer and the electrochemical reaction must be modeled, the removal of the resulting heat and electric current must be ensured by sufficiently large contact surfaces between the bipolar plate and the GDL, and the formation and removal of liquid water must be considered.

Here PINNs can significantly reduce the computation time and therefore combat the bottleneck of CFD simulation in the design process. With a small set of CFD-generated training data, the PINN can be trained to solve the governing equations for the individual model without the need for meshing or discretization, and in a fraction of the time required by a full CFD simulation of all states. This is highlighted for a parameter variation regarding the channel width in a flow-field design in Figure 3, wherein a system without liquid water was modeled. Here, the computation time could be reduced by a factor of 3. For the consideration of liquid water, a much higher reduction of required resources of up to factor 10 is predicted, making this approach even more beneficial (Figure 4).

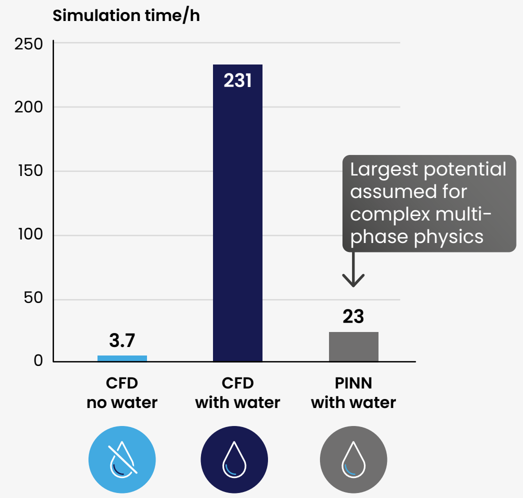
The result of a PINN-based simulation for the pressure of a bipolar plate is shown in Figure 5. The accuracy plot reveals the high agreement of the PINN simulation with only two training-points and CFD simulation.



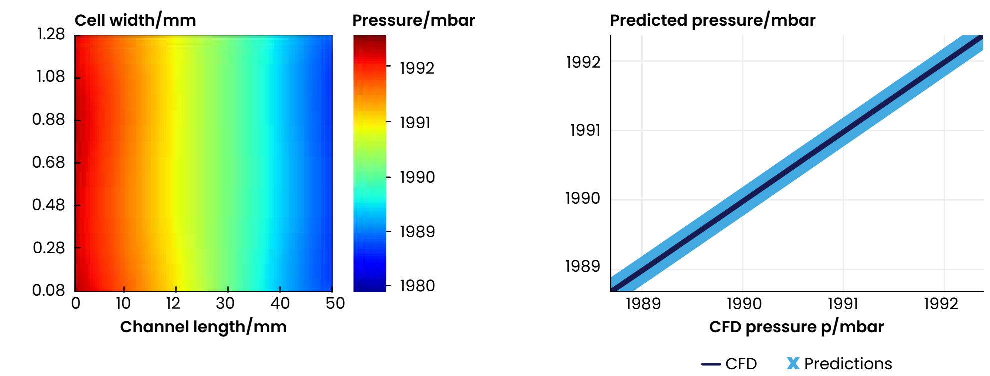
2
Schematic of the PINN architecture consisting of a conventional NN, the governing equations, and their integration into the training algorithm through the loss function.



3
The simulation time of conventional CFD takes significantly longer than a PINN-based simulation. Simulation with AI requires high-performance graphics hardware.



4
The potential benefit of PINN-based simulation for fuel cell models becomes especially lucrative when considering the formation of liquid water.



5
PINN-based simulation results for pressure along a channel, along with their accuracy compared to conventional CFD simulation.

Powertrain co-optimization: Enhancing efficiency through active learning and predictive control

Meeting stringent powertrain targets for torque, efficiency, and thermal reliability requirements for an integrated design approach, FEV's two-layer co-optimization framework combines rapid, data-driven hardware sizing with predictive thermal and torque control; delivering best-in-class performance in under 100 design iterations.

Designers must balance conflicting objectives: larger electric motors improve efficiency but add weight and cost; multi-speed gearboxes expand operating range at the expense of complexity; aggressive cooling protects components but consumes auxiliary power. Hence, treating hardware and controls separately leads to repeated development cycles and delayed product launches.

Rather than trial-and-error, FEV's experts apply a Bayesian-based optimizer that builds a statistical model of how motor dimensions and gear ratios impact overall energy use and torque capability. By intelligently sampling the most promising designs, the engineers determine optimal configurations in ten times fewer simulations than conventional methods (Figure 6).

Each candidate design is validated through a real-time predictive controller that allocates torque between dual motors and adjusts cooling devices to keep temperatures within safe bounds. This ensures every proposed architecture is thermally viable, reducing late-stage redesigns and warranty risks.

Our process alternates between proposing hardware variants and simulating their performance under a representative mission profile. Energy consumption and temperature data feed back into the optimizer, which refines the next set of design parameters. This nested loop concludes when further improvements fall below a predefined threshold – typically in fewer than 100 cycles (Figure 7).

Use case and results A: 7.5 t medium duty truck

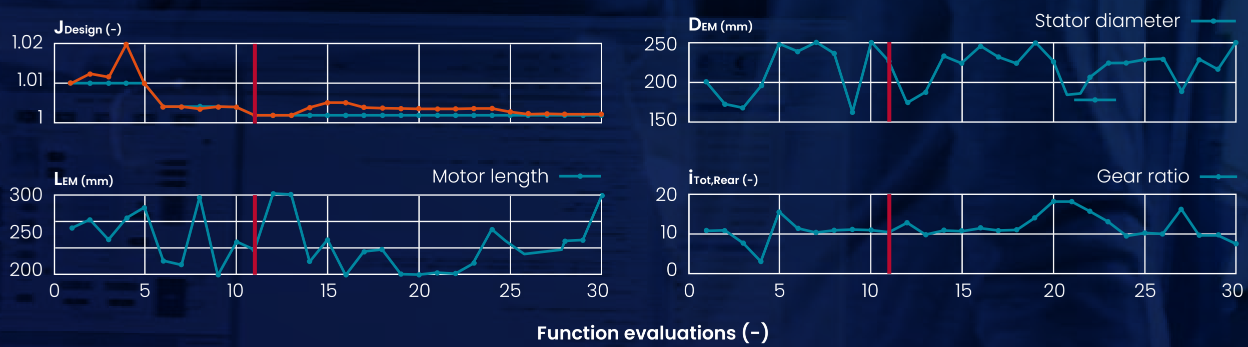
Applied to a 7.5 t electric truck with a two-speed transmission, the framework delivered a dual-motor layout that cut energy use by 3.74% and boosted hill start torque by 15.38% over the baseline (Figure 8). Component sizing and gear ratio adjustments are summarized in Figure 9.

Use case and results B: AWD SUV benchmark

For an AWD SUV reconfigured to RWD, co-optimization increased motor diameter by 25% and reduced length by 16%, aligning the efficiency sweet spot with real-world driving cycles (Figure 10). Overall system losses dropped by 0.35 kWh/100 km.

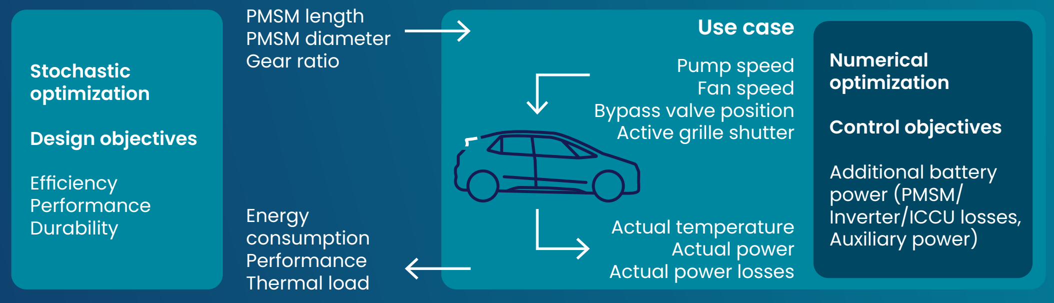
Summary

By uniting data-driven hardware design with predictive control, this two-layer framework accelerates development, cuts energy consumption, and ensures thermal safety advantages in the development of market-leading electric vehicles (Figure 11).



6
Objective and parameter tuning throughout the trainings process.

Application design boundaries



7
Nested co-optimization approach of active learning framework.

Parameter	Value	Unit
Gross vehicle weight	7,500	kg
Towing weight	3,500	Kg
Dynamic wheel radius	0.361	m
Coast down factor F_0	1,050	N
Coast down factor F_1	0	N/(km/h)
Coast down factor F_2	0.1349	N/(km/h)²
HV-battery type	NMC	-
Cell capacity	92	Ah
Number of cell in series	250	-
Number of cell in parallel	4	-

8
Vehicle parameters of 7.5 t truck study.

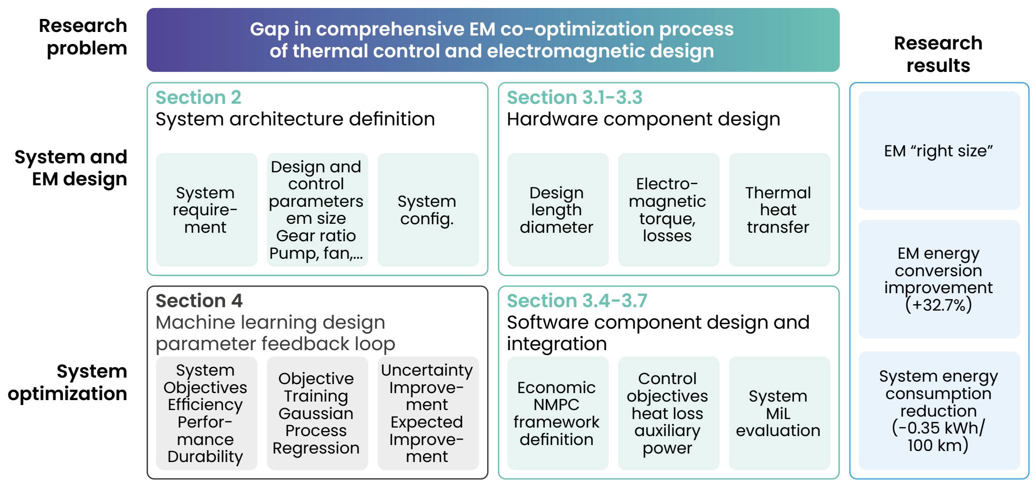
VECTO Urban Delivery Cycle

	Reference	Optimized	Improvement
Optimization variables	$k_A = 1$ $k_R = 1$ $N_{EM} = 1$ $N_G = 1$ $r_{G,1} = 10$	$k_A = 0.53$ $k_R = 1.18$ $N_{EM} = 1$ $N_G = 3$ $r_{G,1} = 15.7$ $r_{G,2} = 11$ $r_{G,3} = 9.2$	-
Energy consumption	50.8 kWh	48.9 kWh	3.74%
Startability	26%	30%	15.38%

9
Optimal design and KPI improvements of 7.5 t truck for common use-case.

Parameter	Specification
Dimensions (L/W/H)	(4,635/1,890/1,605) mm
Powertrain layout	AWD
Maximum torque $M_{Peak,System}$	605 Nm
Maximum power $P_{Peak,System}$	225 kW
Battery capacity $E_{HV,Bat}$	72.6 kWh
Curb weight $m_{Vehicle}$	2,095 kg
Front surface A_{Surf}	2.5 m²
Rolling friction Coeff. f_r	0.0146 –
Drag Coeff. AGS open $c_{d,open}$	0.302 –
Drag Coeff. AGS closed $c_{d,close}$	0.288 –
Dynamic wheel radius r_{dyn}	0.35 m
Gear ratio rear drive $i_{Tot,Rear,Ref}$	10.65 –

10
Vehicle paramaters of AWD SUV benchmark study.



11
Backend functionalities of FEV's signature solution, the "AI-integrated System Development Methodology," along with specific results from the AWD SUV benchmark study.

Moving Morphable Components method

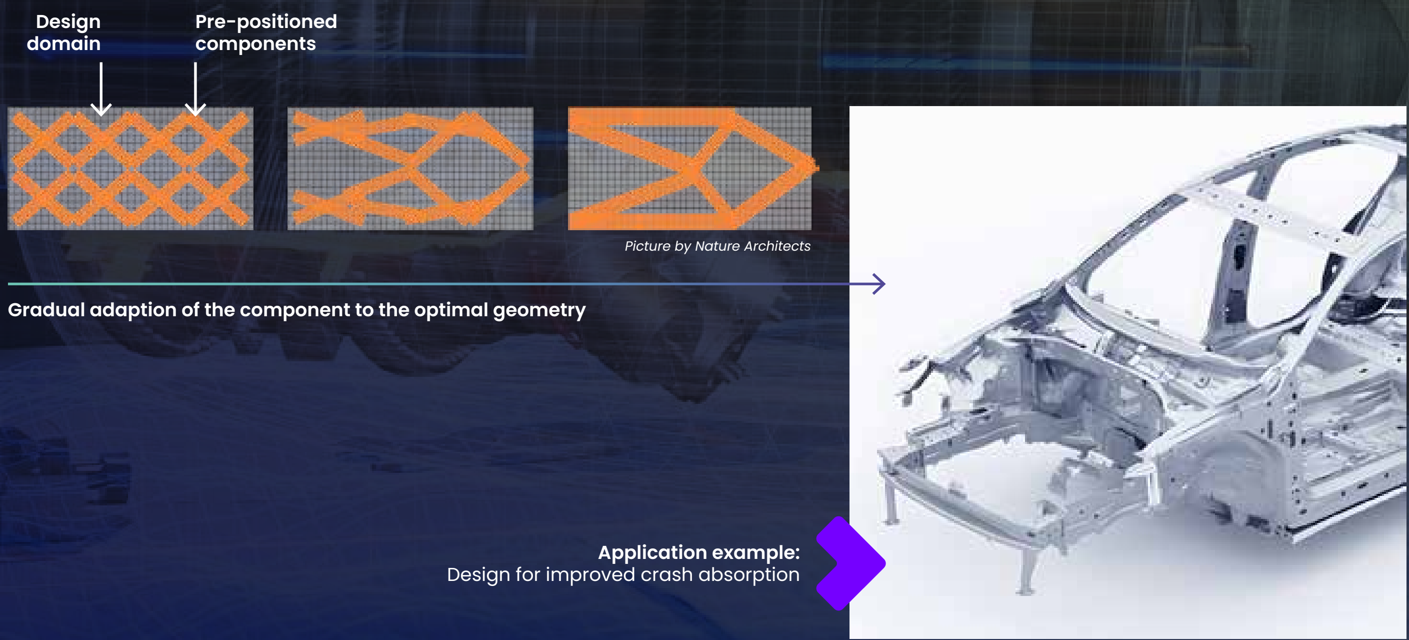
Complete vehicle simulations across all disciplines can become very complex due to the size of the models and the large variety of load cases. To speed up the development process, it can be helpful to select subcomponents and optimize them using a simplified method in an efficient environment. The Moving Morphable Components (MMC) method is a suitable approach for this purpose.

As an optimization approach, the MMC method allows for the incorporation of the designer's intent into the optimization process. The process begins with several components being initially placed within the design domain. The optimal geometry is then represented through the scaling, rotating, translating, and overlapping of these components. As the optimization progresses, the components gradually adapt to the optimal geometry. Figure 9 illustrates this process, showing the evolution from a design domain with pre-positioned components to the final optimal geometry.

Use case

The MMC method can be used to optimize the section of a structural part, such as an extrusion profile, for a specific task. An example task is achieving maximum energy absorption (e.g. in a crash load case) with minimum material effort or weight (Figure 9). The MMC method is a combination of varying the geometrical parameters of initial components, such as length, width, and angle, and using a 2D-based finite elements method for evaluation, such as a stroke-force evaluation – feeds the generated results back into machine learning.

After this optimization at the most efficient level, the cross-section must be implemented and verified in the full vehicle model as well. Furthermore, the generated geometries will then also be validated in regards to industrialization and manufacturability.



12
Moving Morphable Components method.

»FEV is at the forefront of integrating AI into engineering - addressing the most demanding engineering challenges across various industries.«

Conclusion

The integration of Artificial Intelligence is fundamentally transforming computer-aided engineering, moving beyond enhancements to conventional methods and enabling entirely new engineering approaches. The three examples presented in this article showcase this broad impact across different engineering disciplines.

PINNs, for instance, demonstrate how incorporating physical laws into neural network training can dramatically reduce the need for extensive data, accelerating complex simulations like those for fuel cell bipolar plates. Similarly, BO provides a powerful framework for co-design, intelligently navigating vast design spaces to find optimal solutions with significantly fewer iterations. Finally, the MMC method illustrates a targeted approach to structural optimization, allowing designers to efficiently refine subcomponents for specific performance goals, such as maximizing energy absorption.

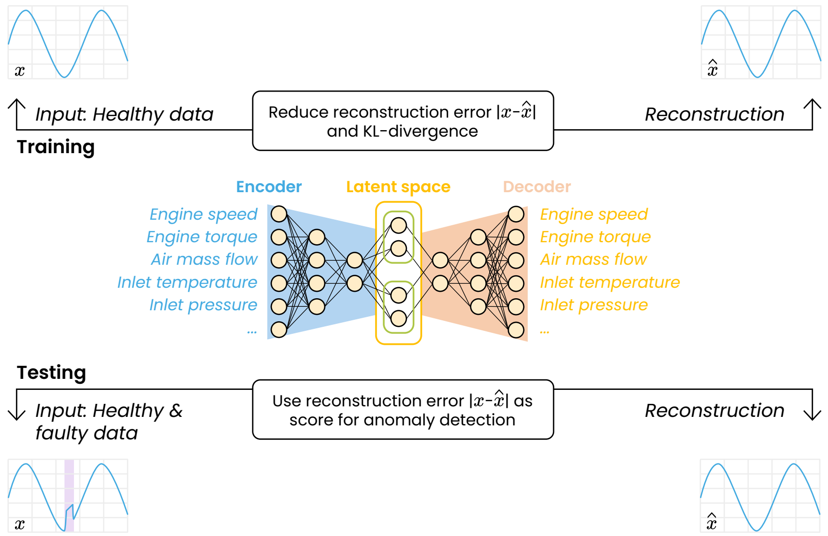
These diverse applications underscore a critical shift: AI is not a one-size-fits-all solution but a versatile toolkit. By strategically applying AI technologies, engineers can overcome traditional bottlenecks, from simulation time to design complexity, leading to faster, more efficient, and more innovative product development cycles. Integrating these intelligent workflows is no longer a competitive advantage but a necessity for staying ahead in today's fast-paced, global market.

BY
Dr. Bastian Morcinkowski
morcinkowski@fev.com
Jan Ophey
ophey@fev.com
Sven Bröhl
ext_broehl@fev.com
Christoph Alexander Wellmann
ext_wellmann@fev.com

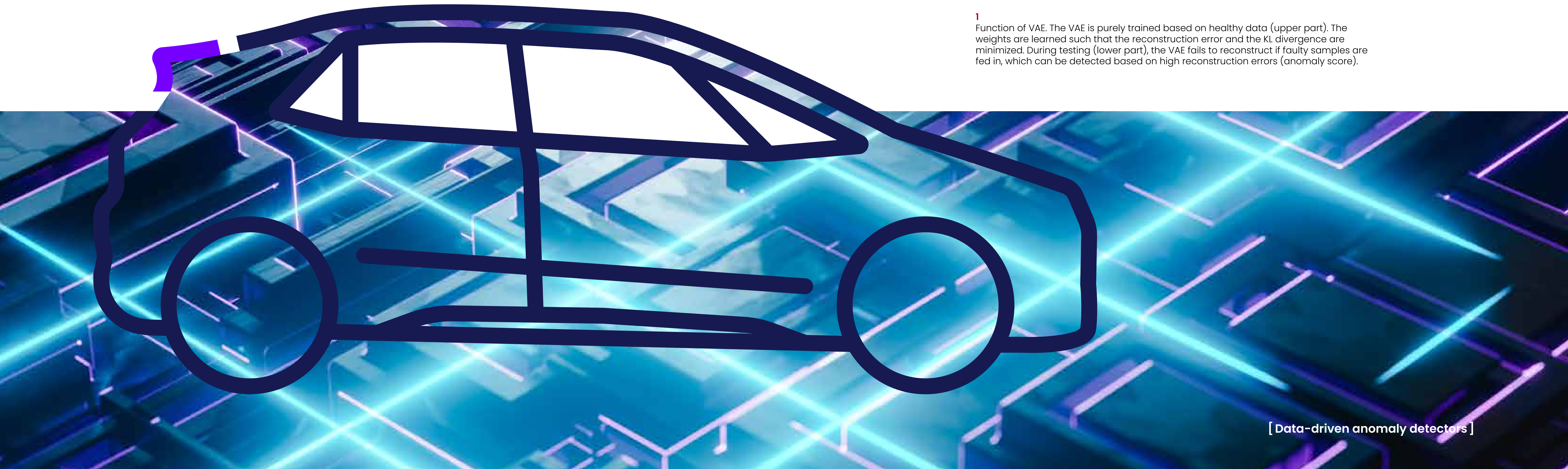
#5 Data-driven anomaly detectors – Smarter diagnostics, less effort

On-board diagnostics (OBD) form the basis for fault monitoring in internal-combustion engines (ICE). About 50% of all software functions in modern engine ECUs are OBD-related, underscoring the complexity of current monitoring. OBD logic is hand-crafted from expert rules and (semi-)physical models, so it's costly to develop and hard to adapt to new systems, especially as architectures or powertrain topologies evolve. Furthermore, OBD calibration is typically based on a predefined catalogue of failure modes, which reduces sensitivity to rare or previously unseen (for example, out-of-distribution) faults. Moreover, human experts are limited in their ability to process high-dimensional, nonlinear correlations across sensors, actuators, and operating conditions (load, temperature, aging, operation mode) simultaneously. This results in multiple tailored monitors and thresholds that fail to reflect component interactions – even as most recent regulations such as on-board monitoring (OBM) call for comprehensive, system-level diagnostics.

Meanwhile, the ever-increasing number of connected vehicles produces rich data that can support detecting emerging issues earlier. We therefore explore adaptive, data-driven methods that reduce calibration effort, are highly adaptable and generalize beyond pre-specified faults. Specifically, we apply variational autoencoders (VAEs) for unsupervised anomaly detection in internal combustion engines (ICEs). Trained solely on healthy data, the VAE learns the joint behavior of multivariate time series and the operating context, capturing correlations that are difficult to model by hand, and flagging statistically meaningful deviations via reconstruction error. In a demonstrator with an artificially injected sensor drift, the proposed methodology successfully detected the induced anomalies, indicating a practical complement to OBD that scales with system complexity, eases monitor maintenance, and enhances reliability as well as emissions compliance.



1
Function of VAE. The VAE is purely trained based on healthy data (upper part). The weights are learned such that the reconstruction error and the KL divergence are minimized. During testing (lower part), the VAE fails to reconstruct if faulty samples are fed in, which can be detected based on high reconstruction errors (anomaly score).



Variational autoencoders

VAEs are a class of generative models that learn to represent high-dimensional input data in a compressed and structured way. At a high level, a VAE consists of two main components: an encoder and a decoder. The encoder maps input data into a lower-dimensional latent space, while the decoder attempts to reconstruct the original data from this compressed representation. Unlike traditional autoencoders, VAEs learn not a fixed but a probabilistic mapping from input to latent space: each input is mapped to a distribution over the latent space rather than a single point.

As can be seen from Figure 1, the VAE does not require labeled data during training which is an advantage compared to supervised learning models. The VAE is purely trained based on healthy data. In this way, it learns to reconstruct the healthy input data via the compact and continuous lower dimensional latent space. Training a VAE involves balancing two objectives

- Reconstruction loss: Encourages accurate reconstruction of the input x to the output $\hat{x}$, typically quantified by a function proportional to $|x - \hat{x}|$
- Kullback-Leibler (KL)-loss: Encourages the learned latent distribution q_θ to follow a predefined prior distribution — typically a standard normal distribution $N(0, I_k)$

After training, the model can detect abnormal data indicated by high reconstruction errors between the input x and the output $\hat{x}$. In this study, this reconstruction error is calculated as the mean squared error and serves as the Anomaly Score where d denotes the dimensionality of x: $l(x,\hat{x}) = \frac{1}{d}\|x-\hat{x}\|_2^2$

Use case: Sensor drift in a 2.0-liter diesel engine

The data used for this study was collected using a passenger vehicle equipped with a 2.0-liter turbocharged diesel engine. The vehicle was operated in full-series specification to ensure relevance for real-world scenarios.

To capture the dynamics of the engine under both nominal and faulty conditions, a targeted subset of signals was logged at different sample rates. These included air path temperatures, pressures, actuators, and signals related to the current operating condition of the engine. The full list is provided in this table:

Parameter	Variable	Sample frequency	Unit
Engine torque	τ	100 Hz	Nm
Engine speed	n	100 Hz	rpm
Exhaust gas pressure upstream turbine	p_{exh}	100 Hz	hPa
Intake pressure	p_{in}	100 Hz	hPa
Air-mass flow	$\dot{m}_{\text{air}}$	100 Hz	kg/h
LP-EGR valve position	$x_{\text{EGR,LP}}$	100 Hz	%
HP-EGR valve position	$x_{\text{EGR,HP}}$	100 Hz	%
Throttle valve position	x_{TV}	100 Hz	%
Turbine vane position	x_{VGT}	100 Hz	%
Exhaust gas lambda	λ	100 Hz	–
Temperature intake	θ_{in}	10 Hz	°C
Exhaust gas temperature turbine upstream	$\theta_{\text{exh,T}}$	10 Hz	°C
Exhaust gas temperature SCR upstream	$\theta_{\text{exh,SCR}}$	10 Hz	°C

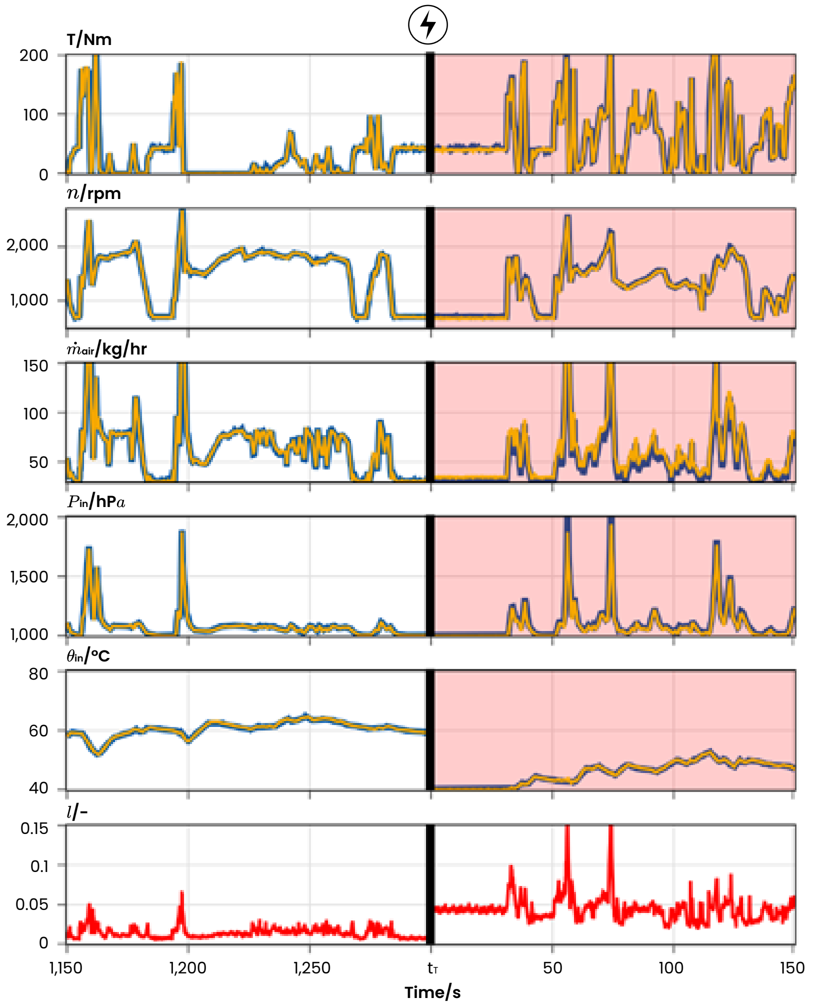
The training data was collected by driving "Real Driving Emissions" (RDE) cycles chosen for their representative character. The diverse operating conditions captured by these cycles allow the model to learn from a wide range of normal behavior. The RDE route driven was approximately 100 km long and took place near Aachen, Germany. This route was driven four times, providing approximately 8 hours of healthy baseline data. Furthermore, another four drive cycles were included with an additional five hours of healthy data. These follow the same principles as RDE but were conducted outside the strict RDE boundary conditions and serve to increase the size of the dataset used for model training. For testing the VAE, a completely different route was used, not included in the training data. Similar to RDE cycles, the route included a representative mix of urban, rural, and motorway driving. This variety ensures that the model is exposed to a wide range of engine loads, vehicle speeds, and transient behaviors, which is essential for validating the robustness of the anomaly detection across different operating conditions. The test route spanned approximately 20 km and was driven under both healthy and faulty vehicle conditions.

To evaluate the performance of the proposed anomaly detection framework under fault conditions, engine parameters were manipulated in the ECU. Specifically, the transfer curve of the Mass Air Flow (MAF) sensor was shifted to simulate a sensor drift. Two different drifts were implemented, by shifting the curve by 10% and 20%, respectively. The transfer curve maps the sensor's raw output – typically a frequency from a hot-film element held at a fixed over-temperature, where airflow cooling alters the required drive power – into an air-mass-flow value. To implement the two aforementioned fault severities, the output of the transfer curve was scaled by a factor of 0.9 and 0.8 across the entire operating range.

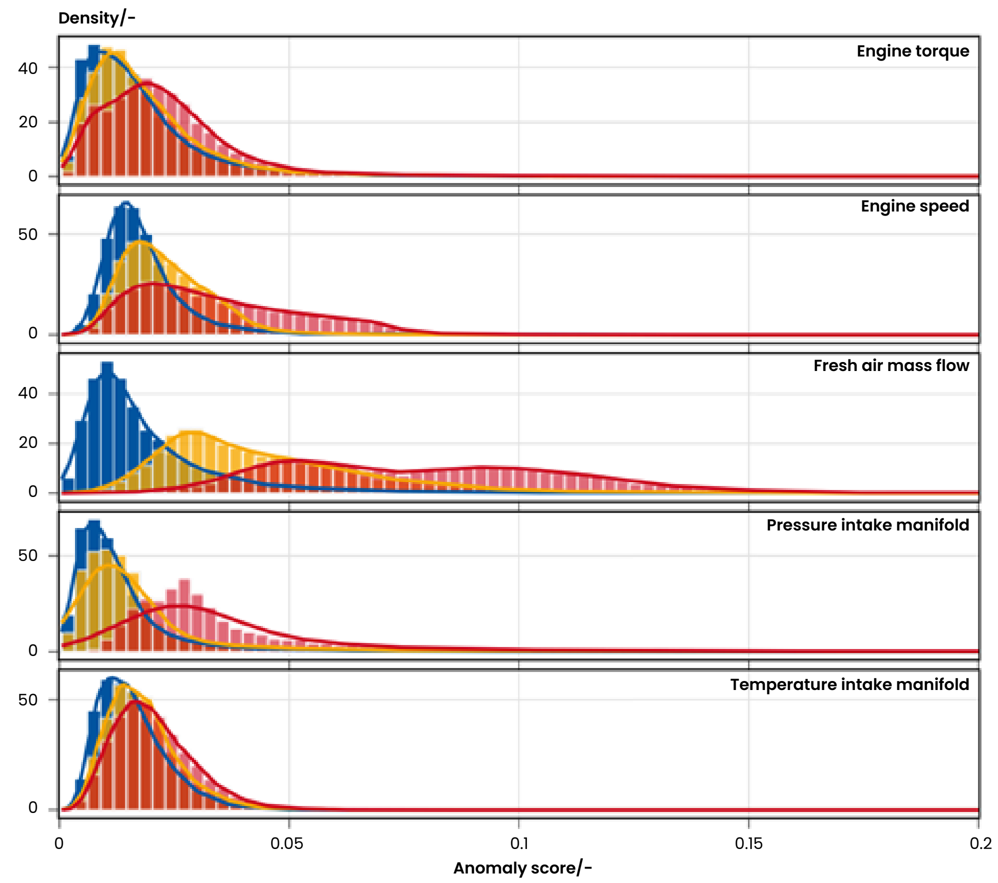
Results

The following presents the results of the proposed method. First, the reconstruction capabilities of the VAE will be evaluated based on time series data, then the distribution of anomaly scores will be analyzed given different conditions of the system.

Figure 2 presents reconstructions for selected channels over a representative test-cycle segment. To enable a direct comparison of the signals and the corresponding anomaly score within a single plot, we concatenated the last 150 s of a healthy drive cycle with the first 150 s of a faulty one, noting that the engine was turned off in between; the transition point $t_{\mathcal{T}}$ is marked by a lightning symbol. For $t < t_{\mathcal{T}}$ the system is assumed healthy, for $t > t_{\mathcal{T}}$ it is assumed faulty with a 20% MAF drift. For the healthy frame, the VAE accurately reconstructs both high dynamic signals (e.g., air-mass flow) and slow-varying signals (e.g., intake temperature), resulting in a low anomaly score (see equation (1)) until $t \approx t_{\mathcal{T}}$. Around the fault injection, only the air-mass flow reconstruction shows a clear large-scale deviation. Nevertheless, the anomaly score increases, indicating that the VAE struggles to reconstruct the abnormal signals.



2
Reconstruction plot that shows the input x and the output $\hat{x}$ of the VAE. At t_f, the transfer curve of the MAF curve is trimmed by 20% to simulate a sensor drift. Note, that the engine was shut-down between healthy and faulty.



3
Distribution of anomaly scores for pre-selected channels from healthy and faulty systems with two different MAF fault severities.

To have a more general view of the reconstruction errors caused by the simulated MAF faults, Figure 3 shows the distributions of channel-wise anomaly scores among the healthy and faulty test drive cycles for the same five channels. In general, healthy samples yield scores near zero, consistent with accurate reconstructions. The reconstruction difficulty varies by channel: The engine speed, for example, exhibits higher scores than the air-mass flow given healthy system state. The same trend holds under faulty conditions. Relative to the healthy baseline, the anomaly score distribution of the engine torque changes only slightly, whereas the air-mass flow distribution shifts significantly toward higher anomaly scores. This can be expected, since this signal is directly affected by the modified MAF transfer curve in the ECU calibration. Moreover, the shift increases with fault severity (from -10% to -20%), which is most evident in the air-mass flow signal. This suggests that the VAE struggles more with reconstructing the major MAF fault than the less severe one. This indicates that, given the MAF fault, the anomaly score magnitude can be used to infer fault severity

BY
Tobias Brinkmann
brinkmann@mmp.rwth-aachen.de
Tim Wolter
tim.wolter@rwth-aachen.de
Lucas Koch
koch_luc@mmp.rwth-aachen.de
Dr. Joschka Schaub
schaub@fev.com

Conclusion

The article investigates VAEs as an unsupervised learning method to improve OBD function development for ICEs. The model learns normal multivariate behaviour from healthy data and indicates potential faults by meaningful deviations via reconstruction error as an anomaly score. The conducted experiments use a production 2.0-liter diesel vehicle. The training data consist of four ~100 km Real Driving Emissions (RDE) routes (~8 h) plus ~5 h of additional healthy driving, the validation uses a distinct ~20 km route recorded in healthy and faulty states. The faults were induced by shifting the ECU's Mass Air Flow (MAF) transfer curve by -10% and -20%, respectively. The results show an accurate reconstruction and low anomaly scores in healthy operation, with clear increase of anomaly scores under fault conditions. Channel-wise analysis reveals sensitivity aligned with fault mechanics (for example, highest shifts for air-mass flow). The study concludes that VAEs can be used for anomaly detection using real sensor data of a production vehicle. Since only unlabelled healthy data is required for training, the calibration effort for OBD can potentially be reduced by complementing it with this method.

To turn anomaly detection into actionable diagnostics, the proposed method could be used for segmenting trips into windows with persistently high anomaly scores and logging the corresponding operating context (for example, load, speed, temperature). These "anomaly snippets" can guide workshop workflows by pinpointing when and where condition-dependent faults can be reproduced through re-testing at similar operating points. Building on this, the extraction of reconstruction profiles as signatures can be used as input for supervised models to map these profiles to likely fault types and locations. To reduce labelling effort, semi-supervised learning strategies can be used.

»REEVs and long-range PHEVs provide a practical solution for users who are not yet ready to switch to BEVs, while still delivering significant emissions reductions.«

#6 REEVs and long-range PHEVs – Bridging the gap to full electrification

As the global automotive industry moves rapidly toward full electrification, range-extended electric vehicles (REEVs) and plug-in hybrid electric vehicles (PHEVs) with extended electric range are gaining traction. These vehicles represent a compelling transitional solution for markets where charging infrastructure, energy pricing, and user behavior are not yet fully aligned with battery electric vehicles (BEVs).

In China, REEVs are thriving, as vehicles with electric-only ranges above 150 km qualify as new energy vehicles (NEVs) and benefit from generous government subsidies. In Europe, interest is also rising, though regulatory hurdles still prevent REEVs from being recognized as zero-emission vehicles. Regardless of region, the combination of everyday practicality, range flexibility, and falling battery costs makes this vehicle class a serious contender in the modern mobility transition.

Battery types for xEV applications: Chemistry meets use case

Battery technology selection depends heavily on the vehicle type and its intended use. Different xEV architectures require different balances of energy density, charging speed, cycle life, and cost.

	 Premium, long range BEV	 Cost optimized, mid range BEV	 REEV/long range PHEV	 Mid/short range PHEV
Vehicle platform	BEV	BEV	BEV/ICE	ICE
Cell chemistry	High energy, mid power: e.g. NMC, NMx, (A)SSB	Mid energy, mid power: e.g. LMFP, LFP, sodium-ion	Mid energy, mid-high power: LFP, sodium-ion, NMC	Mid/low energy, high power: e.g. LFP, sodium-ion
Charging strategy	Fast DC and AC	Fast DC and AC	(Fast) DC and AC	Often AC, no fast charge
Power/energy ratio	2:1 to 3:1	2:1 to 4:1	3:1 to 6:1	> 6:1
Cell energy density	800 – 1,000 Wh/l	300 – 500 Wh/l	250 – 400 Wh/l	250 – 350 Wh/l
Pack voltage (max.)	800 – 1,000 V	400 V/800 V	400 V/800 V	300 – 400 V
Pack energy	100 – 180 kWh	60 – 100 kWh	25 – 60 kWh	8 – 20 kWh
Pack energy density	350 – 450 Wh/l	280 – 330 Wh/l	200 – 250 Wh/l	150 – 200 Wh/l
Pack weight	450 – 700 kg	400 – 600 kg	200 kg – 400 kg	120 – 200 kg
Electric driving range[1]	650 – 1,200 km	400 – 650 km	160 – 400 km	100 – 160 km
Cycle lifetime[2]	750 – 1,500 EFC	1,000 – 2,000 EFC	2,000 – 4,000 EFC	4,000 – 6,000 EFC
Cost prediction 2030+	80 – 120 €/kWh	55 – 65 €/kWh	65 – 75 €/kWh	75 – 100 €/kWh

1) Estimation based on a consumption of ~15 kWh/100km
2) Equivalent Full Cycle (EFC) - Total charge throughput expressed as full charge/discharge cycle equivalents

1
Typical KPIs for xEV batteries.

Key performance indicators for REEVs include:

- **Electric range (> 150 – 200 km):** Benchmark for incentives and daily usability
- **Specific energy (Wh/kg):** Crucial for weight and packaging efficiency
- **Cycle life:** Frequent charging with minimal degradation must be supported
- **Thermal behavior:** Safety across the entire temperature and load window
- **Cost per kWh:** Impacts vehicle pricing and market competitiveness
- **Charging speed:** 400/800 V DC fast charging is increasingly expected
- **Power and system voltage:** Aligned with BEVs of same platform, if applicable especially for charge sustaining operation

Depending on the vehicle's powertrain architecture, the typical values of the battery performance KPIs can vary significantly, see Figure 1. However, there are some similarities between BEV and REEV or long-range PHEV batteries, which unlock the potential to build a common platform strategy for these types of xEV batteries.

Common battery platform: Choosing the right strategy

Figure 1 illustrates the energy capacity and discharge C-rate of battery packs used in various road vehicle platforms, including HEV, PHEV, REEV, and BEV. From this, the following key observations can be made:

- Vehicle application significantly influences the power-to-energy ratio, which in turn dictates the appropriate cell selection.
- A clear distinction exists between energy-oriented applications (e.g., BEVs) and power-oriented applications (e.g., short-range PHEVs and HEVs).
- REEV and long-range PHEV batteries occupy a middle ground between PHEVs and BEVs. Notably, some BEV battery packs available on the market meet the typical performance requirements of REEVs.
- Within a cross-platform battery family, a dedicated REEV battery pack is required. However, design synergies with existing BEV battery architectures can be leveraged to optimize development and integration.
- LFP batteries generally offer lower energy density compared to NMC batteries, but in some cases, they exhibit even higher discharge C-rates.

Several key requirements define the main boundaries for feasible battery configurations:

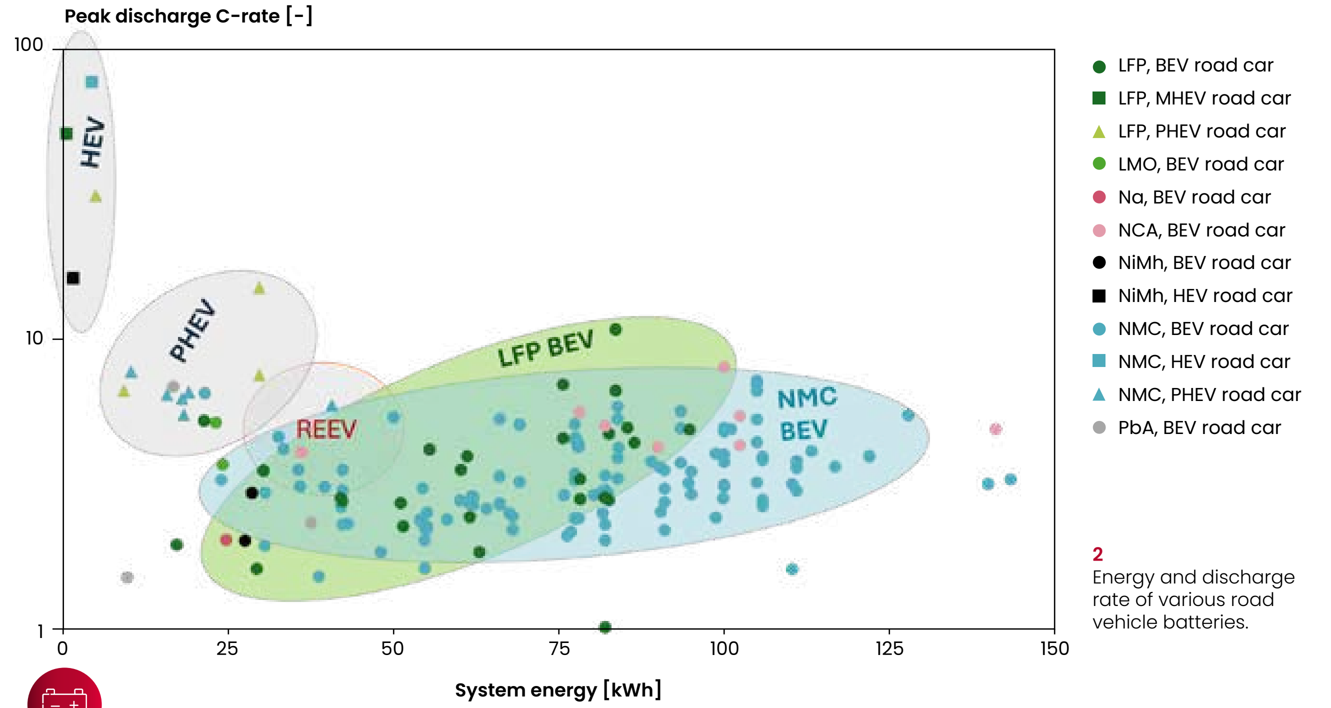
- Number of serial cells required to achieve the target system voltage (yS xP)
- Number of parallel strings needed to meet the desired battery energy (yS xP)
- Available packaging space
- Charging voltage and inverter operating voltage window
- State of Charge (SoC) limits (both low and high)
- Vehicle power management (for example PHEV/REX serial or parallel mode, SoC and power distribution control strategy)
- 400 V/800 V architecture and charging strategy

In high-volume series production, minimizing the number of cells in a battery pack is generally advantageous. It simplifies the assembly process, increases packaging density within the battery pack, and reduces the overall number of components needed for cell integration, connection, and monitoring.

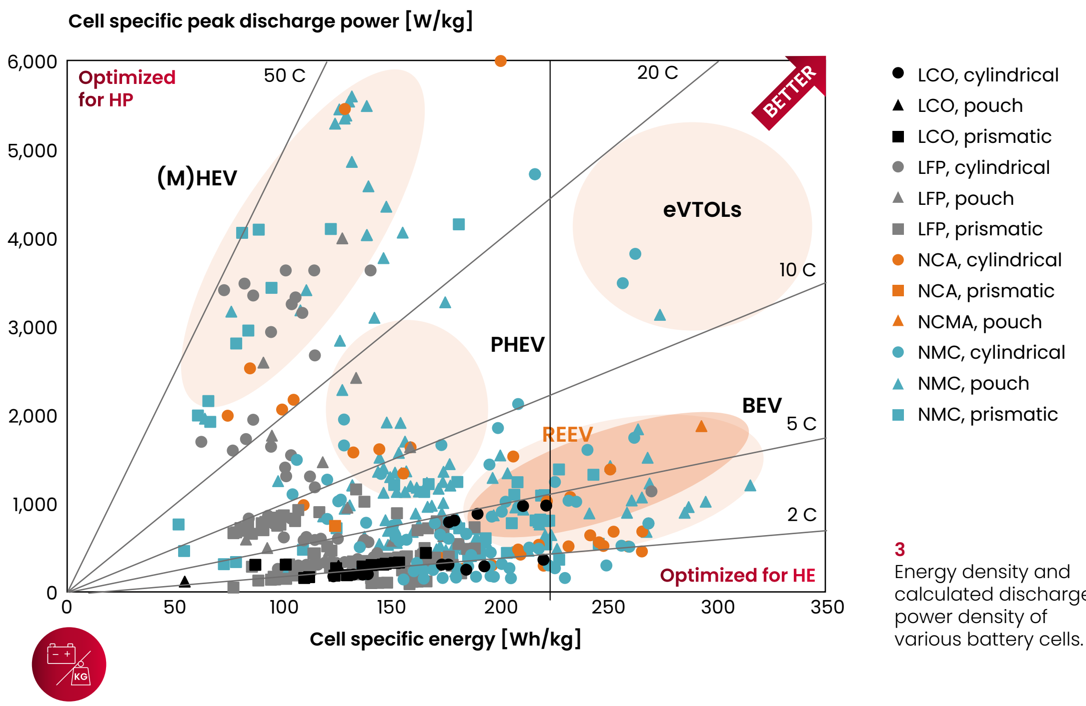
Given these constraints, relevant options for a common battery platform across various vehicle types include:

- Using a single cell type and scaling between BEV and REEV configurations via parallel strings (e.g., 125S 1P for REEV and 125S 2P for BEV)
- Using multiple cell types with scalable dimensions, while maintaining a consistent yS xP configuration across all xEV batteries
- Combining both strategies to balance flexibility and efficiency

Determining the optimal approach is a multi-dimensional challenge. It must account not only for technical requirements and constraints but also for the overall financial business case. For smaller production volumes, a single cell type may offer the best trade-off. In contrast, larger volumes may justify the use of dedicated cells tailored to specific battery types.



2
Energy and discharge rate of various road vehicle batteries.



3
Energy density and calculated discharge power density of various battery cells.

Cell selection: Engineering the right fit

Battery cell selection is a critical step in battery development, influencing performance, safety, cost, and scalability:

- Pouch and cylindrical cells offer flexibility, while large prismatic cells enable highly efficient packaging.
- Chemistry: LFP for robust safety and lower cost; NMC for compact high-performance applications.
- Operation windows: Discharge/charge performance over temperature and SoC range.
- Supply chain: Local cell production, strategic partnerships and circular economy are increasingly important.
- LFP is cheaper cost-wise than NMC, but achieving low market prices requires high production volumes. Lower production volumes typically necessitate off-the-shelf cells.

Figure 3 illustrates the cell-level discharge power density and energy density across various cell types. A clear distinction emerges between power-optimized cells (High Power, characterized by high C-rates) and energy-optimized cells (High Energy, characterized by high specific energy in Wh/kg).

For REEVs and long-range PHEVs, the required power-to-energy ratio closely resembles that of BEVs. As the electric driving range and battery energy content increase, the necessary power-to-energy ratio typically decreases. In such cases, peak discharge rates of 3 to 5C are generally sufficient to meet the power demands for acceleration and uphill driving.

While several other parameters must be considered to match a cell to its intended battery application, the power-to-energy ratio remains a critical factor in cell selection and system design.

Discharge power limits especially at lower state of charge levels must be aligned with the vehicle energy control strategy, enabling sufficient performance throughout the full electric operating range.

Smart transition: FEV delivers tailored battery development services

Typical challenges in transitioning from a full BEV to a REEV, or from a short-range PHEV to a long-range PHEV, include the development of a flexible battery platform that aligns with the OEM's vehicle architecture across multiple xEV platforms.

Two practical examples of derivative battery development include:

- Increasing the energy content of an existing PHEV battery while maintaining the same packaging space.
- Reducing the packaging space of an existing BEV battery while maximizing both energy density and power output.

Innovative architectural concepts such as cell-to-pack (CTP) and cell-to-chassis (CTC) enable higher volumetric efficiency and reduced system complexity. In addition, modular battery systems support scalable platform strategies across various vehicle segments.

Depending on the target performance requirements and vehicle-specific constraints, FEV offers a staged development approach with tailored options for increasing pack energy and/or discharge power to meet the demands of future PHEV and REEV applications, see Figure 4.

	Short range PHEV > long range PHEV		BEV battery > REEV battery	
Base battery	< 20 kWh, < 400 V, <= 60 km electric range		80 – 120 kWh, 400/800 V, up to 800 km electric range	
Option 1	**Cell upgrade** Cell: Chemistry upgrade; format unchanged Approach: Integration unchanged – C2M2P Build space: Installation space unchanged	20 – 25 kWh	**Remove (parallel) string (> = 2P architecture)** x 0.5 Cell: Chemistry, size and format unchanged Approach: Integration unchanged – C2M2P Remarks: Power/energy ratio unchanged, 800 V requires DCDC converter	2 – 3 C
Option 2	**Cell upgrade & pack optimization** Cell: Chemistry and format upgrade Approach: Integration change to lean module/C2P Build space: Installation space unchanged	PHEV pack energy	**Cell upgrade and pack optimization** Cell: Chemistry and form factor unchanged; cell capacity reduced Approach: Integration unchanged – C2M2P Remarks: Power/energy ratio unchanged	REEV power/energy
Option 3	**BEV battery derivative** Cell: Chemistry & format upgrade Approach: Integration change to lean module/C2P Build space: Installation space expansion - REEV battery	35 – 40 kWh	**Dedicated REEV battery** Cell: Chemistry, format and capacity update Approach: Integration change to lean module/C2P Remarks: Use of high power/mid-high energy cell	4 – 6 C

4
Examples and options for FEV's services covering REEV or long-range PHEV battery development.

Concept development: Determining the optimal solution architecture

Efficient battery design for REEVs and long-range PHEVs begins with establishing the right architecture from the beginning.

Typically, REEV platforms are derived from existing BEV architectures, while long-range PHEV batteries often evolve from short-range PHEV designs based on ICE vehicle platforms.

The decision of which cells to use should be made early in the development process. Utilizing a common cell type across multiple battery configurations can offer significant benefits in terms of development efficiency, validation, quality assurance, production, and supply chain management. However, this approach may also limit design flexibility and constrain key performance indicators (KPIs).

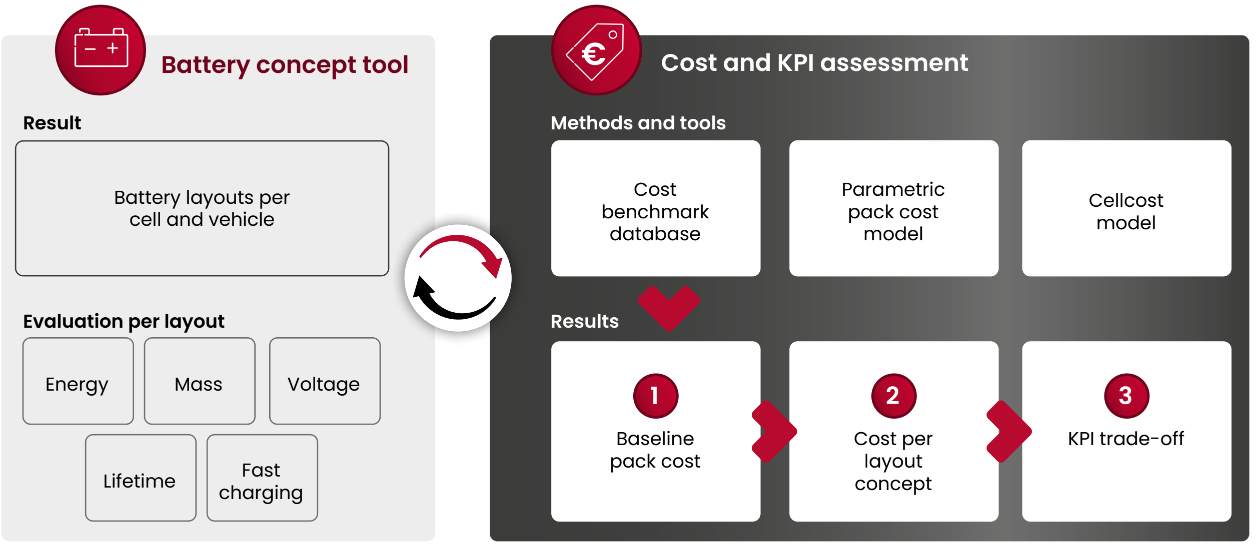
As power density increases and batteries are subjected to prolonged high-power operation, efficient cooling and thermal management become critical to ensure both safety and reliability.

In addition to managing heat, the battery design must also accommodate the controlled routing of venting gases in the event of a thermal incident.

Furthermore, factors such as cell swelling and the required spacing between cells — to prevent thermal propagation — directly influence the achievable energy and power density at the pack level. These constraints also lead to increased packaging space requirements, which must be carefully considered during the design phase.

To support this process, FEV's Signature Solution, BATT.code, provides an automated tool for battery concept development and evaluation, taking into account critical target KPIs (see Figure 5). The tool generates various system concept variants and module configurations based on different cell types, leveraging FEV's extensive cell database containing data on over 1,500 commercially available cells.

In the subsequent phase, the tool enables a cost assessment for each technical concept, allowing for the identification of the most suitable solution that balances performance, technology, and business case requirements.



5
FEV's BATT.code tool to determine the best fitting battery family architecture.

For further FEV Signature Solutions see pages 48-49

Conclusion

REEVs and long-range PHEVs are not merely transitional technologies; they are strategic enablers of electrification. They offer a practical solution for users who are not yet ready or able to switch to BEVs, while still delivering significant emissions reductions.

With the right cell chemistry, optimized KPIs, and intelligent system integration, REEVs can bridge the gap between today's infrastructure and tomorrow's zero-emission goals.

Defining a suitable battery platform and toolbox strategy early in the process is essential for identifying optimal trade-offs between technical and commercial targets, while also accounting for environmental and supply chain constraints.

FEV supports its customers throughout all phases of battery development, offering expertise in:

- Specialized cell scouting
- Cell characterization and qualification
- Battery platform concept development
- Design-to-cost strategies
- Detailed mechanical and electrical design, including BMS and development of AI-powered battery controls and functions
- Prototype assembly and manufacturing support
- Verification and validation processes

This comprehensive approach ensures that battery systems are not only technically robust and cost-effective, but also scalable and aligned with the specific requirements of each vehicle platform.

BY
Matthias Rudolph
rudolph_m@fev.com
Janis Vienenkötter
vienenkoetter@fev.com
Thomas Nemeth
nemeth_t@fev.com
Remi Stohr
stohr@fev.com

#7
Efficient range extension– Next-gen generators for hybrid architecture

The rapid growth of range-extended electric vehicles (REEVs), particularly in the Chinese automotive market, has led to a renewed focus on generator systems specifically designed for series hybrid architectures. Unlike battery electric vehicles (BEVs), which rely solely on stored electrical energy, REEVs incorporate internal combustion engines (ICEs) that generate electricity to extend driving range. This configuration allows for smaller battery packs, mitigates range anxiety, and is a key enabler for additional use cases such as long-distance trailer towing. European manufacturers, having invested heavily in BEV platforms in recent years, are now also exploring REEVs as modular add-ons.

Chinese OEMs have taken the lead in REEV development, often featuring compact ICEs optimized for high efficiency within narrow operating areas. In Chinese REEVs, the generator set (genset) is typically based on a 4-cylinder, 1.5-liter ICE. Because of the narrow operating area, and despite their high efficiency, these engines can be rather low cost, as they allow expensive technological features that are typically necessary for transient operation and low-end torque to be omitted. Just like the engines, the generators and inverters for REEV applications should be designed for the specific requirements of REEV applications. This article explores these specific requirements for generators and inverters and examines the integration challenges, particularly with respect to the mechanical interface of ICE and generator.

Mechanical interface of combustion engine and electric machine

The mechanical connection between the ICE and the generator defines the operating points of the generator in terms of torque and speed, which are two key parameters of motor design. Two connection types are commonly employed: direct and geared.

In a direct connection, the electric machine (EM) is coupled directly to the ICE crankshaft without any gearset. This configuration limits the EM's rotational speed to that of the ICE, typically below 5,000 rpm. While this approach simplifies packaging and reduces mechanical complexity, it restricts the EM's design freedom and will result in unusually low EM design speeds compared to current automotive traction drives, which typically reach maximum speeds between 12,000 rpm and more than 30,000 rpm for some recent developments.

Alternatively, a transmission ratio between the ICE and EM allows the EM to operate at higher speeds, which increases the EM's power density and enables EM downsizing. However, the transmission system also consumes package space and introduces weight, parasitic losses, and complexity to the system, making it mandatory to carefully evaluate the pros and cons of such a connection.

Six different arrangements have been investigated:

	Option 1 Direct connection ICE – EM	Option 2 Direct connection with damper ICE –\/\/– EM	Option 3 High speed EM with PGS ICE – PGS – EM	Option 4 High speed EM with PGS & damper ICE –\/\/– PGS – EM	Option 5 High speed EM with gearset ICE – Gears – EM	Option 6 High speed EM with gearset & damper ICE –\/\/– Gears – EM
Durability & reliability	+	+ +	−	+	−	+
NVH performance	+	+	− −	•	− −	•
Packaging length (X-direction)	+	•	•	−	•	−
Packaging diameter (Z- and Y-direction)	+	+	+	+	−	−
System efficiency	+	+	+	+	+	+
Costs	+	•	−	− −	−	− −
Weight	+	•	+	•	•	−

+ + Very beneficial + Beneficial • Neutral − Negative − − Very negative

Besides the direct connection, geared variants with a planetary gearset or an offset configuration have been investigated. Planetary gearsets are often favored for their compact coaxial layout. They offer good packaging efficiency but can be mechanically complex and prone to noise generation. Off-axis gearsets, while simpler and easier to optimize for good noise, vibration, and harshness (NVH) behavior, require more axial space and may complicate integration into conventional engine bays. However, for special packaging environments, an off-axis gearset is frequently used to reach more distant package locations of the generator.

All of the above-mentioned systems can be combined with a damper, such as a simple torsional damper or a dual mass flywheel. When a damper is included between the ICE and EM in combination with a gearset, it helps mitigate gear rattle and reduces torsional vibrations of the rotor. Omitting the damper simplifies the design and reduces cost but increases the risk of NVH issues and mechanical wear.

Ultimately, the choice between direct and geared connections involves trade-offs between packaging constraints, EM efficiency, NVH performance, and overall system cost. Geared systems offer more design freedom for the electrical components but demand careful integration and validation. Based on FEV's in-depth development experience with many different arrangements, a geared system is hardly viable in terms of NVH without an effective damper system to accompany it. Alternatives such as special gear coatings or pre-loaded split gears have not been sufficient for the demanding NVH requirements. A well-designed direct connection is robust, cost-effective, and can result in highly competitive overall systems.

Generator-specific electric-machine requirements

Generators in REEVs differ significantly from traction motors in terms of operational demands and design priorities. Where efficiency is of utmost importance for traction drives, low cost often takes greater priority with REEV generators due to their low operating time over a vehicle life and the limited impact of small efficiency deficits on overall energy consumption.

Unlike traction motors, which must deliver high torque across a wide speed range and support transient, as well as high speed operation, generator EMs operate under more predictable and constrained conditions. Low-speed operation is generally unnecessary, except during engine start-up. In configurations without a speed-increasing gear ratio, maximum speed is also limited, typically capped below 5,000 rpm.

Power requirements are modest, often below 100 kW, with a strong emphasis on continuous power output, especially for long-distance highway driving scenarios. This enables downsizing of the EM as long as effective cooling strategies are employed.

Packaging constraints also influence motor geometry. When working with conventional inline engines, the crank-train envelope will result in an ICE interface diameter at rear face of block of approximately 300 mm. Motors of short axial length but rather large diameter - often referred to as "pancake" designs - are preferred. These geometries facilitate coaxial integration and reduce overall system volume.

Resulting influence on motor topology

Currently, permanent magnet synchronous machines (PMSMs) are the preferred motor type for REEV generator applications due to their high efficiency and compact size, and because availability of rare earth materials is no major issue in China.

Safety and efficiency concerns under dragged condition are less relevant in generator applications, further supporting the use of PMSMs. Unlike traction motors, PMSMs in REEVs do not require extended field weakening capabilities due to lower maximum speeds, simplifying control and reducing inverter complexity.

Among PMSM variants, designs with short axial length are of particular interest. Advanced topologies such as axial flux and dual rotor radial flux machines have larger diameters but short length and do provide their power at low speeds and high torques, an ideal match for range extenders without gearsets. Axial flux machines have already made their way into first series applications in China, and more widespread use of these topologies is expected for the future.

The generator unit shown on page 44 is based on a dual-rotor radial flux electric machine technology which has been co-developed by DeepDrive and FEV and offers highly attractive properties in terms of efficiency, packaging, and costs. It features a fully integrated 800 V silicon carbide (SiC) inverter; and with 120 kW of continuous power, it can cover even the most demanding applications.

As an alternative to rare-earth-based PMSMs, ferrite-based PMSMs are gaining attention for their cost-effectiveness and supply chain resilience. Although ferrite magnets offer lower energy density than rare-earth alternatives, careful magnetic design can compensate for performance limitations. With powers below 100 kW and low cost as one major criterion, ferrite magnets are an interesting option for generators, also in combination with advanced topologies.

Inverter design considerations

One major parameter for inverter design is the voltage level of the battery. Currently, 400 V and 800 V systems are found in the market, with a trend towards 800 V for increased efficiency and charging speeds. However, as charging speed is less relevant for REEVs due to the presence of the range extender, manufacturers who offer separate BEV and REEV models may use different voltage architectures for each (for example, 800 V for BEVs and 400 V for REEVs) to achieve greater cost efficiencies. If a vehicle model is offered both as a BEV and as a REEV, the voltage level typically remains common across both versions to leverage synergies.

As REEV applications focus on continuous power and often lower e-machine speeds, the advantages of SiC power modules, such as efficiency at part-load and high switching frequencies, are not as relevant as they are for traction applications. IGBTs with SiC diodes may therefore be an attractive option, especially for 400 V systems.

Overall, the lower power level of generators compared to traction drives results in lower currents and consequently in smaller inverters. Thermal performance must be aligned with steady-state operation rather than transient peaks. As a generator is less safety-critical (no risk of significant overspeed, no risk of extended dragging, no risk of blocking the wheels), simpler safety concepts may be implemented.

Thermal and system-level considerations

Thermal management is a critical aspect of generator system design, not only because of the high continuous powers, but also because of the additional thermal load from the combustion engine. Liquid cooling is almost always required, and electric machines are either water- or oil-cooled. Cooling strategies must be integrated into the overall vehicle thermal architecture, ensuring consistent performance across all ambient conditions.

System-level co-design is essential to achieve optimal performance. The EM, inverter, and control logic must be developed in tandem, ensuring that each subsystem complements the others. This approach avoids over-specification, reduces cost, and enhances performance.

Conclusion

Dedicated generators for range-extended electric vehicles represent an increasingly important domain within hybrid powertrain engineering. By tailoring motor topology, inverter characteristics, and the ICE-EM interface to the demands of REEV applications, engineers can deliver efficient, compact, and cost-effective solutions.

BY
Dr. Gereon Hellenbroich
hellenbroich@fev.com

Signature Solutions

ONLY AT FEV!

#8 SPECTRUM regularly presents a selection of unique FEV solutions

Further FEV Signature Solutions:
fev.group/solutions

GenAISys – Redefining propulsion systems design

Developing tomorrow's propulsion systems means facing an ever-growing challenge: complexity. Countless hardware options, control strategies, and regulatory demands create a multi-dimensional design space that is hard to manage with conventional methods. FEV's GenAISys is an AI-integrated system development methodology that changes the game.

With GenAISys, FEV provides the only end-to-end AI-enabled development framework that seamlessly connects requirement analysis, use-case definition, architecture recommendations, system sizing, hardware parametrization, and control strategy integration – all in a fully virtualized environment. The result: a single, intelligent development loop that ensures the right system design, in the right architecture, at the right size, with the right controls – from the very beginning.

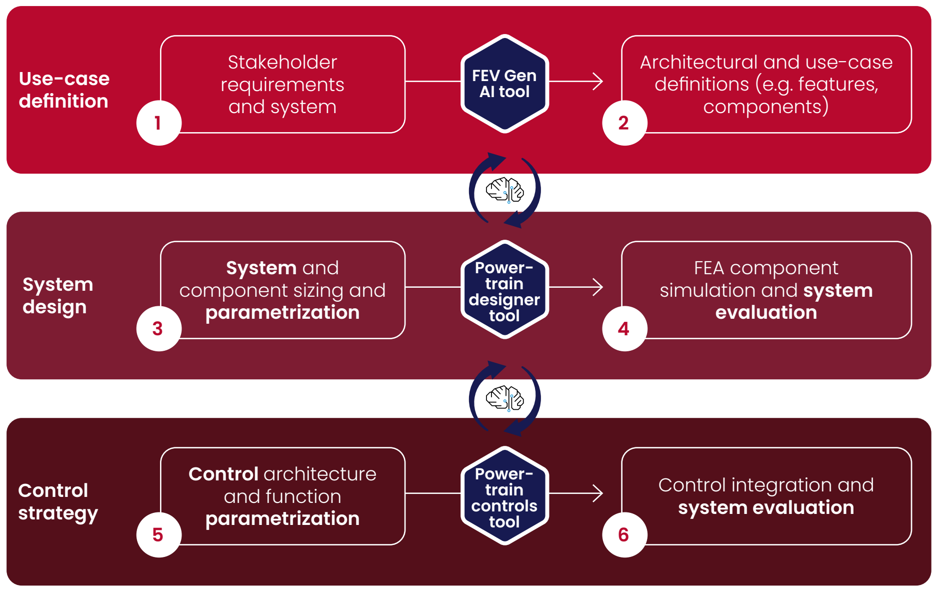
Unique customer benefits:

- Faster development – automated, AI-driven workflows drastically shorten project timelines by avoiding late design iterations.
- Lower cost – early virtualization and "right-sizing" prevent over-engineering and reduce testing effort.
- Better performance – holistic optimization balances efficiency, durability, and driving experience.
- Future-proof integration – GenAISys fits into existing standards such as A-SPICE, and supports cross-industry applications (automotive, aerospace, energy, rail).

Unlike traditional tools or isolated AI approaches, GenAISys is holistic, proven, and unique in the market. It combines decades of system expertise with advanced AI methods to deliver validated design and control strategies that no competitor can match.

With GenAISys, FEV enables its customers to master complexity, reduce risk, and unlock new efficiency potential – establishing it as a true differentiator for the future of propulsion development.

AI-integrated System Development Methodology

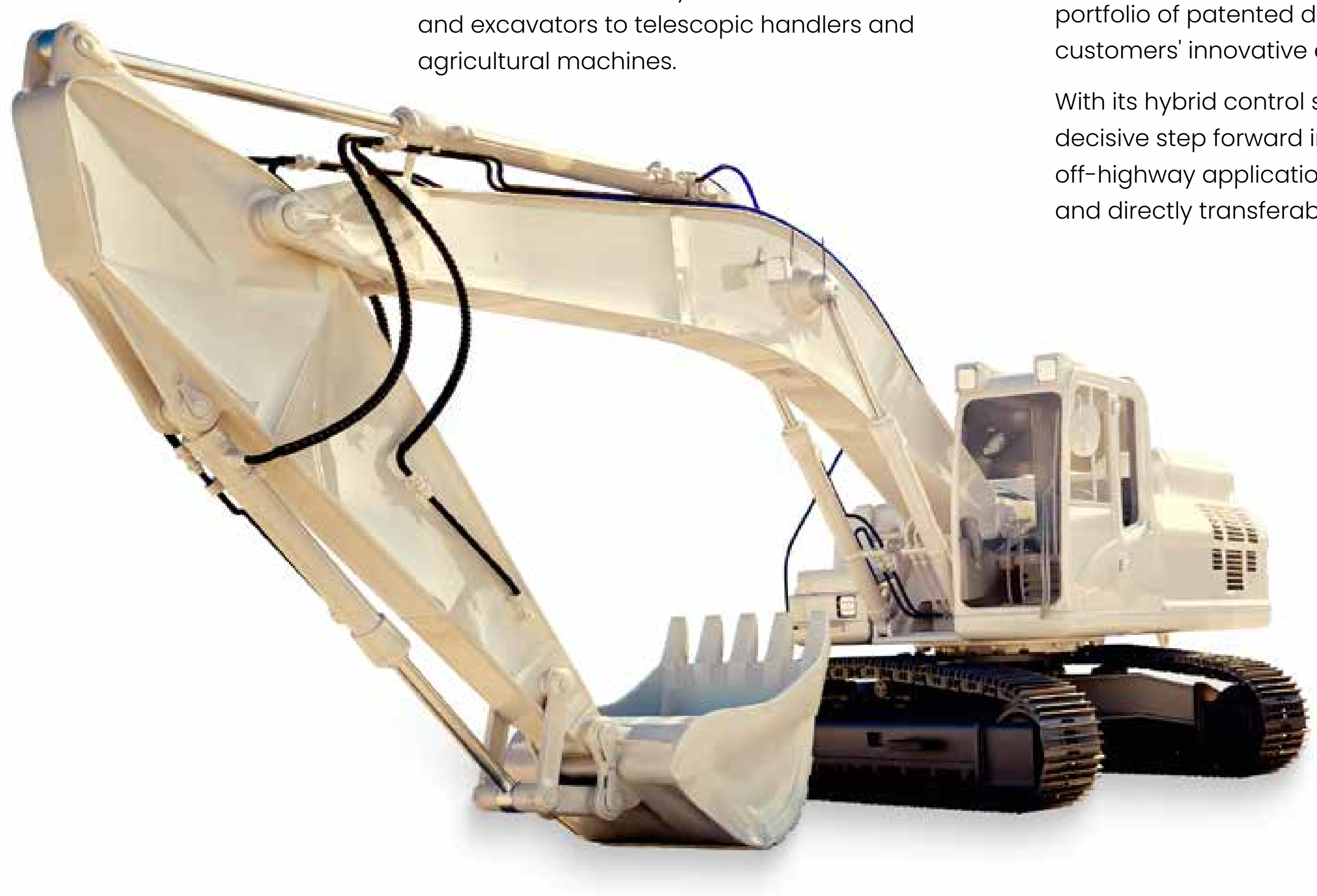


FEA: Finite Element Analysis.

Hybrid controls for non-road machinery

The transformation toward climate-neutral drives is no longer limited to road traffic. Construction, agricultural, and other non-road mobile machinery (NRMM) are also faced with the task of reducing emissions while ensuring maximum reliability under tough operating conditions and in remote areas. With its Hybrid Control Unit (HCU), FEV provides a proven software solution that is specifically tailored to the requirements of this industry.

What makes it unique is that it is based on a function library for hybrid drives that has been extensively tested throughout the automotive industry and used repeatedly in series production. FEV has specifically expanded this library to include functions for off-highway applications, allowing even complex hybrid topologies to be controlled efficiently – from wheel loaders and excavators to telescopic handlers and agricultural machines.



Customers benefit from short project lead times, as demonstrators can be put into operation quickly and new concepts can be validated immediately. The software covers all core areas: from diagnostics, machine coordination, and torque management to predictive energy and work control. Transitions between operating states are also intelligently controlled, taking into account efficiency, driving comfort, and NVH optimization as well as more intelligent machine control. Thus, FEV creates the basis for maximum uptime in daily use.

In addition to preconfigured function packages, the company offers flexible licensing (for example one-time models) and customer-specific adaptations – for both prototypes and series applications. A "white box" approach is available as an option, allowing manufacturers to use the solution as a basis for their own further developments. This is complemented by a broad portfolio of patented developments that secures customers' innovative edge.

With its hybrid control software, FEV is taking a decisive step forward in the decarbonization of off-highway applications – practical, scalable, and directly transferable to real machines.

7,000 FEV experts globally

FEV Europe GmbH
Neuenhofstraße 181
52078 Aachen
Germany
P +49 241 5689-0
marketing@fev.com

FEV North America, Inc.
4554 Glenmeade Lane
Auburn Hills
MI 48326-1766 · USA
P +1 248 373-6000
marketing@fev-et.com

FEV China Co., Ltd.
168 Huada Road
Yanjiao High-Tech Zone
065201 Sanhe City,
Langfang Hebei Province
China
P +86 10 80 84 11 68
fev-china@fev.com

FEV India Pvt, Ltd.
Technical Center India
A-21, Talegaon MIDC
Tal Maval District
Pune 410 507 · India
P +91 2114 666-000
fev-india@fev.com

RECYCLED
Paper made from recycled material
FSC® C106855

SPECTRUM #81
Issue 02/2025

Editorial
Marius Strasdat

Layout
Verena Mainz

FEV Global Marketing
& Communications

Reader service
Would you like to receive future issues of SPECTRUM, or has your address changed? Please send your name, company, and mailing address to: **spectrum@fev.com**

company/fev-group

feel evolution

fev.com