ENGINSOFT

futurities

The Simulation Based Engineering & Sciences Magazine

Year 21
03
Autumn
2024

SPOTLIGHT

Sciences that matter

- Editor's Note

The *Futurities* autumn issue **Spotlight** focuses on the topic of Simulation Based Engineering Science (SBES), a topic and theme that personifies more than any other EnginSoft's approach to business, both for its clients, and in the projects in which it is involved. This edition's **Spotlight** has again been written by veteran engineer and long-time EnginSoft collaborator, Livio Furlan. In it he traces SBES from its earliest beginnings right through to discussing its potential contribution to today's multi-faceted challenges and goes on to provide a number of application cases as examples of situations in which SBES has successfully been used to contrive solutions that would have been unthinkably difficult to achieve a few years ago before the rapid evolution of technology and computing power that now enables SBES to be artfully and knowledgeably applied to these problems.

The **Technology Transfer** section of this edition contains two articles. The article from Cybernet discusses the use of the discrete element method-finite element method (DEM-FEM) coupling function in Multiscale.Sim to optimize the manufacturing conditions of the powdered raw materials used to product all-solid-state batteries to increase the performance of these devices for use in electric transport. The other article, contributed by Magna, continues the theme of electric motors, specifically the rotor of an e-motor. In this case, the topic of plastic deformation under load is investigated, since it significantly affects the service life of a component.

This edition's **Know-how** section has an article contributed by DANA that investigates a methodology to generate data-based road profiles to allow engineers to predict vehicle behaviour more accurately during simulation by reproducing real road and off-road conditions in a data-driven approach. An article from Tecno Logica's examines the use of digital simulation models for flexible factory design and reconfiguration to allow manufacturers to cope with shorter product lifecycles and increased demand for customization. The third article in this section is a further contribution from Endurica that builds on the article in the summer issue in exploring fatigue analysis of rubber and how it differs from metal fatigue. Specifically, linear superposition, widely used in metal fatigue analysis to generate stress-strain history from road loads, is not effective in rubber fatigue analysis due to rubber's nonlinear material behaviour and kinematics and the possibility of nonlinear contact.

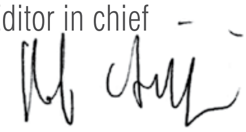
Our **Research and Innovation** section presents the preliminary results of the DIMO (DIgital MOulding) project which focuses on the challenges of better understanding production mechanisms, optimizing production processes and reducing waste in plastic injection moulding, a technique widely used in industrial manufacturing processes to accurately and efficiently produce plastic objects with complex geometries.

This issue is rounded out by a **Product Peek** into Capvidia's suite of QIF (Quality Information Framework)-based tools for model-based workflows. QIF is an ISO CAD-neutral format designed specifically for model-based workflows to provide the digital thread for enabling traceability, collaboration, and automation from a single source of truth in manufacturing. Capvidia software works with native CAD and QIF to provide seamless interoperability from design to inspection to manufacturing and beyond while integrating AI and big data to leverage insights from model-based workflows to realize the full potential of model-based manufacturing.

In closing, I am very pleased to announce that AnteMotion has signed a cooperation agreement with Ansys that will see the use of AnteMotion's two flagship products, MAZE and ProceduralWorlds, to complement Ansys' ADAS technologies and bring a new level of automation and precision to simulation environments for autonomous vehicles. The partnership will facilitate simulation for ADAS/AV engineers in the design, testing and validation of autonomous systems. MAZE and Procedural Worlds enable the automatic creation of OpenDRIVE and simulation-ready 3D-environments for the Ansys AVxcelerate suite both for physical Lidar radar and for camera sensor simulation. Please contact our team for further information.

Stefano Odorizzi

Editor in chief



"SBES has successfully been used to contrive solutions that would have been unthinkably difficult to achieve a few years ago

Futurities
Year 21 n°3 - Autumn 2024

To receive a free copy of the next magazine, please contact our Marketing office at: marketing@enginsoft.com

EnginSoft S.p.A.
24126 BERGAMO c/o Parco Scientifico Tecnologico
Kilometro Rosso - Edificio A1, Via Stezzano 87 • Tel. +39 035 368711
50127 FIRENZE Via Panciatichi, 40 • Tel. +39 055 4376113
35129 PADOVA Via Giambellino, 7 • Tel. +39 049 7705311
72023 MESAGNE (BRINDISI) Via A. Murri, 2 - Z.I. • Tel. +39 0831 730194
38123 TRENTO fraz. Mattarello - Via della Stazione, 27 • Tel. +39 0461 915391
10133 TORINO Corso Marconi, 20 • Tel. +39 011 6525211

www.enginsoft.com
e-mail: info@enginsoft.com

Futurities is a quarterly magazine published by EnginSoft SpA

COMPANY INTERESTS
EnginSoft GmbH - Germany
EnginSoft UK - United Kingdom
EnginSoft Turkey - Turkey
EnginSoft USA
E-SOFT France
Particleworks Europe
www.enginsoft.com

CONSORZIO TCN www.consorziotcn.it • www.improve.it
M3E Mathematical Methods and Models for Engineering www.m3eweb.it
AnteMotion antemotion.com

ASSOCIATION INTERESTS
NAFEMS International www.nafems.it • www.nafems.org
TechNet Alliance www.technet-alliance.com

ADVERTISING
For advertising opportunities, please contact our Marketing office at: marketing@enginsoft.com

RESPONSIBLE DIRECTOR
Stefano Odorizzi

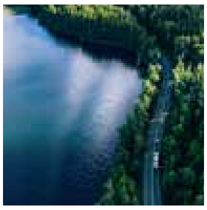
PRINTING
Grafiche Dalpiaz - Trento

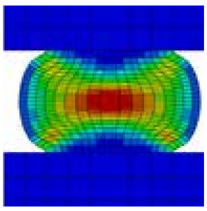
Autorizzazione del Tribunale di Trento
n° 1353 RS di data 2/4/2008

Contents

TECHNOLOGY TRANSFER

KNOW-HOW





SPOTLIGHT

RESEARCH & INNOVATION

PRODUCT PEEKS

NEWS & TRENDS

SPOTLIGHT

Making the case for wider adoption of Simulation Based Engineering Sciences (SBES)

A recent research report produced by McKinsey & Company in collaboration with NAFEMS states that "Simulation is … going through a period of significant technological disruption that is creating new opportunities and challenges for users in multiple areas. Those disruptions are affecting almost every aspect of the simulation value chain." [1]

Another more specific report, published in 2006, also noted that simulation and in particular simulation-based engineering science, has and will continue to play a critical role in much broader contexts. The US National Science Foundation (NSF)' report on SBES stated that "SBES has the potential to deliver designs that are optimized for cost performance and their total impact on the environment (from production to disposal or recycling), all within a short design cycle." [2]

With increasing political and public pressure for more sustainable technologies and answers to the most pressing challenges of the modern world, such as climate change, public health and pandemics, and pollution, the demand for this potential is likely to grow exponentially in the future. At the time of its publication, the report noted that "…we will have to revamp the fundamental ways we conceive of scientific and engineering methodologies… and…overcome…obstacles … in linking highly disparate length and time scales…" [2]

In our **Spotlight** article, written by Livio Furlan, a veteran engineer and long-time EnginSoft collaborator, we discover that the need to rethink these fundamentals remains. Furthermore, Furlan's perspective, as seen in his article, agrees with the NSF report's statement that "… if the engineering sciences are to realize the full benefits of the rapid advances in computing technologies, we must somehow integrate the knowledge and discoveries of mathematics, computer science, engineering, and the domain sciences. We also need to recognize that SBES is located at the intersection of those disciplines. In that sense, we can think of SBES as a super-discipline."

Read the **Spotlight** article to find out more about this super discipline, its state of development, and its application domains with case studies, in more detail.

[1] A. F. Ragani, P. Stein et al, "Unveiling the next frontier of engineering simulation" by McKinsey & Company in collaboration with NAFEMS, 21 June 2023. [Online]. Available: www.mckinsey.com/capabilities/operations/our-insights/unveiling-the-next-frontier-of-engineering-simulation, accessed 17 September 2024.

[2] Simulation Based Engineering Science, Revolutionizing Engineering Science through Simulation, final report of the National Science Foundation Blue Ribbon Panel on Simulation-Based Engineering Science, National Science Foundation, Washington D.C., USA, May 2006. [Online]. Available: www.nsf.gov/pubs/reports/sbes_final_report.pdf, accessed 17 September 2024.

Simulation-Based Engineering Science: a heritage to cherish and invest in for a sustainable future

by Livio Furlan
EnginSoft

Numerical simulation, also known as mathematical modelling, refers to the use of computer models to study the behaviour of engineering systems (even complex ones) and to predict physical events.

A significant and broad pool/spectrum of scientific, mathematical, computational, and engineering knowledge and methodologies has been used to develop numerical simulation, of which the engineering part is one of the most frequented applications/uses, although the methodologies are valid for all applied sciences.

Computer simulation is an extension of theoretical science in that it is based on mathematical models that attempt to characterize the physical predictions or consequences of scientific theories. However, simulation can become so much more because it can be used directly to explore new theories and to design new experiments to test those theories. Simulation is a powerful alternative to experimental science and observational techniques in cases where phenomena cannot be observed or where measurements are impractical or too costly.

Simulation-Based Engineering Science (SBES), defined as the discipline that provides the scientific and mathematical basis for the simulation of engineering systems, is embedded in the context of numerical simulation. These engineering systems range from microelectronic devices to automobiles, from coffee machines to photovoltaic systems, from electro-medical devices to remote surgery equipment, from aircraft to oilfield infrastructure and urban agglomerations (villages, towns, cities).

This means that SBES combines knowledge and techniques from traditional engineering disciplines – electrical/electronic, mechanical, civil, chemical, aerospace, nuclear, biomedical and materials engineering – with knowledge and techniques from fields such as computer science, mathematics, physics, medical and social sciences. As a result, SBES will enable engineers to better predict and optimize systems affecting many aspects of daily life, work, environment, safety, health, and the design/engineering/production/use processes of everyday products. SBES is therefore critical to advances in biomedicine, nanotechnology, microelectronics, energy and environmental sciences, and the use of advanced materials.

Although the use of computer simulation in engineering science began over 70 years ago (in this sense, SBES is a well-known method from

the past), it is only in the last 20 to 25 years that scientific theories and simulation technologies have had a tremendous impact on all areas of engineering. This remarkable change has been driven largely by developments in the fields of computer science and information technology, and by rapid advances in electronic processors and computer systems.
And it is precisely because of these developments (which have also affected interaction and graphical visualization tools to the extent that the SBES approach is essential) that solutions are gradually being found to problems of multiscale and multiphysics modelling, real-time integration of simulation with measurement, model validation and verification, and the management and processing of big data.

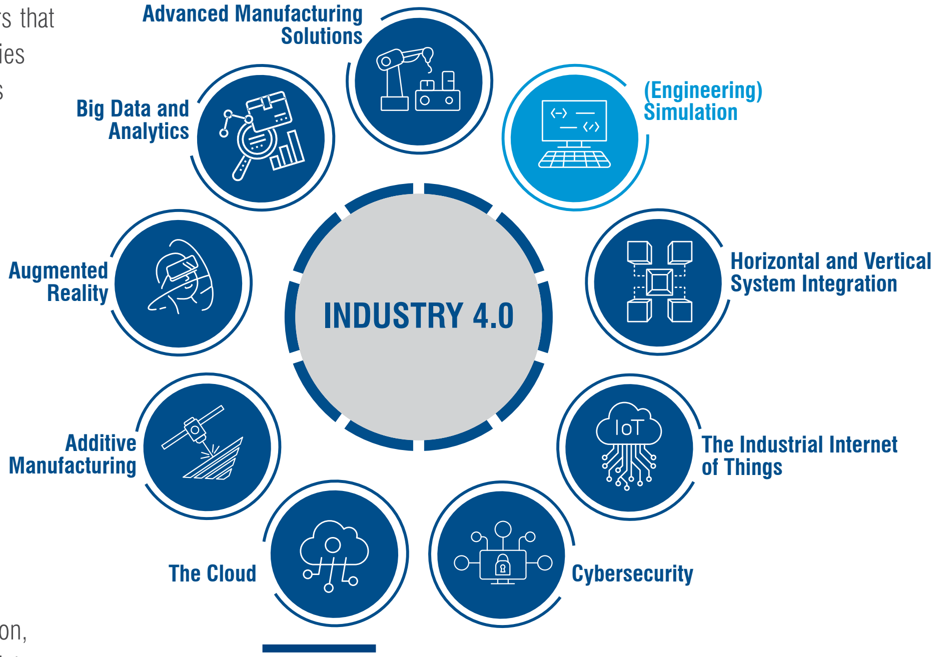


Fig. 1. The nine industry 4.0-enabling technologies.

Industry 4.0 speaks the language of SBES

In industry, the signal for this "revolution" was (and is) nurtured by the European Industry 4.0 initiative, which identified nine core technologies capable of innovating processes, products, and services in all economic sectors of human activity, thereby increasing the value of the production system chain.

The nine enabling technologies (see Fig.1) are briefly described below:

- **Advanced manufacturing solutions,** the main component of which is “collaborative robotics” also known as cobots, that is, humans and robots sharing a workspace safely and efficiently thanks to the artificial intelligence of machines that sense the environment around them.
- **Additive manufacturing,** a technology that creates a product by depositing material in layers, as opposed to traditional manufacturing, which creates products by removing material from a rough workpiece.
- **Augmented Reality,** which integrates additional information in any form (text, graphics, sound, etc.) into the physical environment in real time, with the aim of streamlining the user's activities and enhancing their interactions with the real world.
- **(Engineering) Simulation,** now widely used in design and production processes to analyse and test controlled virtual models of real products to be produced by specific processes, with the aim of reducing installation times, increasing product quality and establishing/improving product functionality.
- **Horizontal/vertical integration,** which uses networked technologies to analyse large volumes of data and creates open systems to share them in real time with all members of the value chain, from suppliers to end customers (vertical integration), to define common working standards and objectives, and with the business units (horizontal integration) that contribute to defining a product's life cycle.
- **The Industrial Internet** is the term used to describe the application of technological components and devices (the Internet of Things or IoT) inside physical items, such as machines, making them "intelligent" and enabling them to communicate and interact with one another and with the surrounding world via the Internet and a standardized language.
- **The cloud** is a shared, flexible, and open IT infrastructure for the sharing of data, information, and applications across the Internet beyond the boundaries of the enterprise, to support the transformation of business models with the necessary capacity.
- **Cybersecurity,** the set of technologies (processes, products, and standards) designed to ensure that, in today’s fully connected world, an organization’s information systems are protected from attacks that could result in the loss or compromise of business-critical data and information.
- **Big Data and Analytics** is the process of collecting and analysing (with appropriate management tools) large data sets containing a variety of data types from many different sources to uncover hidden patterns, unknown correlations, trends and preferences to enable organizations to make better decisions in every business process, from finance, marketing and sales to supply chain, design, production and maintenance.

Of these nine Industry 4.0-enabling technologies, engineering simulation can be seen as the key enabler of the growth of the other functions because of mutual interactions that enables production to move from single automated cells to fully integrated (and automated) organizations capable of communicating with each other, with consequent improvements in flexibility, speed, productivity and quality.

The fact that engineering simulation has become central to the enabling technologies of the Fourth Industrial Revolution is demonstrated by the sharp acceleration in the adoption of SBES methodologies.

However, this increased use is accompanied by the complex dynamics typical of change that depends on new orientations and new metrics. Faced with such a highly innovative approach, the growth prospects are indeed enormous, but companies need to generate (and support) the appropriate skills to adapt the path to their own reality without losing valuable opportunities.

One thing is certain, however: there is an overwhelming consensus that numerical simulation is fundamental to the advancement of engineering and science. Rarely have so many independent studies from experts in different disciplines agreed that computational simulation has had and will continue to have an enormous impact on all areas of engineering, scientific discovery, and efforts to solve major societal problems.
Therefore, if these advances are to be taken seriously and incorporated into everyday social and industrial life, further efforts are needed in the field of research, in the training of academic institutions that produce new generations of engineers, technicians and scientists, and at the level of corporate culture, which must rethink the way it views SBES, recognizing it as an asset rather than as a product/commodity to obtain other products or other goods.

Furthermore, if we have a look at the simulation engineering market, although dominated by general-purpose technologies promoted by large system suppliers, it receives a significant growth contribution from so-called “vertical” products/sectors, i.e. applications that enable the solution of specific/specialized problems that require specific skills and a strong determination to find the best solution. EnginSoft excels here, especially when it comes to the real and measurable added value for the customer.

EnginSoft and SBES

To put it frankly, EnginSoft has been following the evolution of the disciplines related to SBES since the first pioneering applications in the late 1970s/early 1980s, often anticipating their industrial exploitation, in the conviction (confirmed by today’s scenario) that the potential of the virtual approach went far beyond what was gradually being achieved in production contexts – at that time often only experimentally or as research.

The company's success is the result of this longstanding conviction, but also of the skills of its employees, acquired in the course of a journey together with the producers of innovative numeric technology and with customers who have increasingly relied on EnginSoft to help solve their problems and challenges.

EnginSoft's mission has therefore always been to provide cutting-edge solutions and innovative technological services aimed at improving the competitiveness and productivity of engineers and companies involved in design and production, as well as increasing the quality, safety and efficiency of processes and products.

SBES by definition encompasses areas such as Virtual Prototyping (understood as the creation of a virtual prototype of a product and/or structure) and Computer Aided Engineering (CAE), which includes FEM (Finite Element Method), CFD (Computational Fluid Dynamic), MBD (Multi-Body Dynamics simulation), crash/impact simulations, as well as multiphysics and thermo-fluid-structure interaction issues.

Validation and verification

The primary and ultimate goal of numerical simulation lies in predicting physical events or anticipating how engineered systems will behave.

Prediction is the key to engineering design, the foundation for scientific discovery, and the primary means by which computer science is able to move beyond the "realms" of experimentation and physical observation.

It is therefore natural to ask whether specific decisions can be based on the expected outcome of an event. In other words:

- How accurate are the predictions of a computer simulation?
- What level of confidence can be assigned to a predicted outcome, given what is known about the physical system and the model used to describe it?

Science, technology and, in a different way, philosophy (understood here as the activity of thinking that guides the criteria for the determination and quantification of reliability and — why not? — ethics of computer simulations and their predictions) have become known as the V&V (Validation and Verification) process, the methods of which are fundamental to the success and progress of SBES.

To understand the objectives of the V&V process, it is worth analysing how simulation begins.

The analyst (or engineer or scientist) implements/designs/realizes an appropriate mathematical model based, on the one hand, on the conceptual understanding of certain physical events of interest (including social events) and, on the other hand, on the scientific theories that explain the real phenomena or engineering systems to be studied.

The mathematical model is a set of mathematical “constructions”, equations, inequalities, constraints, etc. that represent abstractions of reality and are dictated by the theories that characterize the event or describe how a system behaves. The analyst then develops a computational model. This is a discretized approximation of the mathematical model developed to describe the event, for the purpose of implementing the analysis on a computer.

Validation is the stage of V&V that determines how accurately the mathematical model describes the actual physical event. Verification, in contrast, is the stage that determines the accuracy with which the computer model represents the mathematical model.

Simply put, validation asks: "Are the right equations solved?" or “Has a product/system been built with the right requirements?” whereas verification asks: “Have the equations been solved correctly?” or “Has the product/system been correctly implemented?”

A trivial example of a V&V process concerns the (numerical) solution of the equation:

$$M\,\ddot{x}(t)+C(\,x)^{\cdot}(t)+K\,x(t)=F(t)$$

which governs the dynamic behaviour of a system that is subjected to a set of forces as a function of time.

Validating the numerical model means (for example) fine-tuning the distribution of concentrated and/or distributed masses so that it corresponds to the real one, together with the distribution of damping and stiffness. (i.e. equations written in terms that are consistent with the phenomenon to be simulated/analysed).

On the other hand, again referring to the example, verification consists of ensuring that appropriate methods for solving the differential equations (e.g. Newmark's time integration method for linear transient response systems) are applied to correctly solve the problem.

Many aspects of V&V remain in the grey area between the philosophy of science, the theory of subjective choice, mathematics, and physics. The philosopher of science Karl Popper noted that a scientific theory cannot be validated, it can only be invalidated. Therefore, the mathematical model of a physical event as expressed in a theory can never be validated in the strict sense, it can only be invalidated.

To a certain extent, therefore, all validation processes are based on a pre-established set of acceptance criteria. Consequently, the analyst (or engineer or scientist) judges whether the model is invalid in the light of physical observations, experiments, and criteria. He/she (analyst/engineer/scientist), combining in-depth expertise with analytical skills, generates insights and recognizes/identifies patterns useful for the validation process itself.

The verification process, on the other hand, is already more clearly defined since it is based on mathematical and computational aspects. It involves the use of software engineering protocols, error detection and control, scientific programming methods and, most importantly, a posteriori error estimation.

Ultimately, the most "confounding" ("confounder" in the statistical sense) aspect of the V&V process has to do with the uncertainty in the data that characterizes the robustness of the mathematical models used to represent phenomena.

In some cases, the parameters that define and/or support the models are determined by observations, laboratory tests and field measurements. However, the measured values of these parameters vary from sample to sample or from observation to observation.

In addition, there may be ambiguities or inaccuracies due to uncontrollable factors (so-called noise) or calibration errors in the experimental equipment used to obtain the data. Moreover, some phenomena have little quantitative information or an incomplete or approximate understanding of the physical processes governing them.

Uncertainties may thus result from the variability of the data, which in turn is due to immeasurable or unknown factors, including incomplete knowledge of the underlying physics governing or characterizing the phenomena on which the prediction studies are to be performed.

Developing reliable methodologies — algorithms, data acquisition and management procedures, appropriate software, specific theories — to quantify the uncertainty associated with computational predictions from numerical simulations is therefore one of the major challenges for advancing SBES.

The benefits of simulation and its democratization

As already mentioned, the trends defined by the Fourth Industrial Revolution have marked — and are still marking — a significant change in the way in which industrial equipment (but not only) is designed and manufactured.

Thanks to the technological advances that have been made, it is now possible to carry out numerical analyses on three-dimensional prototypes, even complex ones, considering the interaction of two or more physical phenomena.

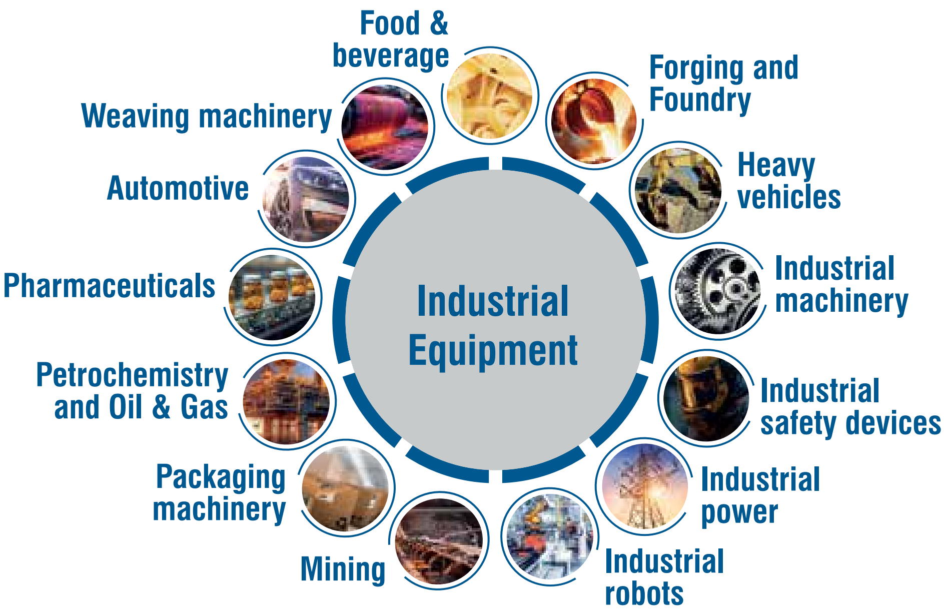
This allows the static, dynamic, fatigue, fluid dynamic and electromagnetic behaviour of a product or component to be simulated virtually at the design stage, using software solutions that are much more agile and intuitive than in the past and, above all, much easier to use.

Emerging technologies are therefore providing advanced and, in some ways, disruptive solutions that are leading to the design, manufacture and supply of sophisticated and efficient machinery and components in all sectors of the Industrial Equipment industry, some of which are graphically summarized below.

We are therefore moving into a phase of democratization of virtual prototyping. This will be accompanied by widespread availability of digital simulation solutions.

This democratization (and, of course, a conscious and appropriate use of the simulation tools available) will bring significant benefits in terms of cost reduction and, at the same time, increased reliability of the products/components designed and manufactured.

Consequently it is becoming becoming routine to be able to digitally simulate the operation of a product or machine in all its aspects and to be able to identify any critical functional and/or cost issues in advance, to make the appropriate corrections, update the model and repeat the simulation during the design phase until the prototype meets the specifications of the final product.
It is clear, therefore, that the greatest opportunity to improve product/component performance and/or reduce costs is in the early stages



of the development process based on numerical simulation, which therefore has the greatest impact when implemented early in the process itself (see Fig. 2).

If we focus on CAE, we can see that, together with CAD (Computer Aided Design), it has become indispensable in manufacturing at all levels, since the simulation software to which CAE is related makes it possible to reproduce on a digital scale what would be obtained by experimenting, sometimes destructively, on real prototypes. CAE thus enables a true virtual prototyping process, not limited to FEM analysis and structural calculations or stress analysis but covering various engineering aspects involving different physics (thermal, vibro-acoustic, fluid dynamics, electromagnetic processes), up to specific areas of predictive and preventive maintenance of products/components, as well as production management and optimization.

And it is the concepts of virtual prototyping and numerical analysis and testing that underpin the Digital Twin: a finished product with all its physical, functional, aesthetic and usability characteristics in a virtual context in which it can be "lived" and experienced, and its behaviour can be examined — even before the "physical twin" is ever manufactured.

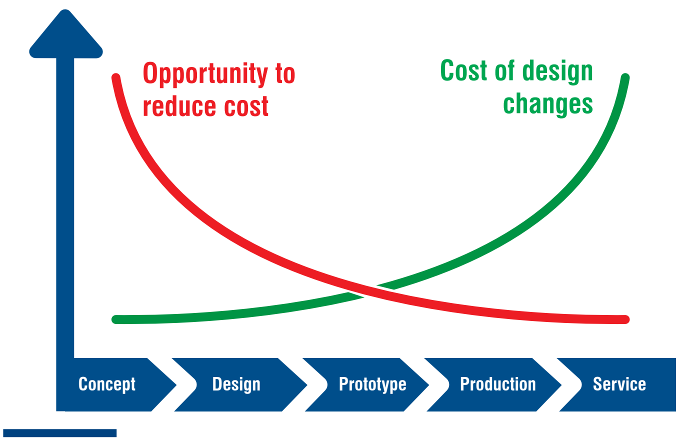


Fig. 2. Variation in the cost of a product depending on the stage of development

The act of "designing" undoubtedly involves the very act that profoundly characterizes the engineering profession: thinking ahead to imagine the product and to anticipate the steps required to calculate, realize and assess its compatibility both with users and with the physical reality that will surround this product during its use and/or operational life.

It is clear, then, that the growing democratization of (numerical) simulation cannot be separated, in terms of the reliability of the design/production process based on virtual prototyping, from a solid knowledge of the theoretical fundamentals on which the specific numerical methods of CAE are implanted.

While the "push-button" approach has made it easier to use tools such as FEA or CFD, putting these tools into the hands of a growing number of engineers and designers and significantly reducing set-up time, it has also introduced several unknowns, mainly related to the hypotheses, formulations and simplifications used to represent the underlying physical and engineering problem.

Inaccurate boundary conditions, choice of finite element type and discretization execution left to the simulation software (perhaps with a meshing phase that is not even guided, thus free to avoid what is considered to be an unnecessary waste of time), inappropriate shape functions for determining (e.g. for the mechanical-structural domain) stress gradients in regions of high geometric discontinuity: this is the way that algorithms can produce inaccurate or even incorrect results.

Democracy thus demands the ability to critically analyse decisions and choices, since it is not (merely) the automated entry of commands via keyboard or mouse (which carries the risk of reaching erroneous or hasty conclusions), but rather an awareness of the potential of numerical simulation when used with skill, wisdom and a certain willingness and curiosity to understand what lies behind the menus proposed on the screen.

A selection of application cases

It was previously noted that areas such as virtual prototyping and computer aided engineering (in its various “offshoots” — FEM, CFD, MBD, etc. — as discussed previously) are, by definition, part of SBES.

To demonstrate the essential role of engineering simulation for implementing projects to produce functional and reliable products in a sustainable manner, we will present a few reference cases, some of which were developed by combining different physics where necessary.

FEM and CFD: fine-tuning a project

This project concerned the design of butterfly valves installed in the Kargi Hydropower Plant in Türkiye. The valves were manufactured by CIB (Carpenteria Industriale Bresciana) in electro-welded steel and had a circular fluid passage section with a diameter of 4,100mm and a weight of approximately 750kN (75 tonnes) each. They were installed at the end of the hydroelectric plant's pressure pipe to interrupt as necessary the flow entering the turbines, which can reach the considerable flow rate of 84,000l/s under severe conditions.

The valve design, entirely developed by EnginSoft, found a synergy between different physics, specifically between fluid dynamics and mechanics, as well as hydraulics for managing the disc opening and closing control.

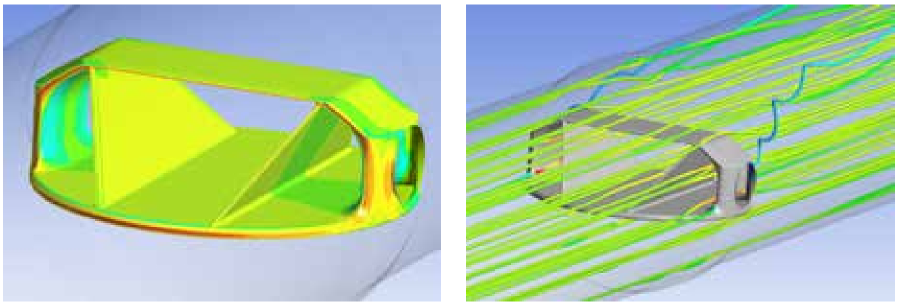


Fig. 4. Fully open disc: right) Disc pressure distribution, left) Flowlines.

The shape of the disc used to laminate the flow of water entering the turbine was designed to minimize pressure losses when the valve is open, while at the same time ensuring the necessary rigidity and tightness when the valve is closed. Obviously, these requirements are completely contradictory, but the “rational” use of numerical simulation (CFD and FEM) made it possible to satisfy both.

The morphology of the disc profile, which was specifically optimized to meet the stringent design requirements for pressure drop, required targeted interventions to achieve shape optimization (see Fig. 3) and thus obtain a highly efficient hydrodynamic profile from a raw component. The hydrodynamic behaviour was simulated by CFD for different sectioned partitions (see Fig. 4).

The structural validation of the valve body, disk and shaft was conducted by transferring the actions experienced by the disk during valve closing (see Fig. 5) from the CFD model to the FEM models (implemented on the basis of geometries obtained from preliminary calculations) and by carrying out appropriate numerical analyses capable of returning the deformations (see Fig. 6) and stress fields for subsequent functional and strength checks of the components (valve body, disk, shaft, opening and closing mechanism).

Standard EN 13445-3 (Unfired Pressure Vessels — Part 3: Design), in particular Annex C — Design by Analysis — Method based on Stress Categories, was used to develop the code verifications required to qualify the safety levels of the various components against specific objective requirements. This standard classifies the stresses calculated by elastic analysis into categories and limits them by allowable values, which are set conservatively so that plastic collapse does not occur.

Fig. 5. Pin torque versus angle in closed state.

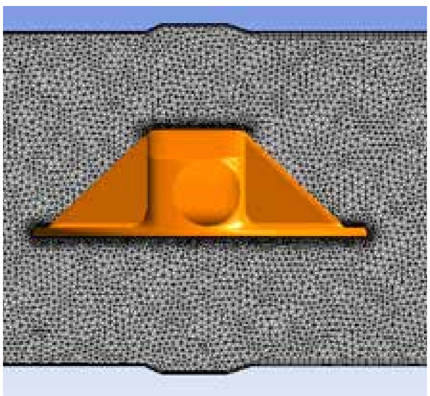
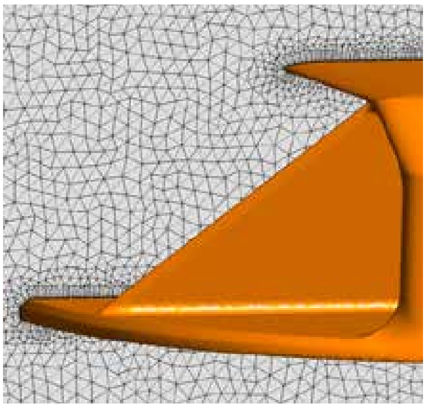


Fig. 3. CFD model for open disc pressure drop analysis.



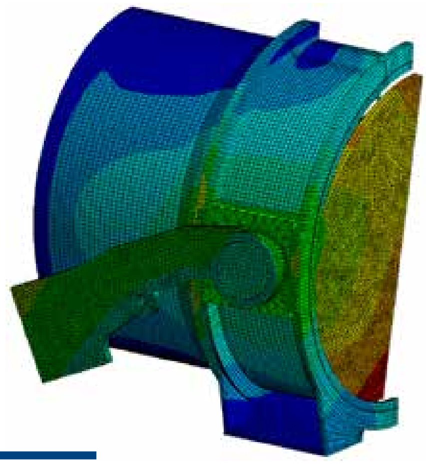


Fig. 6. Displacement range for valve in closed position.

The generous plasticity of steel

Analysis and verification methods for pressure vessels, alternative to the linear elastic approach used for the validation of the structural resistance of the valve body and disc of the project described above, refer to the lower and upper limit theorems of the plasticity limit analysis:

- **Lower limit theorem (static theorem):** The structure will not collapse or can be kept in a state close to collapse if an equilibrium moment distribution can be found that balances the applied loads and is everywhere less than or equal to the plastic moment.
- **Upper limit theorem (kinematic theorem):** The structure will collapse if there is a compatible model of a plastic failure mechanism for which the work per unit time of the external forces (external power) is equal to or greater than the work per unit time of the internal dissipations (internal power).

The lower limit theorem states that, if possible, the structure will adapt to resist the applied load. It gives the lower or safe limits of the collapse load. The maximum lower limit is the collapse load itself.

The upper limit theorem states that if a plastic failure mechanism is present, the structure will not hold. It defines the upper or unsafe limits of the collapse load. The minimum upper limit is the collapse load itself.

It is on these theoretical argu-ments (supported by ASME VIII Div. 2, Part 5 – Limit Load Analysis Method and Elastic Plastic Stress Analysis Method) that the stress analysis of a specific pressure component used in the Oil&Gas sector (see Fig. 7) was based and on which EnginSoft conducted significant calculation and verification activities.

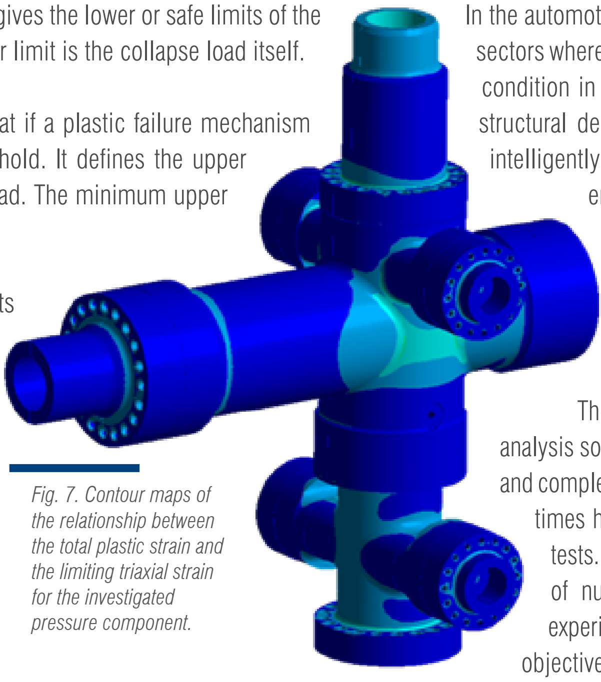


Fig. 7. Contour maps of the relationship between the total plastic strain and the limiting triaxial strain for the investigated pressure component.

Starting from the design geometries, a finite element model was implemented with an adequate degree of detail, fully considering the elasto-plastic behaviour of the material to determine the limit load condition (combination of internal pressure and external loads) beyond which the component itself would collapse by exceeding the resistance capacity defined, in addition to the non-convergence of the numerical analyses, by a very specific limit (ε_L) on the plastic deformations that accrue during the application of the design/calculation actions.

This limit is given by the following relationship:

$$\varepsilon_L = \varepsilon_{Lu}\, e^{-\left[\left(\frac{\alpha_{sl}}{1+m_2}\right)\left(\left\{\frac{\sigma_1+\sigma_2+\sigma_3}{3\,\sigma_e}\right\}-\frac{1}{3}\right)\right]}$$

where:

- ε_{Lu} is the uniaxial strain limit
- α_{sl} and m_2 are parameters as defined in ASME VIII Div. 2, Part 5
- the term $(\sigma_1+\sigma_2+\sigma_3)/3\sigma_e$ is the triaxiality index of the local stress field, where σ_1, σ_2, σ_3 are the principal stresses of the local stress field and σ_e is the equivalent von Mises stress of the local stress field.

The approach adopted (specifically the elastic plastic stress analysis method) allowed the extension of theoretical formulations (theorems) to virtual realities (numerical models) in order to find the limit beyond which the essential component analysed presents a risk of collapse, using all due safety margins and without the need to carry out a "design by experiment", which is much more costly than "design by analysis".

Impact: a numerical solution to a dynamic problem

Understanding what happens during a vehicle collision or impact is necessary for improving the safety of a vehicle and, consequently, the chances of survival for its occupants.

In the automotive sector (as well as in aeronautics and other sectors where impact phenomena constitute a dimensioning condition in the design process), the main interest of the structural designer is to create bodies/frames capable of intelligently participating in the dissipation of impact energy so that each part contributes to energy absorption, to avoid damage to people from structural collapse and, when relevant for safety and related costs, to avoid damage to the payload.

The development of kinematic and dynamic analysis software capable of producing ever more complex and complete calculation models in ever shorter calculation times has significantly improved the success of crash tests. In fact, the systematic (and competent) use of numerical simulation to predict the results of experimental tests is key to achieving the design objectives, and considerable savings in all respects.

The advantage lies precisely in predicting the actual course of the experiment without unnecessarily destroying the vehicles (or components) being analysed.

In industry, for example, the cost and development time of new designs has been significantly reduced thanks to the widespread use of numerical methods based on the finite element method, an approach that has become indispensable for creating efficient and robust models for simulating dynamic problems in structures with non-linear behaviour.

The term non-linear refers to all dynamic phenomena where structures are subjected to:

- large displacements and small deformations or large displacements and large deformations also known as geometric non-linearities.

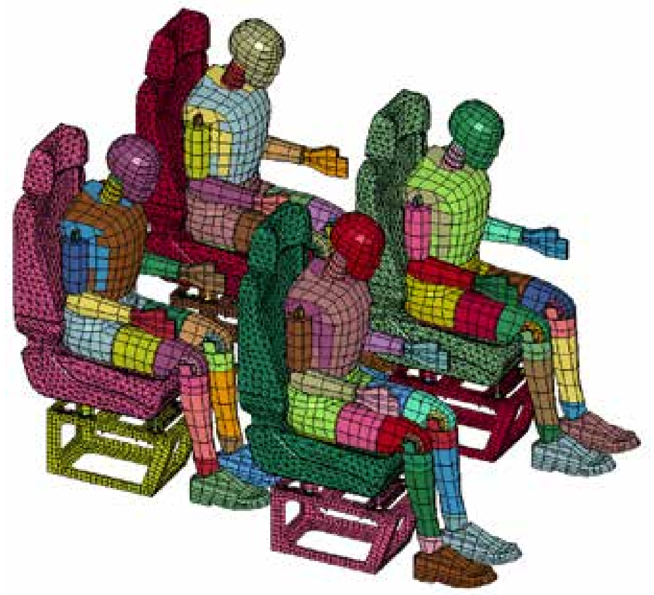


Fig. 8. Hybrid III 50th percentile male LSTC virtual dummies positioned in the cabin of a special vehicle.

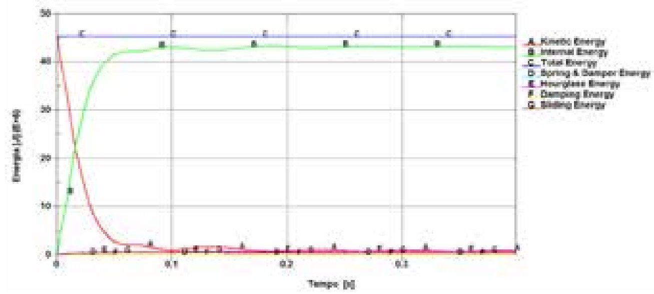


Fig. 9. Energy balance of a frontal impact on the cabin of a special vehicle.

- plasticization phenomena or material non-linearity.
- contact problems, where non-linearity is related to the nature of the external and/or internal constraints, i.e. non-linearity of contacts and self-contacts.
- the impulsive nature of the acting loads, which includes the non-linear behaviour listed above.

In (non-linear) dynamics, the equilibrium equation is obtained from the static case by adding the inertial and viscous terms; the time variable must also be considered, which involves a workload proportional to the duration of the integration over time.

The system of second-order differential equations, in matrix form, is as follows (see also the earlier report on V&V):

$$M\ddot{x}(t)+C\dot{x}(t)+Kx(t)=F(t)$$

where the various terms are familiar.

There are two possible approaches to the solution process: the implicit method and the explicit method. In the implicit formulation, a step-by-step calculation method is used in which an appropriate convergence criterion allows the analysis to continue or not, possibly reducing the time increment and depending on the accuracy of the results and the achievement of an equilibrium condition at the end of each step. This method requires the inversion of the stiffness matrix, which makes it computationally expensive for very complex models with many degrees of freedom.

The explicit method was developed as a particularly efficient computational tool for solving highly non-linear structural dynamics problems characterized by many variables (large-scale problems) but defined over very short time intervals. In this case, the analysis is not conditioned by a convergence criterion, and the time increment, which is defined at the beginning of the analysis, remains constant during the computation.

The choice of such a time step is constrained by the stability or CFL (Courant-Friedrichs-Lewy) criterion; this condition implies that a mechanical wave propagating through the material cannot move more than the smallest characteristic dimension of all mesh elements in a single time step.

In the simplest case, the maximum allowable Δt equals

$$\Delta t = \frac{d_{min}}{c} = \frac{d_{min}}{\sqrt{E/\rho}}$$

where

- d_{min} is the minimum distance between two nodes in the mesh,
- c is the velocity of sound propagation in the material,
- E is the Young's modulus of the material in which the perturbation travels,
- ρ is the density of the material through which the perturbation travels.

Therefore, the size of the finite element discretization used to implement the model will determine whether this criterion is met.

As mentioned above, fast dynamics applications are common in the automotive sector when it is necessary to simulate crash phenomena in relation to specific requirements, such as avoiding any damage to the occupants of the vehicle.

A specific case analysed by EnginSoft (among many that have been addressed and solved) concerned the study of the impact behaviour of the cabin of a special vehicle.

The aim was to evaluate both the structural resistance of the cabin itself under crash conditions (crash verification according to ECE-R29) and the preservation of the vital space of the occupants during the crash, simulated using Hybrid III 50th percentile male LSTC virtual dummies (see Fig. 8) placed inside the full cabin model.

Fig. 9 shows the energy balance of the frontal impact on the cabin. The reliability and accuracy of the simulation can be seen from the fact that the total energy, which remains constant for the duration of the impact (0.3s), is gradually converted from kinetic energy to internal dissipated energy.

EnginSoft also applies fast dynamics to domestic appliances (e.g. refrigerators, washing machines, dishwashers) to assess their impact behaviour as a result of accidental dropping during loading/unloading from the bed of a lorry or from a forklift truck.

Since the equipment is supplied with packaging protection for such scenarios, and in situations where it is fully represented in the calculation models, the numerical simulations also make it possible to evaluate the effectiveness of this protection and, if deemed necessary, to carry out optimization measures to reduce its cost while maintaining the level of effective protection.

Casting simulation prevents expensive prototyping

Another area where numerical simulation helps to improve product quality and reduce production costs is the foundry. The quality and profitability of die-cast parts depend on the design of the tool, the layout of the casting system, the thermal control of the mould and the reproducibility of the production conditions.

In other words, determining the correct casting configuration to consider during the die casting production phase is a relatively complex process, the results of which can only be known in advance by relying on virtual prototyping guided by practical experience and knowledge.

Numerical simulation applied to casting and die-casting processes makes a significant contribution to the overall design of the processes themselves and to the quality of the cast components.

In fact, it is estimated that more than 90% of casting defects are typically due to design errors and only 10% are due to real production problems. Many design errors can thus be avoided by using predictive simulation.

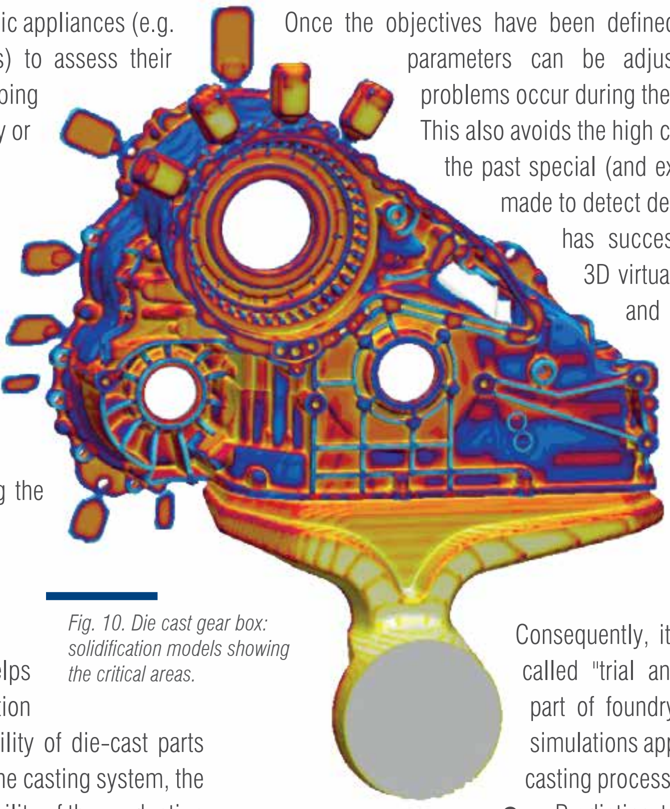


Fig. 10. Die cast gear box: solidification models showing the critical areas.

Once the objectives have been defined, the design or process parameters can be adjusted to ensure that no problems occur during the production of the casting. This also avoids the high cost of defective casting. In the past special (and expensive) prototypes were made to detect defects; nowadays this stage has successfully been replaced by 3D virtual prototyping. The casting and die-casting simulations developed almost daily at EnginSoft provide a high degree of process safety, prevent technical problems, and ensure that a project is not delayed.

Consequently, it can be said that the so-called "trial and error" process is now part of foundry history. The benefits of simulations applied to the casting and die casting process are briefly outlined below:

- Predicting turbulence or laminar flow of the liquid metal during melting
- Detecting possible inclusions
- Predicting the timing and nature of solidification
- Predicting residual (tensile) stresses and deformations during cooling and/or heat treatment of the casting
- Improving product quality
- Significantly reducing scrap
- Reducing production times
- Identifying areas of the casting where porosity and/or cracking may occur
- Providing information on critical temperature and pressure ranges for mould design.

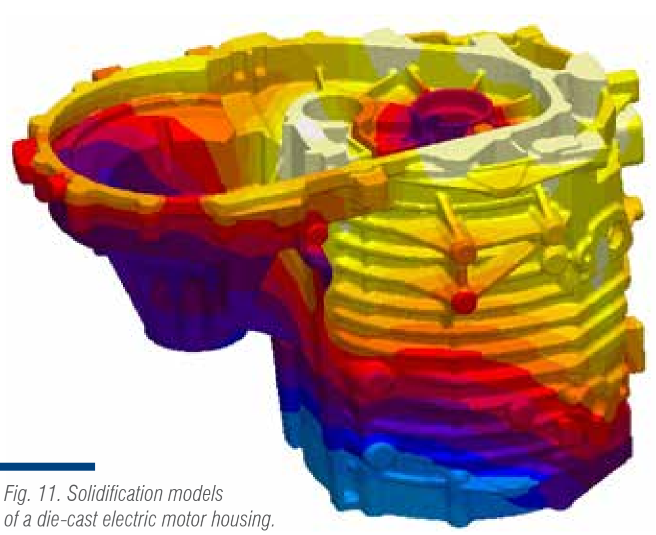


Fig. 11. Solidification models of a die-cast electric motor housing.

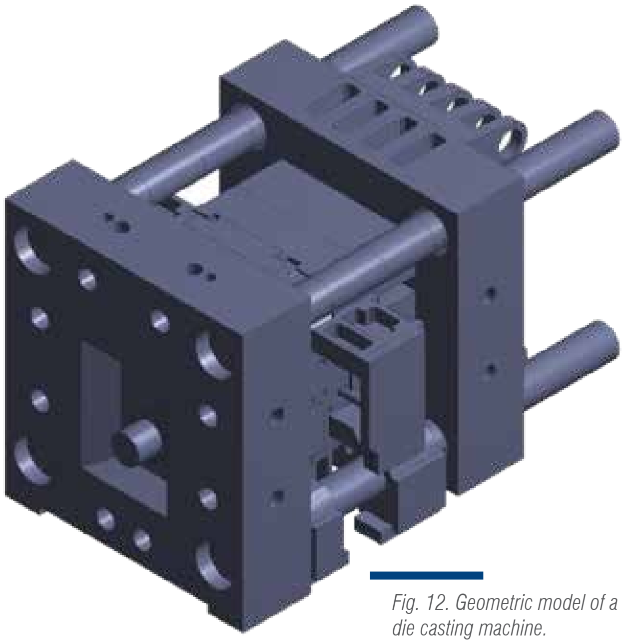


Fig. 12. Geometric model of a die casting machine.

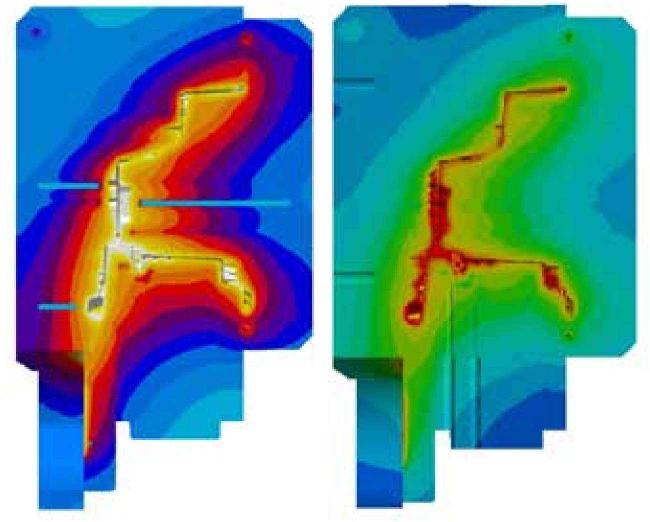


Fig. 13. a) Temperature distribution at cavity transferred from casting simulation to b) Structural simulation to assess the thermal steady state stress analysis.

As can be seen from the last item in the brief list above, in addition to quality control of the die-cast product, simulation of the die-casting processes also provides useful information for the development of the mechanical-structural design of the moulds.

In fact, it is possible to perform thermo-structural analyses on specific FEM models of the entire mould structure based on the distribution of temperature and the pressure fields in the cavities of the mould into which the molten metal is injected to obtain the relevant product/ casting component (see Fig. 12 — the model is composed of the various parts that make up the mould assembly, such as tie bars, cover holder, cover cavity, ejector holder, ejector cavity, columns, cover holder block, ejector holder block, slide supports, ejector box, side supports, side cavities).

Once the temperatures obtained from the analysis of the casting process have been transferred to the FEM model of the die (see Fig. 13), taking into account the prestressing applied to the tie bars, the thermal fields over the entire die, as well as the stress and deformation states of the sensitive/significant parts of the die itself, are determined in relation to resistance and fatigue aspects (stress states — see Fig. 14) on the one hand, and to aspects relevant to flashing that could occur if there were excessive gaps between parts (e.g. between ejector cavities and side cavities) on the other hand.

Obviously, to obtain reliable results, all parts of the mould that are not in structural continuity but in contact with each other are placed in contact, which means that numerical analyses are performed in geometric non-linearity (specifically defined as the presence of non-linear contacts).

Meshless CFD

In the changing landscape of product design and development, the engineer is challenged to optimize performance, reduce costs and minimize time to market. As already mentioned, the creation of traditional physical prototypes, while essential, can be time consuming and expensive. As a result, virtual models and digital simulations are becoming the foundation of innovation, especially for complex processes.

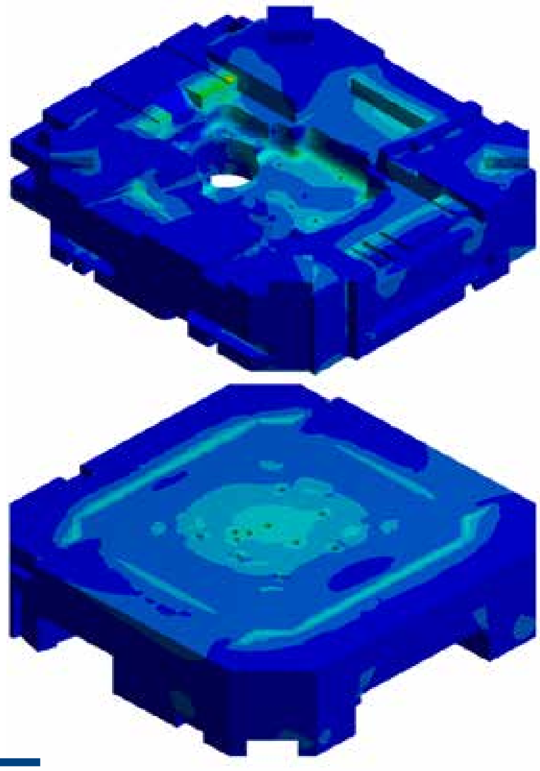


Fig. 14. Von Mises stress distribution in some structural components of the die casting tool.

Digital twins, which bridge the gap between the conceptual and physical worlds by allowing rapid iteration and informed decision-making, have already been mentioned, but the importance of making numerical simulation reliable when it replaces all or part of physical reality must be reiterated. It is therefore essential to validate the results obtained from digital models against the corresponding results obtained from experimental tests, to find paths that are minimally affected by the approximations introduced at the method (computation) level.

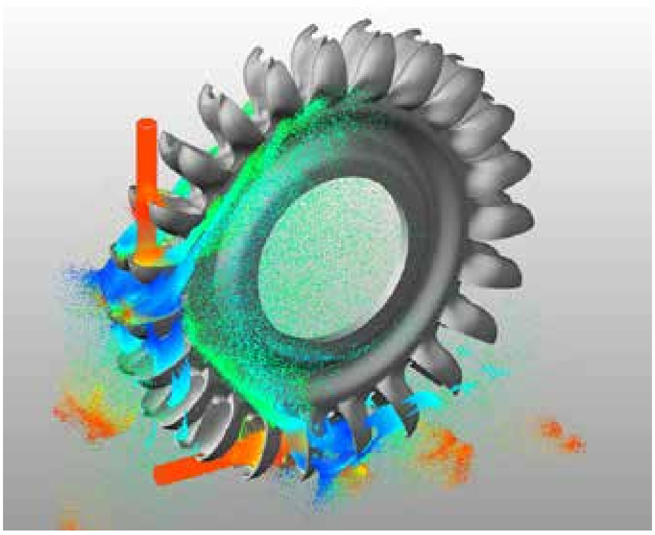


Fig. 15. Application of MPS to optimize power generation from Pelton turbines.

This is the case with moving particle simulation (MPS), historically known as the moving particle semi-implicit method.

This is a more intelligent approach to CFD, applicable to the simulation of incompressible free surface flows.

Where traditional CFD, by means of a fixed mesh throughout the domain, uses the Eulerian approach of solving the Navier-Stokes equation to calculate fluid flow, the MPS method instead uses the Lagrangian approach by representing the fluid with particles, eliminating the need for a computational grid. Its mesh-free nature makes the simulation mesh independent, simplifying and accelerating the process, especially when dealing with complex geometries and moving parts.

The MPS approach has been widely adopted in the automotive sector in recent years, mainly for powertrain applications such as the simulation of oil mist and lubrication of engines and transmissions, accompanied by the determination of operating temperatures to allow the correct design of the cooling system.

The advantage of this method is its ability to simulate free surface flows and fluid jets in very complex geometries, such as an entire gearbox or engine, in a short modelling and simulation time. This is made possible by the meshless nature of MPS.

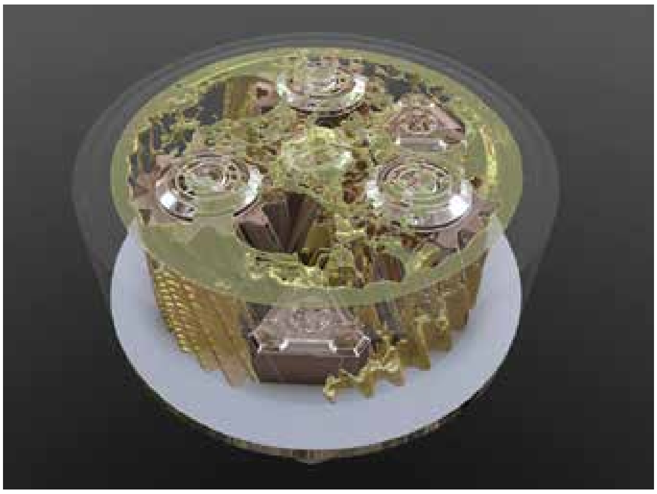
Conclusions

Summing up, SBES is a discipline that focuses on the computer modelling and simulation of complex, interconnected engineered systems, and the acquisition of information that enables these systems to meet specific standards of accuracy and reliability. SBES takes advances in scientific understanding and uses computer simulation to translate them into innovative approaches to solving engineering problems.

There is no doubt that over the past 50-odd years, developments in mathematical modelling, computational algorithms, and technologies for processing enormous amounts of data/information have led to significant improvements in industrial productivity, safety, quality of life and health.

But the acceleration of scientific research over the last half century has also led to the current phase in which the enormous expansion of the capacity to model and simulate an almost unlimited variety of physical phenomena has become apparent. This potential has profound implications, some of them ethical.

Firstly, computer modelling and simulation make it possible to study natural events and engineered systems that for too long have relied largely on experimental methods. In effect, empirical assumptions are replaced by computational models grafted onto scientific approaches and findings. Modelling and simulation extend the ability to address problems too complex to be solved by traditional analysis. These include problems involving micro and macro scales (both



space and time) or problems involving several physical processes simultaneously (multiphysics).

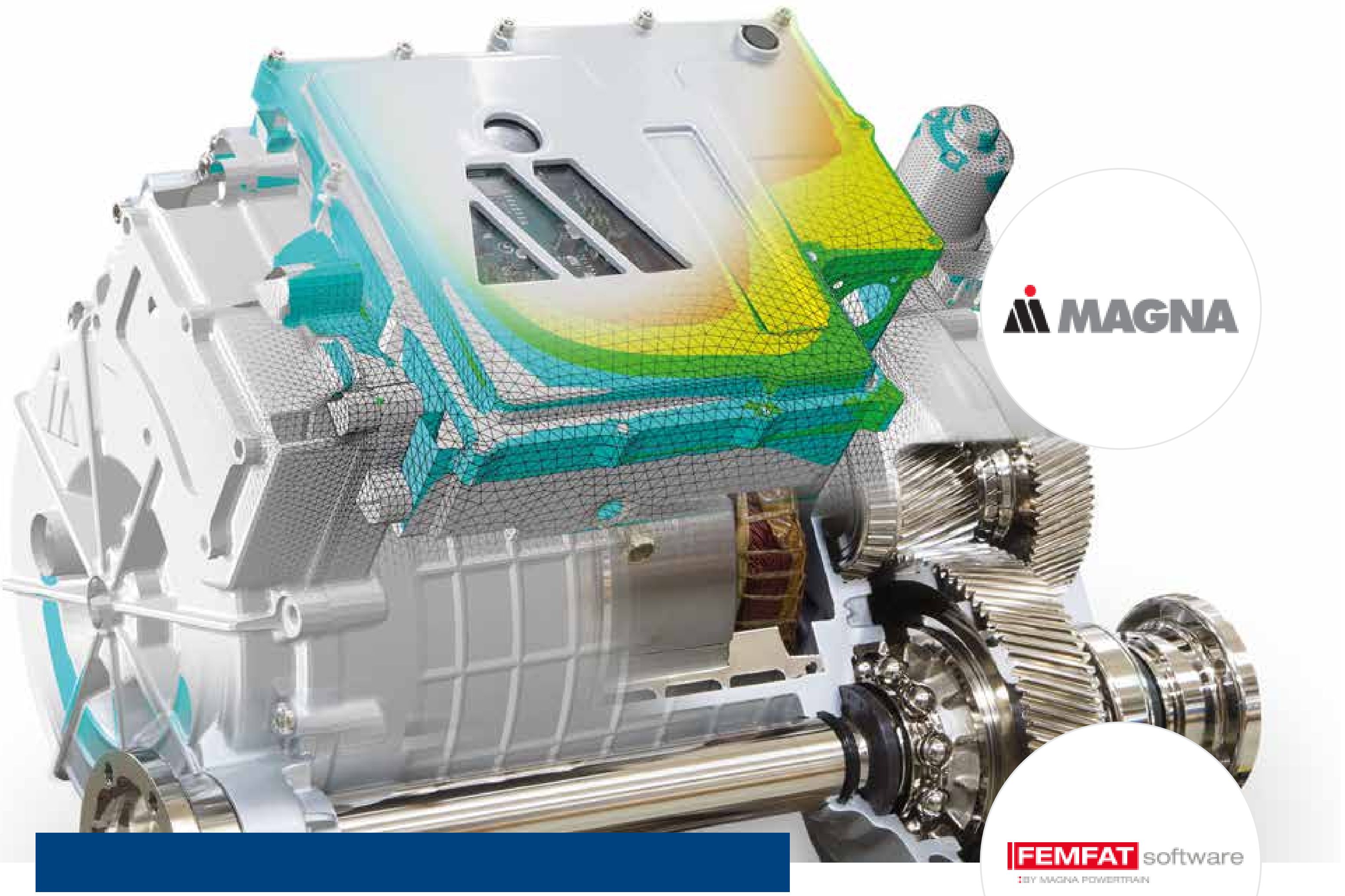
Secondly, modelling and simulation enable design and production to be more scientifically based, with less trial and error and shorter design-production cycles, resulting in greater sustainability (including environmental sustainability) and less waste. In other words, modelling and simulation improve the ability to predict outcomes and optimize solutions, allowing the right resources to be allocated to specific projects and/or the right strategic decisions to be made.

Thirdly, modelling and simulation introduce tools and methods into everyday life that are applicable to all engineering disciplines (electrical, computer, mechanical, civil, chemical, aerospace, nuclear, biomedical), allowing each to benefit from advances in optimization, control, uncertainty quantification, verification and validation, design decision-making and real-time response.

As to the ethical implications, the great "power to do" that is available today must be governed by the "ability to foresee" the effects of formidable technical intuitions/ideas. To approach an ethics that guides technology and directs it towards a safe and sustainable future, we need to recover and pay due attention to the virtues of "those who see in advance".

This ability cannot be and must not be lost. It is essential to tap into the wisdom of imagining and anticipating the ultimate effects of action. Lest we lose the hope of expanding our capacity to understand and perceive the “infinite” that surrounds us. Lest, in the age of automation and artificial intelligence processes, technology itself, from being a rational tool to support and safeguard human life, be transformed into an autonomous and self-sustaining power apparatus, emptying human labour of content.

For more information:
Livio Furlan – EnginSoft
l.furlan@enginsoft.com



Enhanced low cycle fatigue analysis and the influence of load sequence for an e-motor's rotor

by Gerhard Spindelberger, Klaus Hofwimmer
Magna Powertrain

In many engineering applications, the stresses experienced by materials can exceed their yield strength resulting in plastic deformation.
This plasticization of a material under load is a significant factor in determining the service life of a component. Accurately predicting this phenomenon is critical to ensuring reliable and enduring components.

Until now, the fatigue tool FEMFAT has used a simple approach based on stress redistribution of the rainflow matrix elements according to Neuber's approach [1]. However, this results in the loss of information about the sequence of load peaks. This can lead to inaccuracies in determining the actual plasticized state of a material.

A new approach has been developed in FEMFAT that calculates the Neuber elastoplastic stresses at each time point. This makes it possible to include the influence of the sequence in fatigue life analysis. By considering the effects of peak load sequence, plasticization can be more accurately predicted and, consequently, component life can be improved.

Isotropic and kinematic hardening

Mathematical models such as the von Mises yield criterion and strain hardening models are widely used to estimate the plastic deformation of metals. Hardening models describe the behaviour of materials under load above the yield point.

The hardening process in materials can occur by expansion or translation of the yield surface. This concept is fundamental to

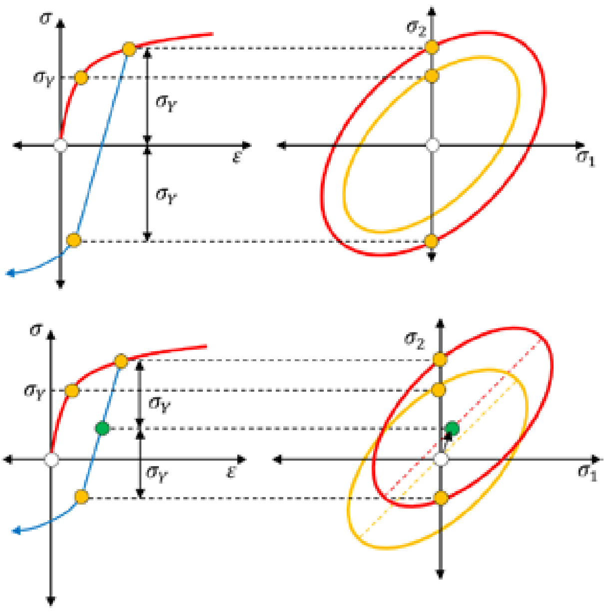


Fig.1. Yield surface for isotropic hardening (above) and kinematic hardening (bottom).

understanding the behaviour of materials under plastic deformation. The two main types of hardening mechanisms based on the nature of yield surface changes are isotropic hardening and kinematic hardening.

Isotropic hardening refers to the expansion of the yield surface uniformly in all directions. In this case, the size of the yield surface increases as plastic deformation progresses. Isotropic hardening is commonly observed in materials that undergo uniform plastic deformation, such as mild steels. As the material undergoes more plastic deformation, the yield surface expands – the yield stress increases, indicating a greater resistance to further deformation.

Kinematic hardening, on the other hand, involves the displacement of the yield surface while maintaining its size. This type of hardening is associated with materials that exhibit non-uniform plastic deformation, such as certain types of metals and alloys. As the material undergoes plastic deformation, the yield surface shifts, indicating a change in the material's ability to accommodate further deformation. Kinematic hardening is often characterized by a Bauschinger effect, where the yield strength of the material decreases after reverse loading.

The kinematic hardening model was described in terms of back-stresses α_i which depend on the material parameters C_i and γ_i.

$$\alpha_i = \frac{C_i}{\gamma_i}\left(1 - e^{-\gamma_i \varepsilon_p}\right) \quad \text{and} \quad \alpha_{total} = \sum_{i=1}^{N} \alpha_i$$

γ_i Rate of hardening coefficient reduction
C_i Initial kinematic strain hardening modulus
ε_p Plastic strain

Multiple back-stresses are used to improve the correlation between measured data and the kinematic hardening model.

However, incorporating material non-linearity into finite element analysis (FEA) can significantly increase computing time and complexity. This is a challenge for engineers who need to perform efficient and reliable low cycle fatigue analysis.

The new PLAST method in FEMFAT fatigue software

To address the problem of increased analysis time due to material non-linearity, the use of PLAST methods in FEMFAT to estimate elasto-plastic stresses were proposed. The PLAST methods provide an alternative approach that reduces computing time while maintaining the same level of accuracy. The two main components of the new FEMFAT PLAST approach are:

- Fitting a kinematic hardening model to the first branch of the stress-strain curve: the kinematic hardening model captures the material's behaviour during cyclic loading and provides a more accurate representation of the stress-strain response, particularly in the plastic regime. By fitting this model to the first branch of the stress-strain curve, the PLAST method considers the hardening behaviour of the material.
- Stress rearrangement according to the Neuber or ESED (equivalent strain energy density) methods: stress rearrangement methods are used to account for the redistribution of stresses due to cyclic loading. The Neuber

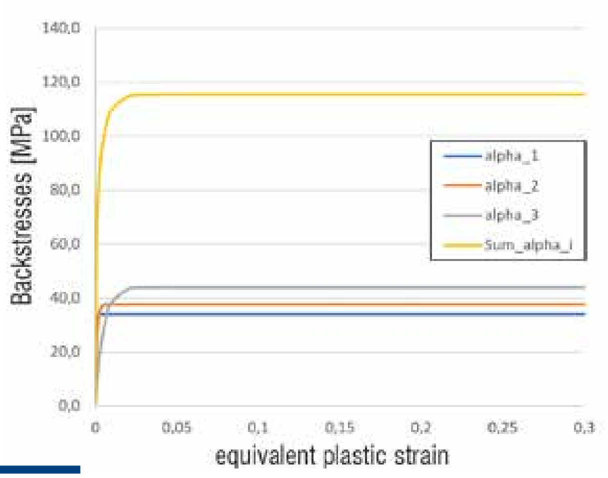


Fig.2. Kinematic hardening with three back-stresses.

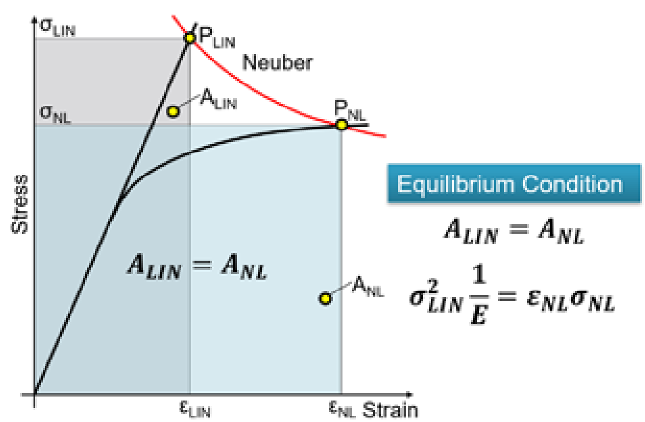


Fig.3. Stress rearrangement according to Neuber.

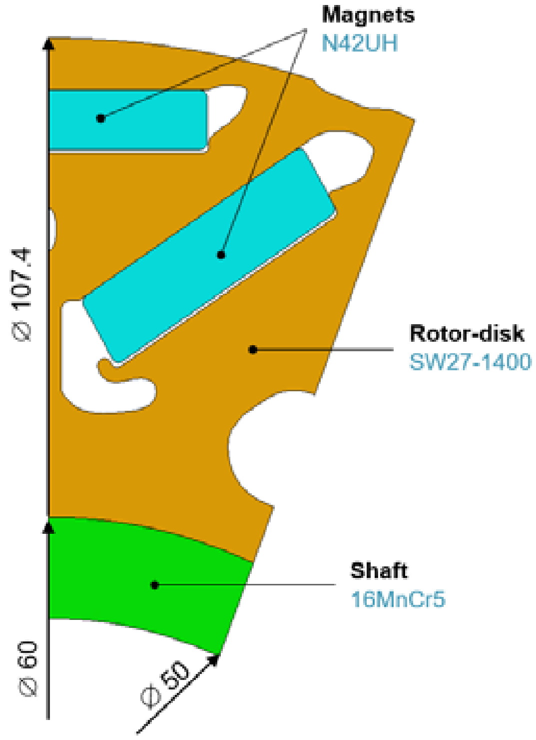


Fig. 4. Rotor plate of an electric motor.

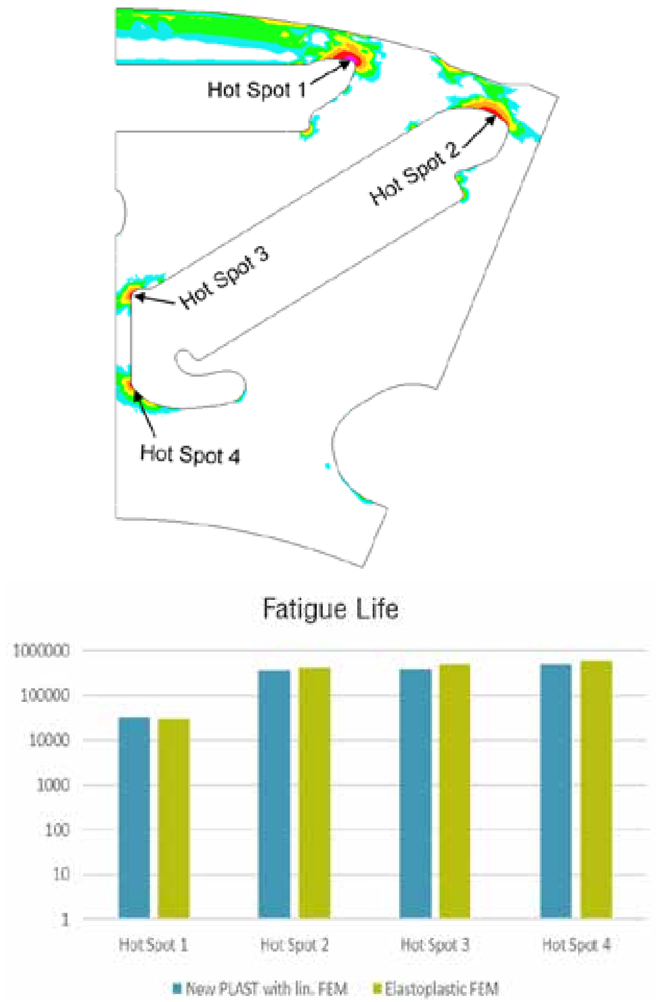


Fig.5. Comparable fatigue life results for the new PLAST approach with linear FEM and elastoplastic FEM.

and ESED methods are commonly used stress rearrangement approaches. These methods ensure that the elasto-plastic stresses are properly distributed, resulting in more accurate fatigue life predictions.

New PLAST method procedure:

- Calculation of material parameters: for each material parameter pair (C_i, γ_i), an optimization process is performed to determine the values that minimize the error to the cyclic stabilized stress-strain curve. These parameters are specific to the material being analysed and are essential for accurately predicting its behaviour under cyclic loading. The Ramberg-Osgood parameters K' and n', which define the cyclically stabilized data, are used as benchmarks for the optimization process.
- Kinematic hardening model: in the cutting plane, the equivalent stress history is rearranged using the kinematic hardening model. This model uses the optimized parameters obtained in step 1 for each sample of the load time history. The kinematic hardening model considers the material's response to cyclic loading, considering the accumulation and redistribution of plastic deformation.
- Rainflow counting: The rearranged stress history obtained from the kinematic hardening model undergoes rainflow counting.

Application: Rotor plate of an electric motor and influence of sequence

The advantage of the FEMFAT PLAST approach is that it avoids the need for computationally expensive elastoplastic FE analysis. Engineers can significantly reduce analysis time without compromising the reliability of their predictions. To demonstrate the effectiveness of the FEMFAT PLAST approach, we studied the case of the plates of a rotor in an electric motor.

The case study compares two different approaches:

- Linear elastic FEA and channel-based multiaxial fatigue analysis (channelMAX) using load signals and the new PLAST method in FEMFAT.
- Transient, elasto-plastic FEA and transient multiaxial fatigue analysis in FEMFAT (transMAX) without PLAST.

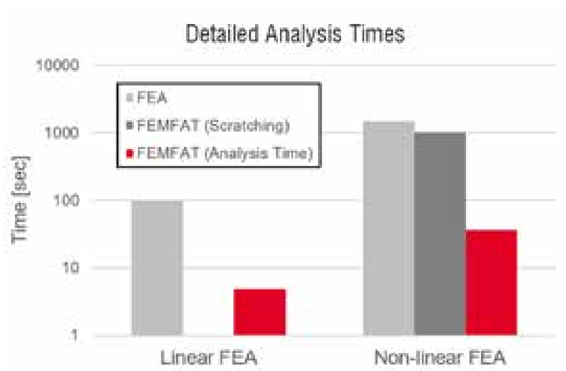


Fig.6. Analysis time for finite element analysis (FEA) and fatigue analysis.

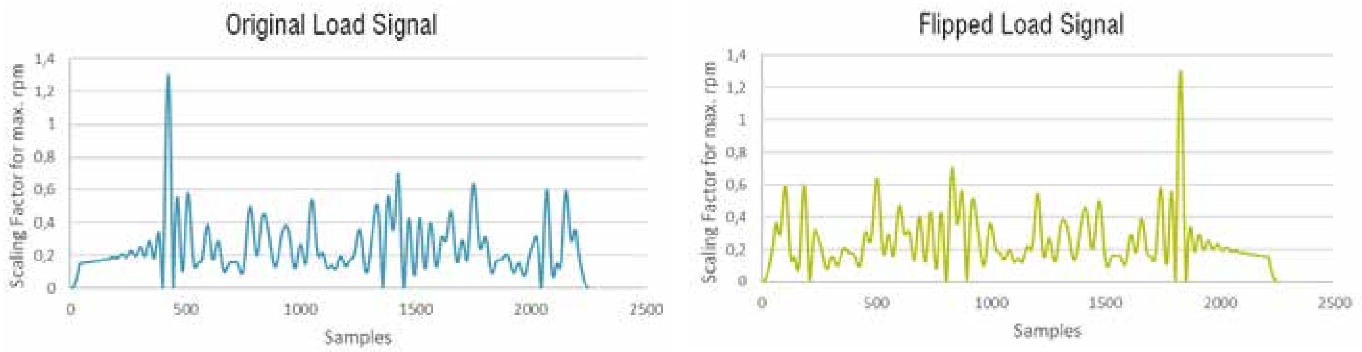


Fig.7. Original signal (left) and flipped signal (right) to study the influence of sequence.

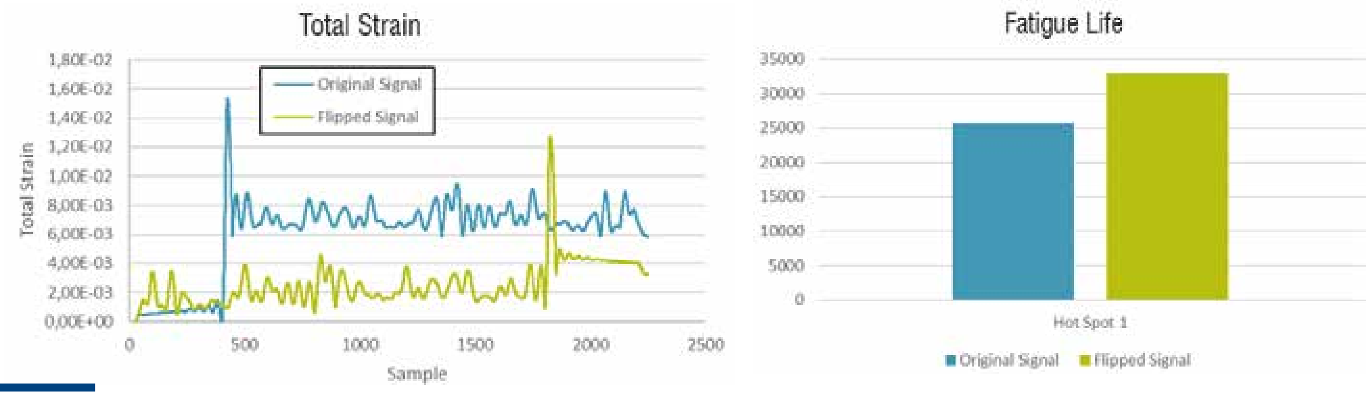


Fig.8. Original signal (left) and flipped signal (right) to study the influence of sequence.

The results obtained using the new PLAST approach were compared with those obtained from elastoplastic FE analysis.

The results show that the PLAST approach yields similar results to the elastoplastic FE analysis while significantly reducing analysis time.

The fatigue results in Fig.4 are very similar between the new FEMFAT PLAST approach with linear FEM and the standard approach with elastoplastic FEM. However, the total analysis time (FEM + fatigue analysis) of the new method is about 25 times faster!

Influence of load sequence on damage outcome:

In general, damage depends on the sequence of load peaks. If a high load peak occurs at the beginning of load history, the resulting residual stresses will have a positive effect on the subsequent load cycles.

To illustrate the influence of sequence, two signals that generate the same rainflow matrix are analysed. The second signal was generated by simply reversing the first signal.

Both signals were analysed using the new the FEMFAT PLAST method. The stress peak at the beginning leads to plastic hardening, thus reducing the damage of the subsequent cycles.

Conclusions

The enhanced low cycle fatigue analysis with the new FEMFAT PLAST method provides a practical and efficient solution for engineers to accurately predict the fatigue life of components subjected to high-stress applications.

By incorporating kinematic hardening into multiaxial fatigue analysis, the influence of the sequence of high load peaks can be predicted with high accuracy, even for long time histories.

For more information:
Paolo Bortolato – EnginSoft
p.bortolato@enginsoft.com

References

[1] H. Neuber, "Theory of Stress Concentration for Shear-Strained Prismatical Bodies with Arbitrary nonlinear Stress-Strain Law", *Journal of Applied Mechanics*, vol. 28, pp. 544–550, 1961, American Society of Mechanical Engineering (ASME), New York.

Multiscale.Sim

DEM-FEM coupling for simulating the manufacturing process of all-solid-state batteries

by Koji Yamamoto
CYBERNET

All-solid-state batteries (ASSBs) are attracting attention as safe energy storage devices for use in electric transport. However, although high safety can be guaranteed, it can be difficult to achieve high ion conductivity within ASSBs compared to conventional lithium-ion batteries (LIBs). The keys to achieving high performance lie in improving the performance of the materials that comprise the product and in optimizing the manufacturing conditions of the powdered raw materials used. This article focuses on the latter issue and introduces analysis techniques that simulate the manufacturing processes for ASSBs and even enable the performance of the final moulded products to be predicted. The article, "Filling and compression analysis of metallic powders composed of spherical particles"[1], introduced a similar analysis method using a simple model. This article is a follow-up to that report and introduces recently developed technology that enables more rigorous analysis using the discrete element method-finite element method (DEM-FEM) coupling function provided by Multiscale.Sim[2].

What is an all-solid-state battery (ASSB)?

Lithium-ion, nickel-metal hydride, and lead-acid batteries are commonly used in both hybrid and conventional electric vehicles. In particular, LIBs are highly practical due to their ease of charging and excellent energy density. However, one of their constituent materials, the electrolyte, is a flammable liquid that frequently combusts due to thermal runaway.

As their name suggests, ASSBs are entirely composed of solid materials, which are non-flammable and the solid electrolyte makes ASSBs highly safe. They also have the advantage of high energy density and the potential for high capacity. On the other hand, however, technical challenges include high internal resistance due to poor connection in the contact area between the solid electrolyte and the electrode material, and low ionic conductivity of the electrolyte. Active research and development is underway to solve these problems.

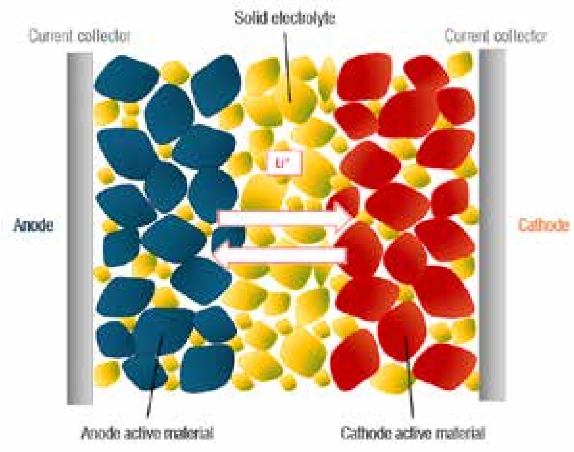


Fig.1. Diagram of the internal microstructure of an all-solid-state battery.

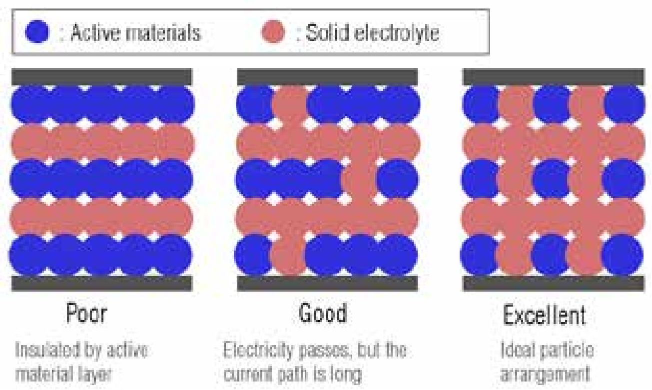


Fig.2. The relationship between microstructure and performance of all-solid-state batteries

In order to maximize the properties of the battery, its internal microstructure needs to be optimized. The following is a simplified description of a system consisting of electrolyte and active material, which are typical components. The active material, shown in blue in Fig.1, stores electrical energy, and the electrolyte (shown in red) acts as a conduit for the electrical energy. In Fig.2a, the ionic pathway is interrupted in the middle and cannot transport any more electrical energy. The electrical path (called a percolation path) should be continuous from inlet to outlet. Ideally, for efficient ion transport a lattice-like microstructure (see Fig.2c) should be formed rather than a tortuous structure (Fig. 2b), but these microstructures are determined by the manufacturing process.

Manufacturing process

There are two main approaches to the production of solid-state batteries: wet and dry. Both approaches have their advantages and disadvantages, and the most suitable method is chosen based on the desired product characteristics and the production costs.

In the wet method, an organic solvent is added to the powder, which is then mixed, applied and dried. This technique is often used in sheet batteries because the liquid improves the uniformity and precision of film formation.

This article focuses on the dry process, in which powdered materials are compacted directly without the use of liquids. This reduces material wastage and simplifies the process, but has the disadvantage of making it difficult to control the microstructure.

When attempting to analytically predict the performance of the product obtained using the dry method, it is necessary to consider four steps: mixing, filling, compressing, and performance evaluation, shown in Fig.3. Since the material properties change from powder to solid during the manufacturing process, appropriate analysis techniques must be used for each step. This requires knowledge of the physical properties governing the behaviour of the material in each step of the process (see Fig.3).

Although the mixing and filling steps do not strictly result in zero particle deformation, it is the movement of each particle that governs the phenomenon. In these steps, density is the material property that determines material behaviour. During the compression process, on the other hand, particle movement is restricted and deformation is negligible, but the stiffness behaviour and strength information are important.

For problems in the first two steps where deformations are negligible, the discrete element method (DEM) is recommended for its efficiency. For compression where deformation must be considered, the finite element method (FEM) is preferred. FEM has the great advantage of accurately representing the microstructure for use in later stages of the performance evaluation process.

Approach to simulating each step in the manufacturing process

In the previous section we discussed suitable analysis methods to simulate each step of the dry manufacturing process. It is also important to ensure that the analysis results from the upstream processes are correctly reflected in the analysis conditions of the downstream processes otherwise the microstructure of the final moulded products cannot be accurately predicted.

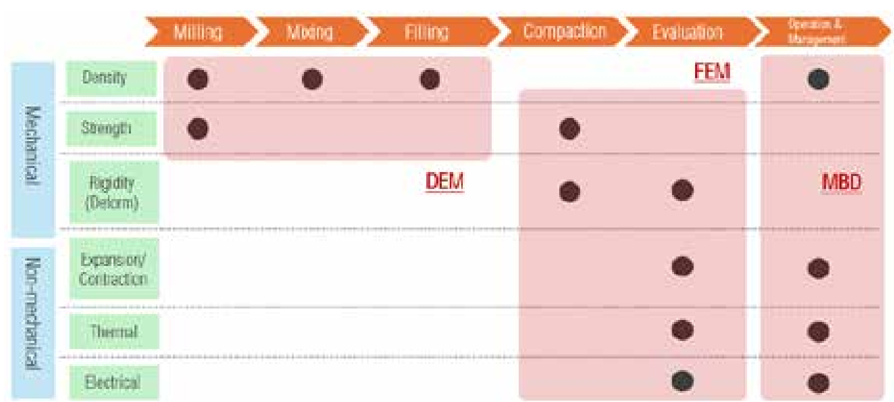


Fig.3. Material constants governing each step in the dry production process of all-solid-state batteries.

Fig.4 shows the analysis flow to achieve this: the DEM analysis provides information on the particle configuration. Since it is not always possible to achieve a homogeneous mixture over the entire area, the size and arrangement of each particle after filling is defined in the CAD data.

Multiscale.Sim, a multiscale analysis tool developed in Japan, provides a DEM-FEM coupling interface, and automatically converts models using primitive spherical shapes instead of STL (standard tessellation language) to create high-quality FE models. The interface also makes it easier to assign the correct material properties to each part using Ansys Mechanical, even for powders composed of multiple materials.

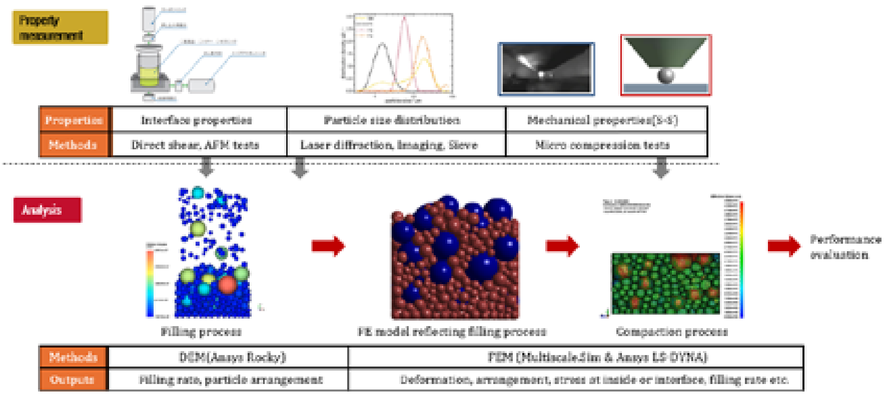


Fig.4. Workflow to simulate a series of manufacturing processes using DEM-FEM coupling.

The resulting FE is used to perform a compression analysis. Due to the strong nonlinearity involved, we recommend using the explicit method in Ansys LS-DYNA. Fig.4 summarizes the particle material information required to analyse each step of the process and the methods used to obtain this information.

Ansys Rocky offers various functions to calibrate material properties from these test results. The properties required for DEM analysis can be easily identified by comparing experimental data and analytical results. Micro-compression tests generate the mechanical properties of the particles necessary for the compression analysis. The FE analysis also reproduces the load-displacement characteristics of compressing a single particle obtained by inserting the material properties as unknown parameters. The actual material properties are identified retrospectively by combining the experimental and analytical results.

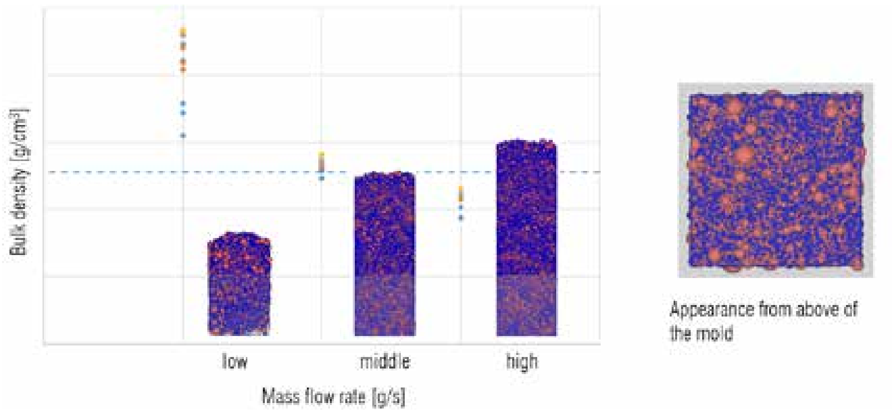


Fig.5. Analysis of the filling step of the process as a function of particle mass flow rate.

The microstructure obtained from the compression analysis is used to evaluate the performance of the final product, which requires the use of Multiscale.Sim's homogenization method. As mentioned in Fig.2, battery performance is determined by various geometric factors, including the percolation path of the solid electrolyte. Electrical tests conducted on virtual materials using the homogenization method enable the macroscale properties such as internal resistance to be predicted. For details on the homogenization method, please refer to the article "Predicting the strength of composite materials using Ansys Software"[3].

Use cases

The following is a brief description of the use case to analyse the production process from filling to compression. In the filling step, active material and solid electrolyte blended in a given weight ratio are placed in a cubic mould with an open top.

The solid electrolyte, which has a particle size in the order of submicrons, is strongly affected by microscopic adhesion. The adhesion force and coefficient of friction between each material, and between the mould and the material are measured using the single plane shear test and reflected in the analysis. The mass flow rate is carefully determined as a condition of particle delivery.

Since this value is difficult to measure, it is used as a tuning parameter to ensure that the bulk density after the filling process

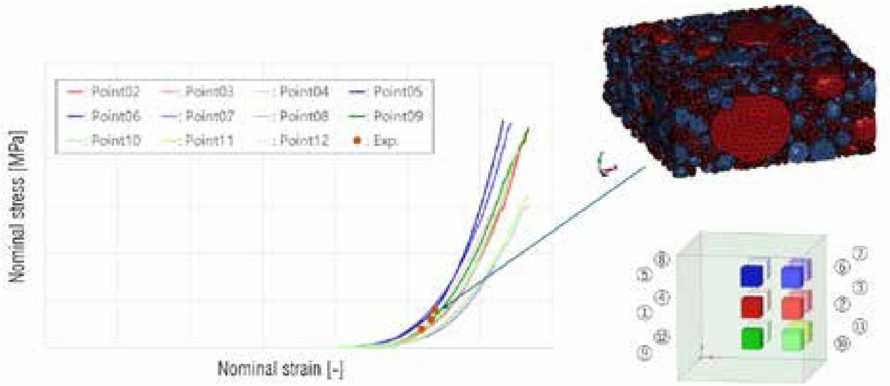


Fig.6. Stress-strain curves at 12 typical locations, obtained by compression analysis. The analysis results could be validated in the small strain region. (Specific value for each axis is hidden for confidentiality).

matches the experimental results to ensure consistency with the actual problem. Fig.5 plots the relationship between mass flow rate and bulk density after filling.

Due to computational costs, it is not practical to use the same conditions as in the experiments, so the mould size is made smaller than in reality. (The use of a coarse-grained method is also not recommended in order to maintain consistency with the compression process). The analysis results showed a strong dependence on the mass flow rate. If clear conditions cannot be determined in the actual process, the conditions should be adjusted by comparing the experimental result with the analysis results.

Fig.6. summarizes the results of an example analysis of the compression process. These results show the macroscopic stress-strain relationship obtained from the FE model focusing on the 12 representative regions shown in the figure. Particles can be crushed in high pressure regions, but that was not considered in this case. For the particles, the elasto-plastic properties identified in the micro-compression tests for all materials were taken into account.

Particles partially out of the extraction area were cut and modelled to fit within the rectangular bounding box. Since the solid electrolyte has a lower stiffness than the active material, the solid electrolyte is preferentially deformed as it is compacted, which may cause partial breakdown of the percolation path. It is therefore important to check the appropriate material mix ratio and the particle arrangement prior to compacting based on the results of the analysis that considers the deformed state of the particles.

The graph shows that the results are somewhat dependent on the area being sampled. This may be due to different mixing conditions at different locations or an insufficient sample size. In any case, the experimental results obtained are close to the average value of these analysis results, showing that the actual problem can be reproduced with a certain degree of accuracy, at least in the small strain range.

Conclusion

This article introduced an analytical technique to predict the performance of all-solid-state batteries.

Performance predictions can be made using Multiscale.Sim, but it requires a microstructural model. We therefore introduced a method to analyse a series of manufacturing processes to obtain a microstructure model incorporating the effects of each step in the process.

Since the raw materials for solid-state batteries change from powder to solid during manufacturing, the appropriate analysis method varies according to the characteristics of each process. Multiscale.Sim's DEM-FEM interface allows you to perform analyses of downstream manufacturing processes using models that accurately reflect upstream processes.

For more information:
Francesco Lori – EnginSoft
f.lori@enginsoft.com

About CYBERNET

CYBERNET is a leading CAE company established in 1985, headquartered in Tokyo, Japan. Their corporate vision is "Creating a sustainable society and inspiring the world through technology and ideas". Their goal is to solve the problems of their customers, who face increasingly diverse and complex technological issues every day, with technology and ideas that exceed their expectations, and to lead them to the next level of innovation.

CYBERNET is an Apex Channel Partner and a Technology Partner (Software) of Ansys. They have been developing Multiscale.Sim since 2007 and it's being used by many customers in Japan and in other countries.

For more information, visit:
www.cybernet.co.jp/ansys/product/lineup/multiscale/en/ or email: cmas@cybernet.co.jp

References

[1] K. Yamamoto, "Filling and compression analysis of metallic powders composed of spherical particles", EnginSoft *Newsletter*, Autumn 2020.

[2] www.cybernet.co.jp/ansys/product/multiscale/en/

[3] K. Yamamoto, "Predicting the strength of composite materials using Ansys Software", EnginSoft *Newsletter*, Summer 2020.

Real data integration in a data-driven approach for track signal definition

Methodology to generate road profiles for predicting vehicle behaviour in a virtual environment: reproduction of real road and off-road conditions.

by Lorenzo Bellorini[1], Pier Luca Todesco[2], Federico Bavaresco[1]
1. Dana Incorporated- 2. Alten Italia

The more progress is made in developing a new product, the more expensive it becomes to make changes. Hence the need to identify possible problems in advance and make changes at an early stage, before the product becomes ready for mass production.

Although designers and engineers evaluate the probability of iterations against the probability of success step by step, a single verification test is often not enough: changes and rethinking may occur in the design process and consequently costs may increase rapidly. Integrating simulation into the design development process is increasingly important to guide design decisions, and accelerate development times, product optimization, and performance prediction.

Analysis in a virtual environment allows the influence of the design parameters on product performance to be understood before a physical prototype is available, enabling successful strategy implementation from the outset. Simulation has therefore become more and more important in recent years and industry is increasingly requiring the exclusive use of virtual validation to replace field testing, especially in the early stages of product development.

The ability to use an accurate, reliable and validated virtual model typically reduces development costs and time considerably, enabling prototype testing to be restricted to the final design stages. Reducing the use of resources, materials and energy consumption during validation by minimising the number of times tests are performed adds enormous value and supports sustainability.

Integrating real data into the virtual model is, however, key to improving the accuracy of simulation results. This is the topic of discussion in this article, which focuses on evaluating track signals from field data for use in a virtual environment.

Objective

To replicate a vehicle field test in a virtual simulation environment, the many physical phenomena that are involved must be accounted for, including vehicle kinematics and dynamics, suspension hydrodynamics, thermal, electrical, and structural aspects.

In an Off-Highway environment, it is especially important to incorporate the increased excitations of the vehicle that are caused when it traverses a bumpy track. Since we do not have a database of bumpy tracks, our aim was to define a generalizable method to reconstruct the profile of the roads on which a vehicle has travelled based on the acceleration signals measured at its hubs. Using this approach, our goal was to compile a repository of classified tracks to use in a virtual environment.

The virtual tracks generated should be similar to the actual ones in terms of energy content, and in terms of the amplitude and frequency of the accelerations that the virtual model of the vehicle experiences as it traverses the track, which should be comparable to those measured in the field. The virtual tracks derived must be independent of the type and speed of the vehicle used to characterize them.

The available regulatory documents could be used as a starting point for the creation of these virtual tracks. For example, the ISO8608 standard proposes a classification of road profiles for determining the average energy content of a track. It specifies an 8-band classification grid and a power spectral density (PSD)-based analysis.

From this categorization, certain artificial and random paths per specific class can be deduced. However, these artificial profiles frequently do not accurately represent the real amplitudes or frequency content. Hence, the need to define a procedure based on actual field data to obtain realistic tracks for use in design and validation.

Step 1a: Primal Drive Signals (DS)

The method proposed in this article focuses on a data-driven approach: our aim was to develop multiple meta-models in the form of response surface functions (RSM) by exploiting the potential of modeFRONTIER. The models were to be trained on a large enough database of dummy tracks to represent all possible scenarios and dynamics.

As previously mentioned, the first thing required were the data sets from an acquisition campaign. To this end, an equipped vehicle sampled the accelerations occurring at the hubs as the vehicle traversed various tracks. These acceleration signals were fed into the model to reconstruct the road tracks.

Secondly, a multibody model of the vehicle used for data acquisition was developed using the Adams View software. This model was validated and found to be representative of the vehicle being studied.

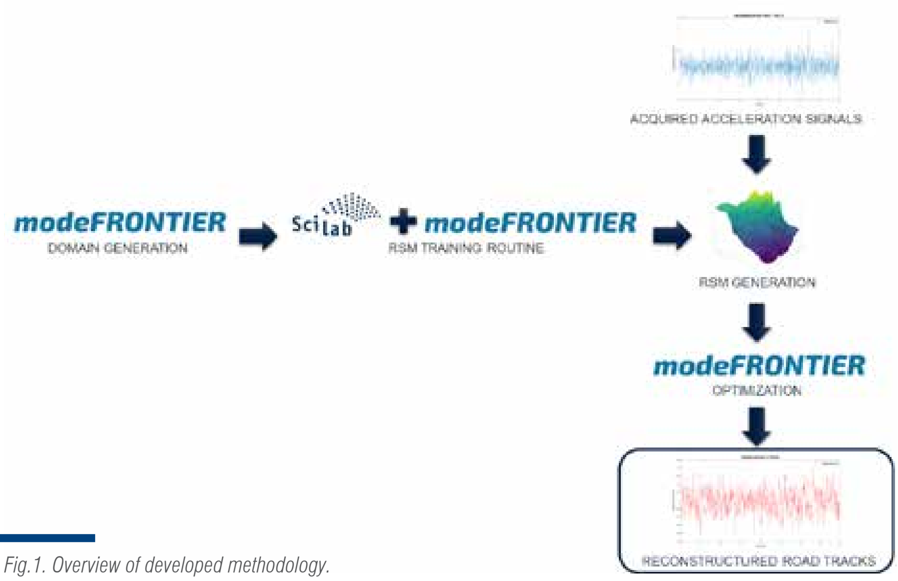


Fig.1. Overview of developed methodology.

Step 1b: Domain creation

We used modeFRONTIER to define a domain for the RSM training and then constructed a design of experiment (DoE) with many scenarios. A wide range of dummy tracks, resulting from the random superposition of sinusoidal functions with various amplitudes and frequencies, was inserted into the DoE, which generated a set of consequent accelerations occurring at the hubs of the multibody vehicle model as it traversed the tracks.

Step 1c: RSM training

We then developed an RSM training routine. After obtaining the Fast Fourier Transform (FFT) of the dummy tracks previously defined, the frequency components were sorted into decreasing amplitudes for each of them.

Next, we selected the N frequency components recurring most often among all evaluated scenarios. These represent the most significant N frequency components to describe all the tracks.

The routine invokes the Scilab scripts and modeFRONTIER successively in batch-mode to generate $2*N$ meta-models: i.e. for a specific frequency component, there is one RSM for its real part (Re) and one for its imaginary part (Im). Each of these meta-models is trained on the input of all N components, Re or Im, of the acceleration signals obtained previously and on the specific Re or Im of the displacement component related to that RSM.

Therefore, the acceleration input signal provided to the model is broken down into the N fundamental frequency components used in the training phase. Subsequently, for each of the $2*N$ RSMs, the Re and Im parts of all specific frequencies are obtained, the i^{th} amplitude A_i and the phase ψ_i are derived, and the displacement signal is reconstructed using Fourier by superimposing N sinusoidal functions, each characterized by A_i and ψ_i.

Given that there is no two-way correspondence between excitation frequency and output frequency, we accept that all acceleration components can contribute to defining the specific displacement component and vice versa.

If the proposed method were able to use and combine real track signals into the training domain it would be more valuable since the N components selected as fundamental would have a better congruence with real stresses. The backward analysis revealed inaccuracies in the first version of the drive signals, so corrective measures were taken.

Step 2: Optimization

The method was improved by implementing an optimization process with modeFRONTIER. This mitigates potential sources of error including the effect of the reciprocal influence between the vehicle's four wheels. Therefore, the modeFRONTIER optimization workflow (Fig.2) simulates the entire vehicle by exciting all four wheels simultaneously.

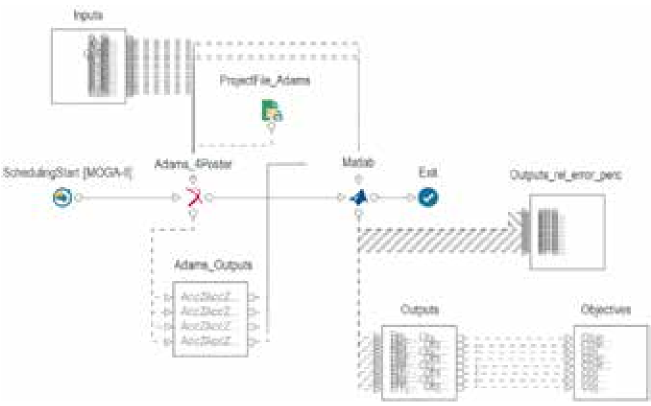


Fig.2. modeFRONTIER optimization workflow.

The optimization process aims to minimize the differences occurring between the measured acceleration PSDs and those obtained from the multibody simulation.

Eight objective functions describing the disparities between PSD acceleration curves in terms of subtended area, therefore energy content, and in terms of shape, were thus defined.

To reduce the objective functions to zero, the initial track signals were tuned by adding sinusoidal functions for each specific frequency range. Twenty-eight input variables, seven for each vehicle tyre, one per frequency range, were then used as modifying coefficients of the linear combinations of the additional sine waves and configured at each optimization step.

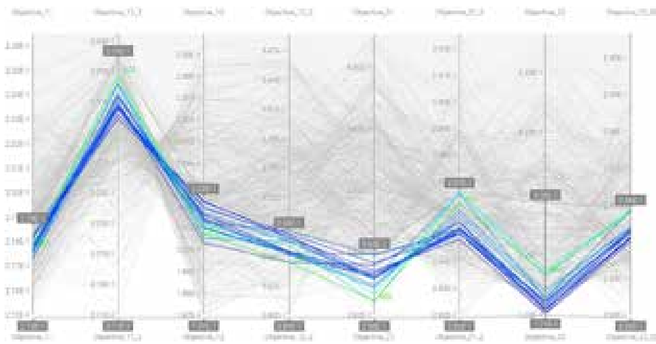


Fig.3. Qualitative post-processing using a parallel coordinates diagram.

The previously defined number of objective functions and input variables is a first attempt: these values can be increased to improve the initial results shown in this article while striving for a trade-off between accuracy and computing cost. This and the large number of variables are the reason a MOGA-II algorithm was used with discretized steps of the input variables.

With the large number of parameters involved, a single optimization step is typically not sufficient to achieve the desired accuracy. Therefore, post-processing (Fig.3) was performed after every iteration using qualitative and quantitative analysis to refine the variation domains of the input variables and to guide the optimization process into the following cycle. The optimization process ends after a few cycles once sufficient qualitative or quantitative accuracy has been achieved.

Results

An initial implementation of the full proposed methodology yielded the results shown in Fig.4. These results refer to a vehicle travelling at an almost constant speed of 8km/h across a field consisting of soft ground and containing boulders.

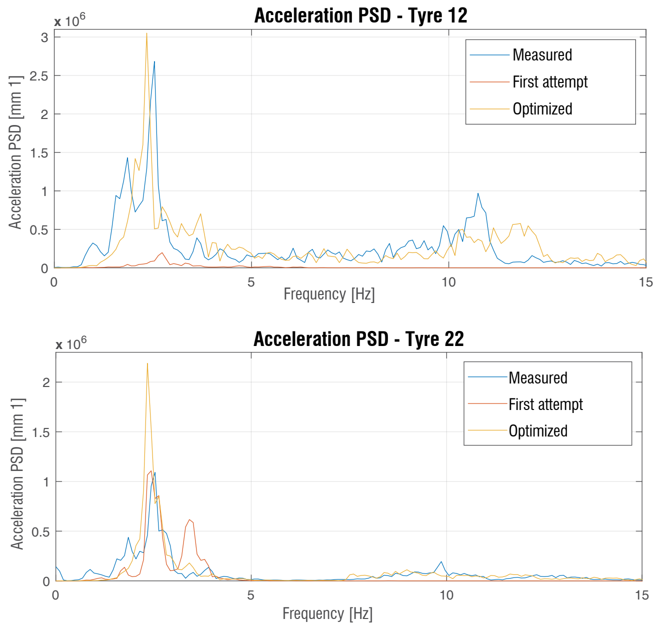


Fig.4. Optimization results: right side tyres.

Development phases	Required calculation time
Primary road tracks	2 days
1st optimization	5 days
2nd optimization	4 days
3rd optimization	2 days

Table 1. Required calculation time.

	Objective function 0-7.5Hz		Objective function 7.5-15Hz	
	First trial	Optimized	First trial	Optimized
11	93.35%	21.83%	99.89%	33.70%
12	90.97%	19.98%	99.78%	37.07%
21	36.09%	27.91%	99.81%	29.14%
22	14.19%	19.67%	99.85%	29.30%

Table 2. Evolution of objective functions.

The procedure with its individual phases required the calculation time shown in Table 1. A major improvement (Table 2) was achieved thanks to the optimization procedure undertaken, with errors of less than 37%.

A compromise was sought between the desired accuracy and acceptable computing times. Improved results could have been achieved by revising the number of parameters in the optimization, as specified above.

Conclusions

The approach developed works towards the goal of reproducing the tests usually conducted in the field during all stages of product development in a virtual environment. The aim is to perform a final validation of the product by running simulations that harness a reliable virtual model of the vehicle and realistic road profiles.

Focusing on the second aspect, the methodology presented demonstrates how to reconstruct a road track's characteristics using measured accelerations and a virtual model of the associated vehicle.

The main purpose of the method is to ensure that accelerations of similar energy content to the actual signals acquired occur for the virtual model of the vehicle in transit over the entire frequency domain of interest.

The development of this methodology has enabled the creation of a repository of classified tracks that can be used in a virtual environment to guide design and validate components.

For more information:
Stefano Carrino – EnginSoft
s.carrino@enginsoft.com

About Dana

Dana is a leader in the design and manufacture of highly efficient propulsion and energy-management solutions that power vehicles and machines in all mobility markets across the globe. The company is shaping sustainable progress through its conventional and clean-energy solutions that support nearly every vehicle manufacturer with drive and motion systems; electrodynamic technologies, including software and controls; and thermal, sealing, and digital solutions.

Based in Maumee, Ohio, USA, the company reported sales of $10.6 billion in 2023 with 42,000 people in 31 countries across six continents. With a history dating back to 1904, Dana was named among the "World's Most Ethical Companies" in 2023 and 2024 by *Ethisphere* and as one of "America's Most Responsible Companies 2023" by *Newsweek*. The company is driven by a high-performance culture that focuses on valuing others, inspiring innovation, growing responsibly, and winning together, earning it global recognition as a top employer.

Flexible factory design and reconfiguration using digital simulation models

by Anteneh Teferi Yemane[1], Mirko Piasentin[2], Thomas Bickl[2], Enrico Favero[2]
1. EnginSoft - 2. Tecno Logica

In today's rapidly changing industrial landscape, the complexity and demands of factory design and reconfiguration are greater than ever. To cope with shorter product lifecycles and increased demand for customization, manufacturers need to maximize the flexibility, reconfigurability and adaptability of system capacity.

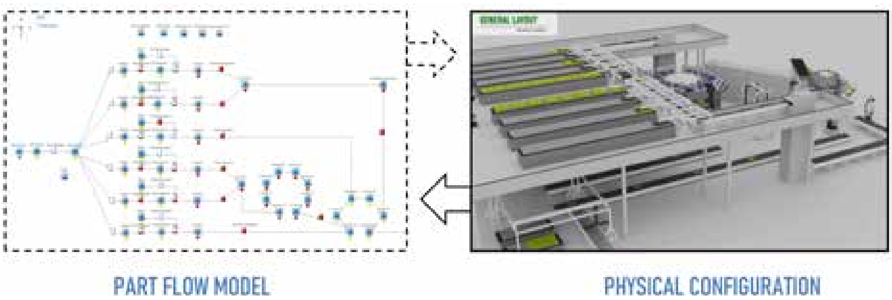


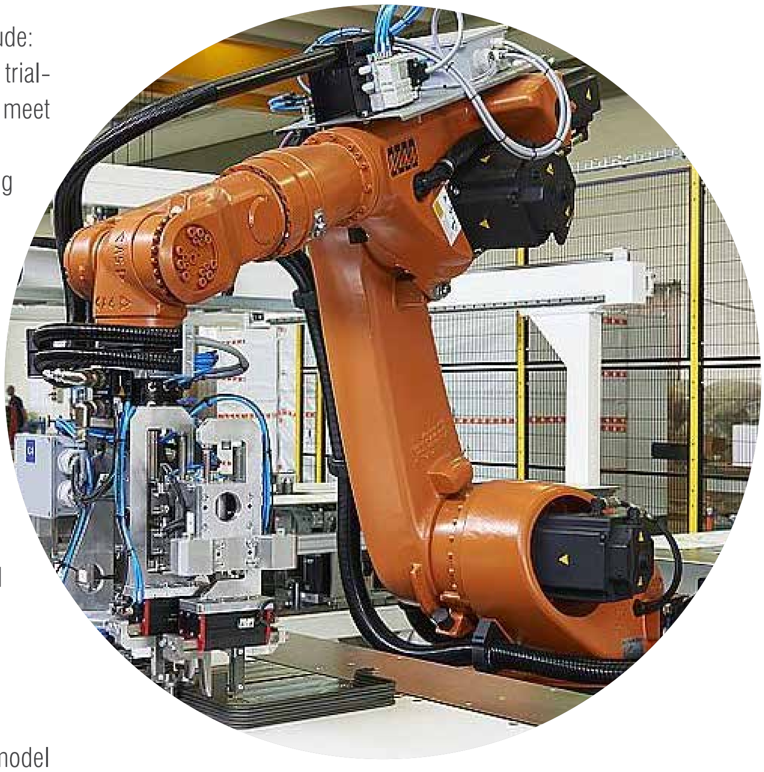
Fig.1. Part flow simulation model of the configuration of a physical asset.

Traditional design and reconfigurations methods, which rely on simplified models and calculations, often involve many challenges, including inefficiency, high costs, and inflexibility.

Digital simulation models are one of the most powerful tools to overcome these limitations, enabling companies to design and test efficient and cost-effective production systems before irreversible capital investments are made during physical development. Their importance cannot be overstated in helping companies to stay competitive and innovative in a rapidly changing market.

Some of the main advantages of digital simulation models include:

- Accurate and robust designs reduce the need for costly trial-and-error methods and enable rapid adjustments to meet changing demand.
- Save time by accelerating design and decision-making processes, resulting in faster time-to-market for new products.
- Virtual prototyping – companies can visualize the entire factory layout, anticipating potential issues early in the design process and refining them before physical implementation.
- Simplified production planning allows for quicker adjustments and refinements, ensuring that production schedules are met more efficiently.
- The use of real-time data improves predictive analysis capabilities, leading to better forecasts and more informed decisions.



An industrial application of digital simulation: designing a furniture assembly factory

This section presents an example of a digital simulation model successfully applied to support factory design. The customer is a manufacturer of pre-assembled kitchen furniture modules ready for installation in end-customer kitchens. The production system must be able to fully assemble each type of furniture specified in an order before shipping the full set of kitchen cabinets to the end-customer.

These orders are highly customized, with each kitchen design being uniquely based on the end-customer's requirements, using a combination of over 185 pieces of furniture and different colour options.

This scenario posed the challenge of designing a production line to efficiently handle a high variety of products. System integrator Tecno Logica was requested by the cabinet manufacturer to design and install a robotic, cabinet assembly line able to guarantee a target production rate while efficiently handling the high variety of products. The design teams were tasked with quickly creating a layout configuration to meet the requirements and to optimize investment and resource efficiency by virtually validating the designs before proceeding to award the contract and its development.

Factory design requirements

The layout design consists of the following areas and operations (see Fig.2):

- Panel storage area
- Shuttle for transporting material between the panel storage area and the bays
- Pallets for positioning panels in the bays
- Robots for removing the panels from the pallets and loading them onto the carousels
- Automated carousels to process the panels and assemble them into cabinets
- Buffer area for storing finished cabinets waiting for delivery to the customer

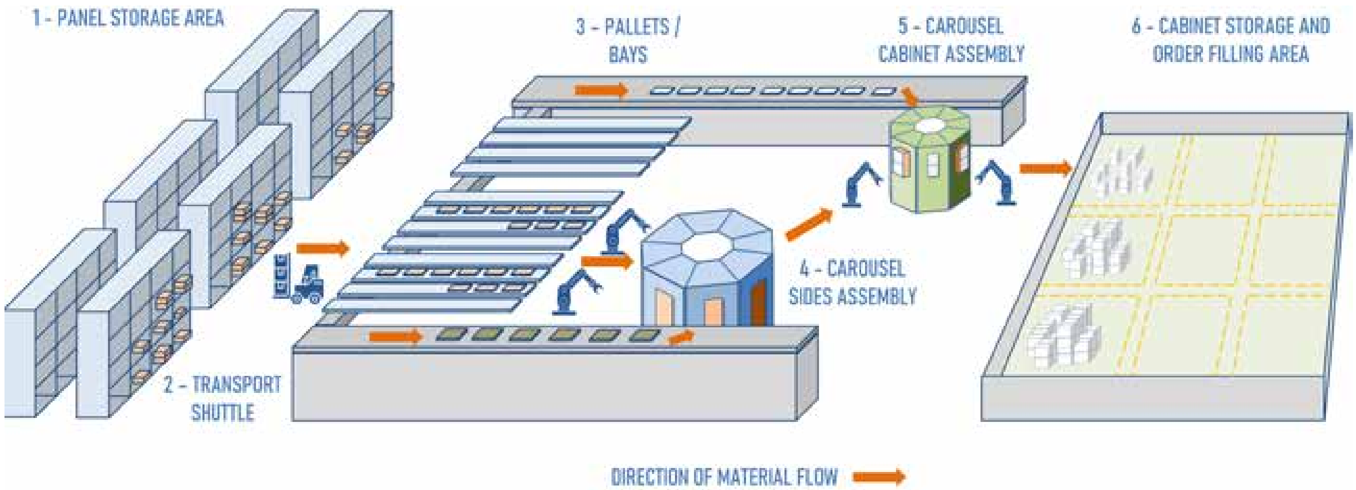


Fig.2. Diagram of the layout showing the main processes.

Customer orders consist of a mix of cabinet types and all types must be completed before orders can be shipped, otherwise the finished cabinets must wait in storage until the missing cabinets are produced, taking up valuable space in the final buffer area. When this situation occurs, the production line is forced to stop for a production change to make the missing cabinet types.

To reduce downtime from buffer blockages and frequent production changes, two macro requirements were defined:

- Group similar orders using an algorithm so that more cabinets can be produced in the same batch before switching to a different type.
- Improve system flexibility by:
  - increasing the number of pallets to allow more types of panels to be produced simultaneously, reducing the frequency of downtime to change cabinet type;
  - creating sufficient buffer capacity to store enough cabinets without blocking the production line, while remaining within the acceptable limit available to the factory.

The challenge was to provide a digitally simulated and validated solution with the optimal configuration of shuttles, pallets, robots and buffer size before building the physical system.

Simulation development, study and optimization

For brevity, we have skipped the order clustering algorithm and will proceed to describe the digital simulation construction process, consisting of 1) problem formalization, 2) simulation implementation, 3) validation, and 4) optimization. Lastly, selected optimal solutions are further studied and presented.

1. Formalization of the problem and objectives

This phase prioritizes the challenges, and collects and organizes the information (divided into four areas, see Fig.3) to quantitatively model and formulate strategies to calculate the simulation objectives. The following dataset was collected in discussion with Tecno Logica and the cabinet manufacturer who ordered the production line.

- Data on process flows, resources, cycle times.
- Example data on full order types and the quantities of cabinets.

The expected results of the simulation were production rate, equipment utilization, and efficiency KPIs.

2. Implementation of the detailed simulation engine

A discrete event simulation (DES) model was developed to mimic key behaviours affecting product flow. For example, how the shuttle picks up panels from storage and loads them onto pallets, how pallets are exchanged in bays, how robots load panels onto carousels, etc.

The DES model allows the current layout performance to be simulated based on historical production order output and export performance statistics, e.g. production rate, percentage of orders completed, robot utilization, shuttle, etc.

In addition to the simulation model, an intelligent order aggregation and production planning algorithm was developed and used to sequence production based on intelligent aggregation of customer orders to improve production performance. Dashboards, animations and visualizations were integrated to facilitate understanding of system behaviour and part flow, and to summarize and report important KPIs. The DES model was built using SIMUL8 (see Fig.4).

3. Testing and validation of simulation with test cases

This step verifies that the simulation accurately reflects the behaviour of the real system. It verifies the rules for order grouping, scheduling, production, storage, and shipping to the customer (see Fig.5).

It also checks whether the production equipment acted in the specified sequences and whether the subsystems interacted as expected. An extensive experimental campaign is conducted using the DES engine with dummy scenarios to validate the simulation.

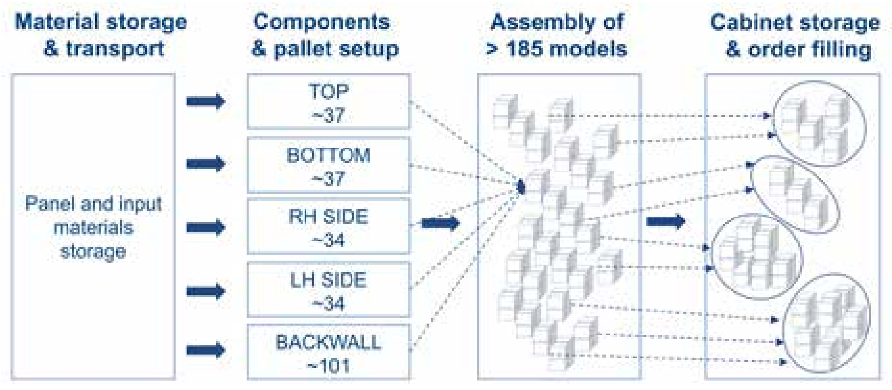


Fig.3. Diagram of material flow and data collected for simulation.

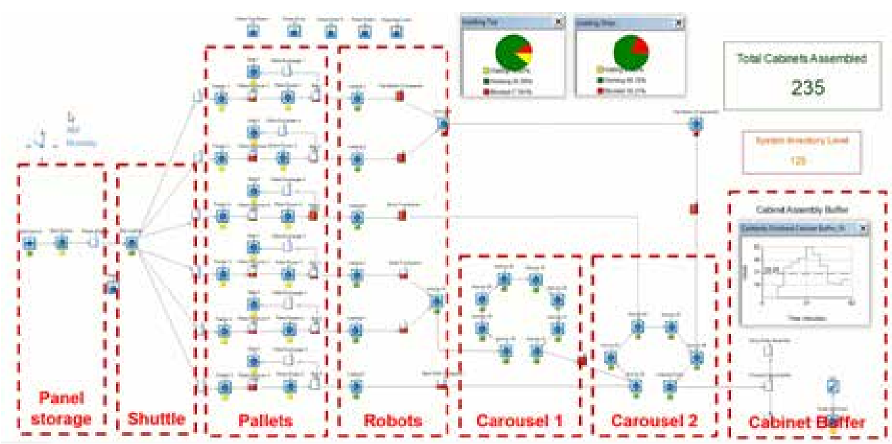


Fig.4. Discrete event simulation model created with Simul8.

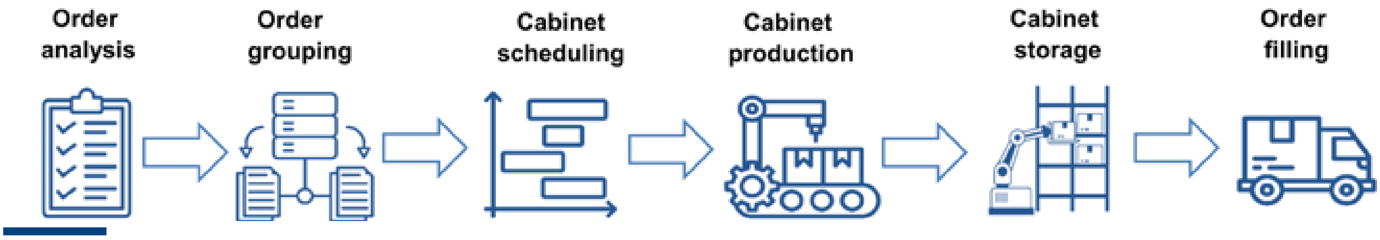
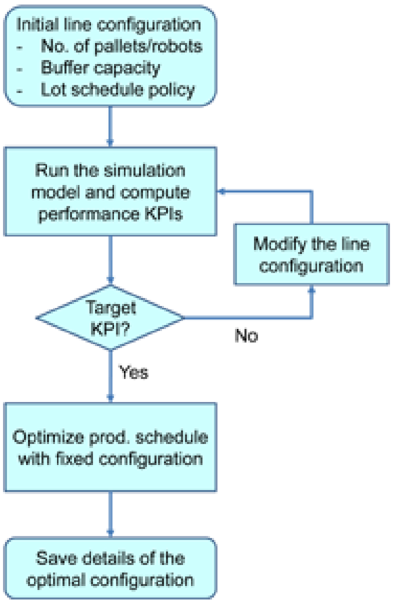


Fig.5. Test procedures applied to the modules of the simulation model.



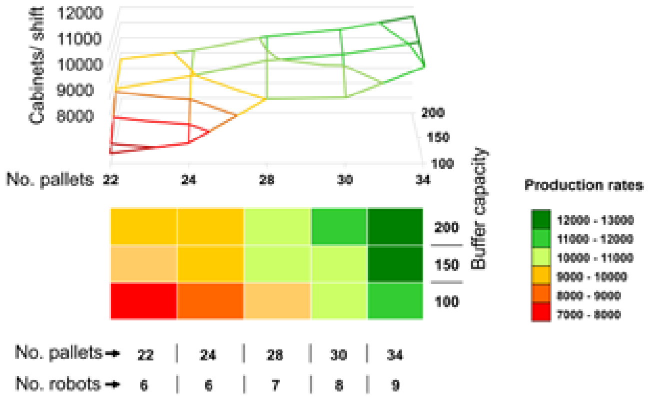


Fig.6. Simulation model submitted to workflow optimization (L), and performance of configurations (R).

The results and feedback from these experiments are shared with Tecno Logica to refine the accuracy of the model and to consolidate the final version to be used for optimization and study.

4. Optimization of pallet bays and buffer configurations of cabinets

After the simulation had been tested and validated, it was submitted to an optimization algorithm to find the best bay and cabinet buffer configurations. Optimization was performed using historical order logs and target production rates to investigate both the optimality and robustness of the configurations.

Sensitivity analysis, performed by simulating varying conditions around the optimal configurations, statistically validated the results. The 3D graphs and heat map in Fig.6 show the optimization workflow, configurations, and associated production performance as a function of the number of pallets, robots and buffer capacities. Green configurations met or exceeded target performance; red and yellow had below-target performance. Each configuration had an associated investment cost that was further assessed by Tecno Logica before it made its final choice of the best layout. The entire study was completed in six weeks, allowing Tecno Logica to present the analysis results in a timely manner to the cabinet manufacturer who finally approved the physical development of the system.

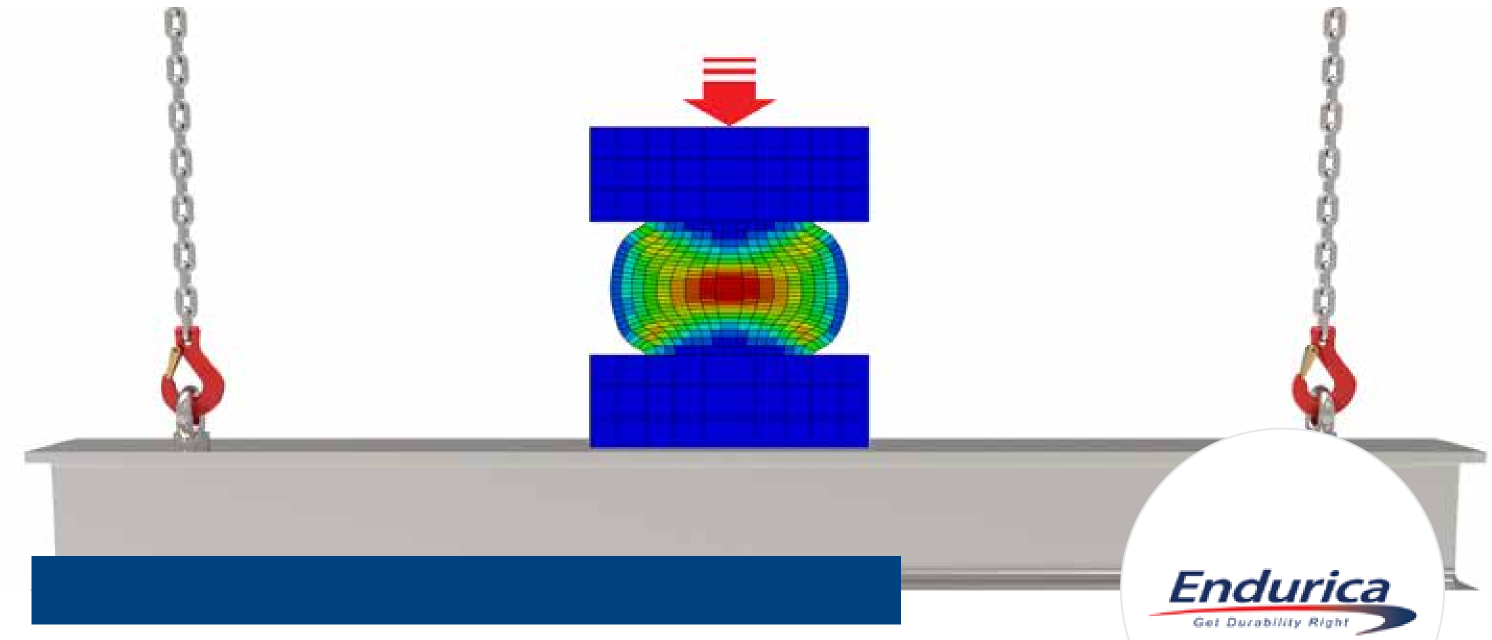
Conclusions

- Using digital simulation models during the design phase reduces investment risks arising from inaccurate and rigid designs by planning efficient adaptation strategies for changes in product type and production volumes.
- By incorporating simulation models into optimization algorithms, resources are optimized on configurations that require less capital investment.
- Parametric simulation models reduce design and development time by identifying and resolving potential errors during the virtual validation process.
- Design phase simulation models can be adapted into simulation models for operational management to support operational efficiency throughout the production system's lifecycle.

For more information:
Anteneh Teferi Yemane – EnginSoft
a.yemane@enginsoft.com

About Tecno Logica

Tecno Logica was founded in 1998 by Mirko Piasentin to meet the need for industrial automation and robotic solutions. It became a highly qualified partner for major industrial groups in solving complex engineering problems and developing production processes for machining, assembly stations, and testing machines. Tecno Logica is registered in the Italian National Register of Research Laboratories to develop competitive methods at multiple levels: to reduce production costs, target innovation in production processes, and to work with products with unique quality characteristics that may be developed and co-funded by public grants. It is an ISO:9001 certified enterprise. Since 2024 Tecno Logica has been part of Scm Group, a world leader in processing a wide variety of materials: wood, plastic, glass, stone, metal and composites.



Rubber fatigue ≠ metal fatigue: what to do when linear superposition fails

by William V. Mars
Endurica

The load cases to be considered in fatigue analysis can be very lengthy and can involve multiple load axes. Often, load cases are much longer than can be calculated via direct time-domain finite element analysis (FEA).

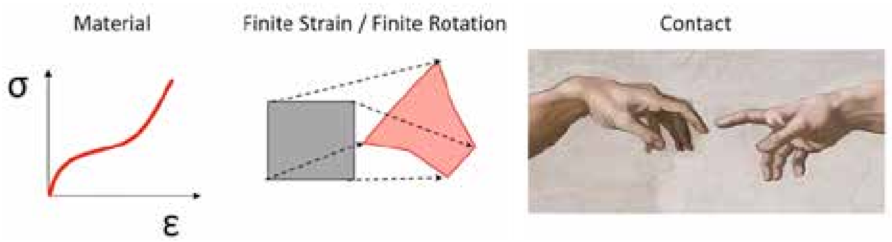


Fig.1. Nonlinearity figures in the analysis of rubbery materials in several ways including material nonlinearity, kinematic nonlinearity, and contact linearity. Endurica's EIE solver provides an efficient and accurate method for generating stress-strain history when there is strong nonlinearity.

In metal fatigue analysis, linear superposition is a widely used technique to generate stress-strain history from road loads [1], [2], [3]. When structures behave linearly, this approach is accurate and computationally efficient, allowing the analysis of lengthy load signals. For single axis problems, the finite element (FE) solution for a single unit load case is simply scaled according to the input load history. For multiaxial problems, unit load cases are solved for each of the axes, then scaled and combined according to the input load history.

Due to rubber's 1) nonlinear material behaviour, 2) nonlinear kinematics, and 3) the possibility of nonlinear contact, linear superposition cannot be applied to rubber fatigue analysis. This article is the second in a series examining how rubber fatigue analysis procedures differ from those used for metal fatigue. Here we present the Endurica EIE (Efficient Interpolation Engine) solver, which is a tool for the rapid generation of stress-strain histories for fatigue analysis in cases where linear superposition fails.

Brief review of the linear superposition procedure for metals

For linear structures, the relationship between forces $[F]$ and displacements $[u]$ can be written as a matrix multiplication where $[k]$ is the stiffness matrix.

$$[F]=[k][u]$$

The associative property of function composition means that multiplying the displacements by a scalar α produces proportionally larger forces.

$$\alpha[F]=[k](\alpha[u])$$

The distributive property of addition means that a force system resulting from combined displacements $[u]$ and $[v]$

$$[F]=[k][u]+[k][v]$$

can also be calculated as

$$[F]=[k]([u]+[v])$$

Similarly, stress and strain fields can be scaled and combined by linear superposition. Engineers have been using this principle for many years in metal fatigue analysis, particularly for treating multiaxial cases arising from field-recorded load-displacement histories.

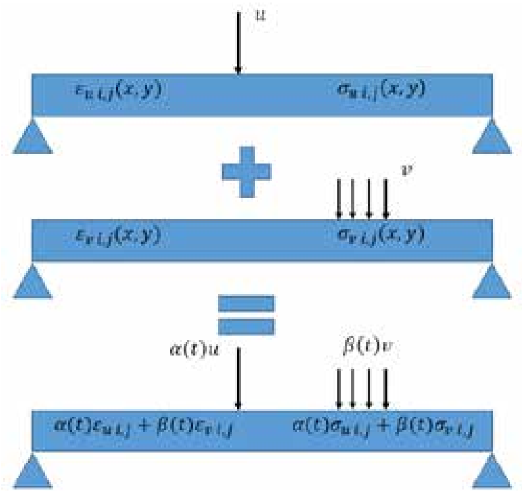


Fig.2. Linear superposition of single load case FE solutions has long been used to generate stress-strain histories from road load histories in metal fatigue analysis.

The stress and strain fields in a part are assumed to result from a linear combination of unit load cases, where the scale factor for each unit load case is applied to the stress or strain field corresponding to a given input channel.

For example, for the beam shown in Fig.2, if channel 1 is the unit displacement u with magnitude $\alpha(t)$, and channel 2 is another unit displacement v elsewhere in the structure with magnitude $\beta(t)$, then the entire history of stress and strain at all points in the beam can be recovered by linear superposition.

Note that the FE solver only needs to produce a single time-independent solution for each unit load case. The time dependence of the solution is obtained entirely through the time variations of the scale factors $\alpha(t)$ and $\beta(t)$. This extremely efficient method has been used for many years in metal fatigue analysis. It allows rapid analysis of complete road load histories consisting of millions of time steps.

Endurica EIE: load space discretization and interpolation for nonlinear cases

Solving the nonlinear case requires a completely different approach. We wish to retain the advantages of efficiently constructing stress-strain time histories from precomputed FE solutions. Instead of precomputing a single unit load case for each input channel, we precompute a set of load cases from a discretized load space. We call this set a map.

The number of load cases in the map must be sufficient so that we can use interpolation to obtain a reasonable approximation of the nonlinear response at any point within the map.

Fig.3 shows a map with two channels defined by x and z displacements. The blue points in the map are precalculated using an FE solver such as Ansys or LS-Dyna following the path traced by the blue line. Once the map is defined, the stress-strain history along the red line can be interpolated from the precomputed solutions in the map.

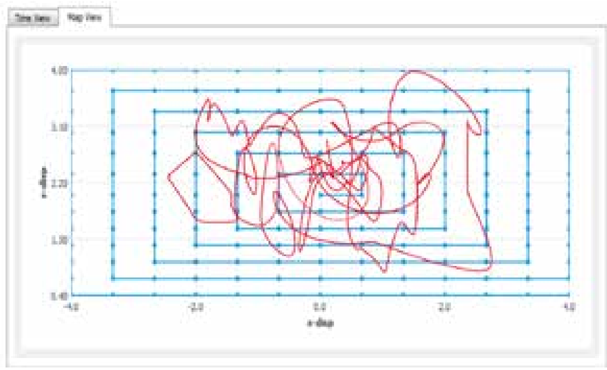


Fig.3. Two-channel map discretizing a space defined by the x and z displacements. Blue dots represent FE solutions for which the stress-strain fields are precomputed. The blue line represents a solution path, which defines the order in which the solutions are computed and stored in the results database. The red line represents a possible actual displacement history. The stress-strain history for points on the red path is obtained by interpolation from points on the precomputed map.

Endurica EIE is a general-purpose tool for creating and using non-linear maps to generate stress-strain histories for fatigue analysis [4], [5]. EIE is an abbreviation for efficient interpolation engine. EIE provides a simple workflow and powerful utilities for creating and using maps for interpolation. It supports up to six independent input channels.

The entire EIE workflow consists of three main steps. The first step is to create a map. The next step is to specify your history in terms of forces or displacements. Note that any quantity that can be applied as a boundary condition to the FE model can be set up as a channel. The last step is to perform the specified interpolation. The process produces a time history of strain tensor components for each element in your FE model.

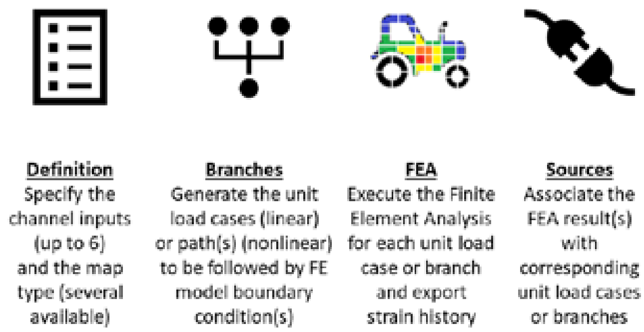


Fig.4. Steps to specify a map for use by Endurica EIE.

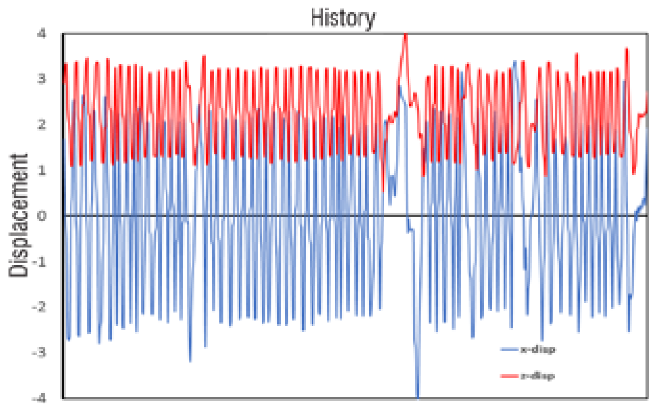


Fig.5. Example two-channel displacement history for interpolation.

The map creation process involves four steps, as shown in Fig.4. First, the number of independent channels that will be used to specify the history must be defined. The map type must also be specified. Several types are available, including a completely customizable map. Grid-based maps are often appropriate for one-, two- and three-dimensional maps. For higher dimensional maps, case vector-based maps are often the most convenient.

Once the map type has been defined, EIE generates solution paths. These consist of enumerated load states that should be applied as boundary conditions to the FE model to generate the map. One or more paths may be generated depending on map type. Each path is called a branch. For each branch, EIE writes a file with the appropriate boundary condition history, which is necessary for the generation of the map. Next, the FE model is set up and executed using EIE's boundary conditions. Finally, the database of FE results is linked to the corresponding branch in the definition of the map.

At this point the map is complete and ready for interpolation. Note that linear superposition can be implemented as a special case in EIE when unit load case solutions are collected and defined as a map. In general, however, a non-linear map will contain a greater number of solution steps.

Specifying the load history is as simple as selecting a file containing the time history of each input channel. In the file, each row represents one-time step and each column represents an input channel. EIE supports .csv and .rsp formats, both common data formats. Fig.5 shows an example history with x and z displacements. Note that the range of displacements in the history should not exceed the range of the precalculated map. Although interpolated solutions can be quite accurate, extrapolation for non-linear problems can be very risky and inaccurate.

Once the map and history are specified, interpolation can begin. Endurica EIE supports multi-threading, meaning that interpolation calculations can be distributed and executed in parallel across available

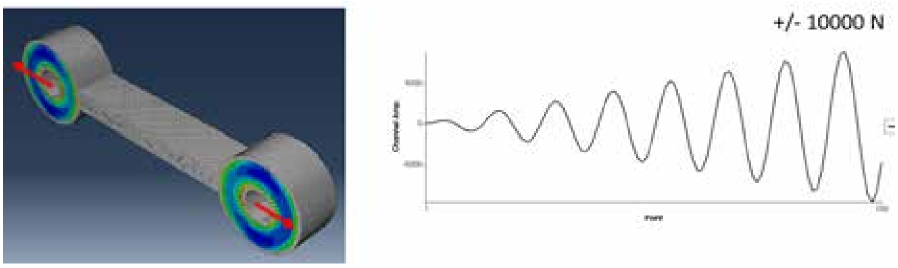


Fig.6. Sway bar link under uniaxial loading (left). Axial load history input for strain history interpolation (right).

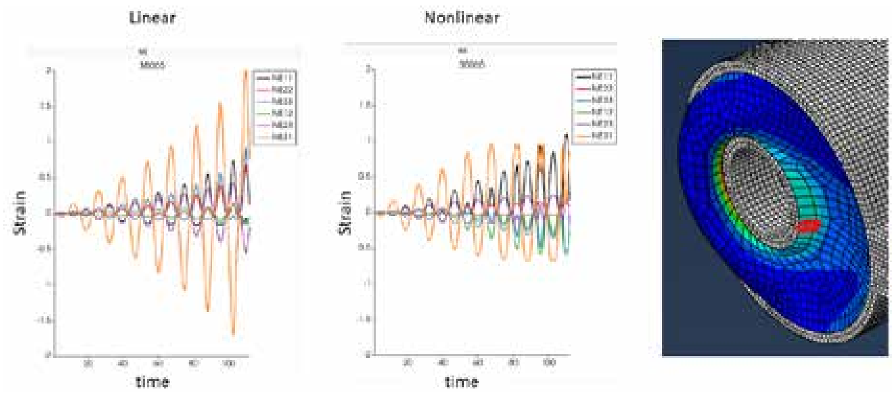


Fig.7. Comparison of linear (left) and non-linear (middle) interpolation results for strain tensor components at the location indicated on the right.

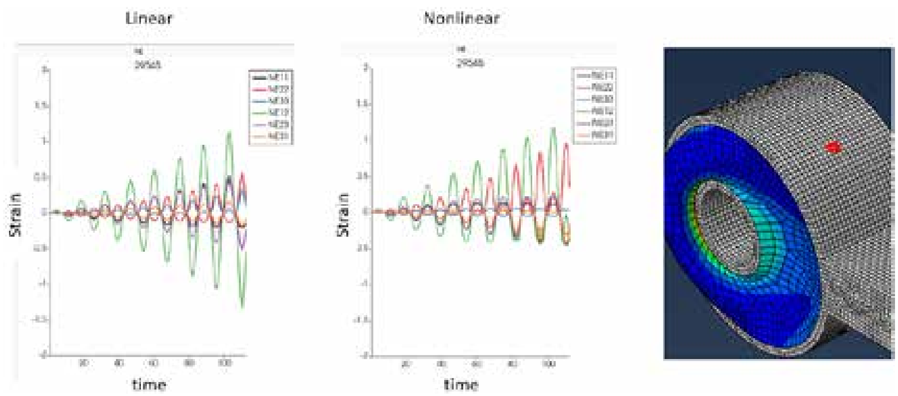


Fig.8. Comparison of linear (left) and non-linear (middle) interpolation results for strain tensor components at the location indicated on the right.

CPUs. This makes interpolating very fast and very scalable to large models and lengthy histories. Note that Endurica EIE generates large files because it calculates stress and strain tensor components for each time step of each finite element. It is therefore important to ensure that you have sufficient disk space available when running Endurica EIE.

Comparing linear and non-linear interpolation results for a sway bar under uniaxial loading

As a first example, consider an automotive sway bar link, shown in Fig.7. The sway bar transmits load in a single axial direction. This model uses Ogden's hyper elastic law, which involves a non-linear relationship between stress and strain. The large deformation solution also involves non-linear kinematics due to the incompressibility of rubber and finite displacements and rotations. To compare the linear and non-linear interpolation methods, we will run the analysis using both: 1) the linear scaling method (where the map consists of a single load case in which we apply one newton of total load in the x-direction to the link and solve for the strain distribution in the part); and 2) the non-linear method (where the map consists of 11 precomputed steps ranging from -10000N to +10000N).

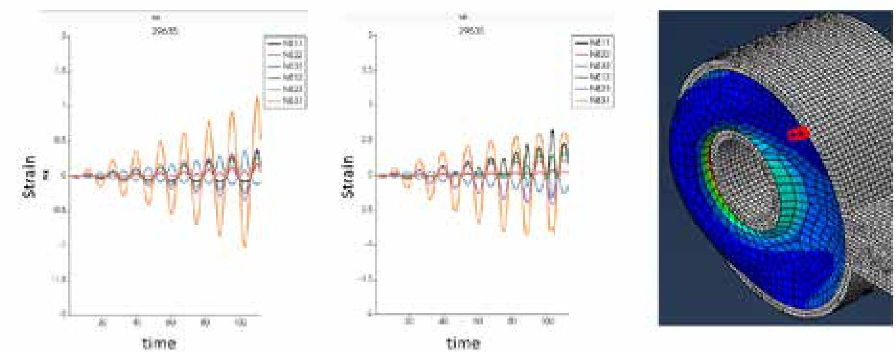


Fig.9. Comparison of linear (left) and non-linear (middle) interpolation results for strain tensor components at the location indicated on the right.

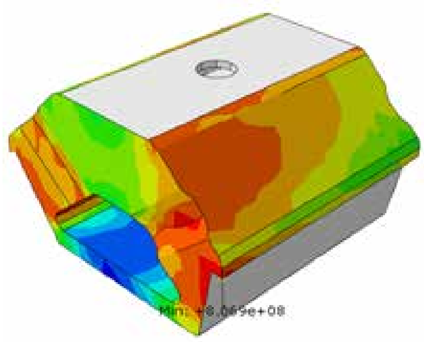


Fig.11. Gearbox mount analysis. All forces and moments (x, y, and z) were applied at the centre of the top rigid mounting plate.

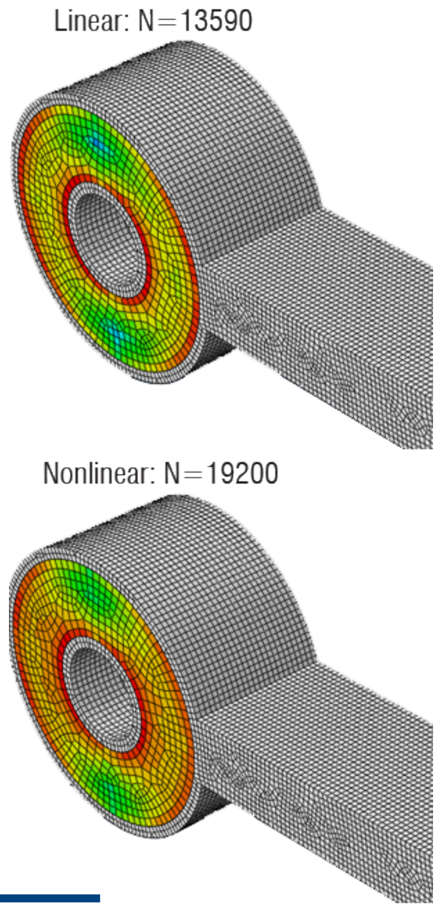


Fig.10. Comparison of fatigue life calculations based on linear (left) and non-linear (right) interpolated strain history.

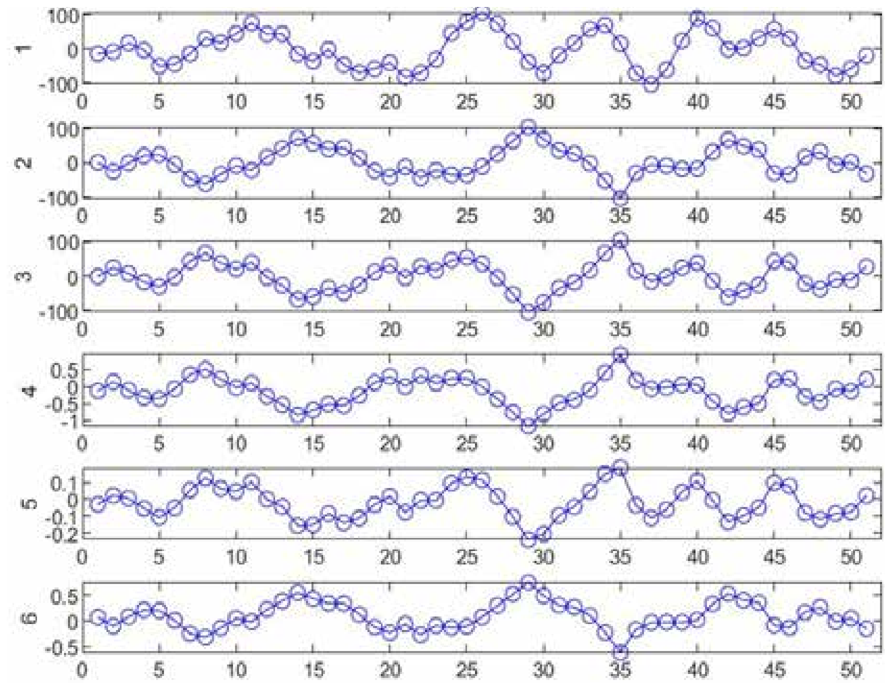


Fig.12. Six-channel map containing 51 precalculated finite element solutions.

Figs. 8–10 show the six-engineering strain tensor component history results for both the linear superposition procedure (left) and the nonlinear EIE procedure (right). The results are shown for three different locations on the sway bar bushing (highlighted in red). The largest strain component is the 31 shears (orange line). Note that for the linear procedure, a linear increase in the amplitude of the global force results in a linear increase in the strain components. The non-linear procedure produces quite different results. In fact, where the linear solution predicts symmetry of tension and compression loads, the non-linear solution correctly captures asymmetries.

As a final comparison, Fig.11 shows the fatigue life calculated using Endurica CL.
A longer fatigue life is predicted for the non-linearly interpolated case compared to the linearly interpolated case. Note that the fatigue damage is more concentrated in the linear case and more spatially distributed for the non-linear solution.

Endurica EIE validation for a six-channel non-linear interpolation

As a further test of the non-linear interpolation procedure for a six-channel (x,y,z forces + x,y,z moments) multiaxial load analysis of the gearbox mount shown in Fig.11, the map shown in Fig.12 was defined. This map contained 51 precalculated non-linear FE solutions. The complete loading history to be interpolated is shown in Fig.13. This history was solved in full directly and interpolated from the map using Endurica EIE.

The strain tensor histories for the 11, 22 and 12 strain components are compared between the directly solved and interpolated solutions in Fig.14 at the location of the most critical element. A fairly accurate interpolation was obtained with a much shorter run time than the direct finite element analysis of the full history. The fatigue life of the gearbox mount was calculated with Endurica CL using both the EIE-interpolated strain history and the directly solved strain history. The fatigue contours for both cases are shown in Fig.15.

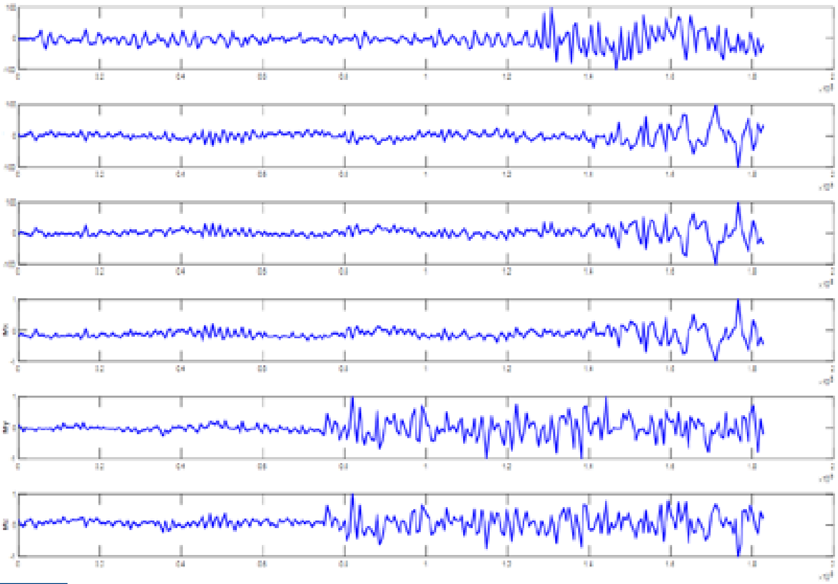


Fig.13. Full six-channel road load history used for validation analysis of gearbox mount.

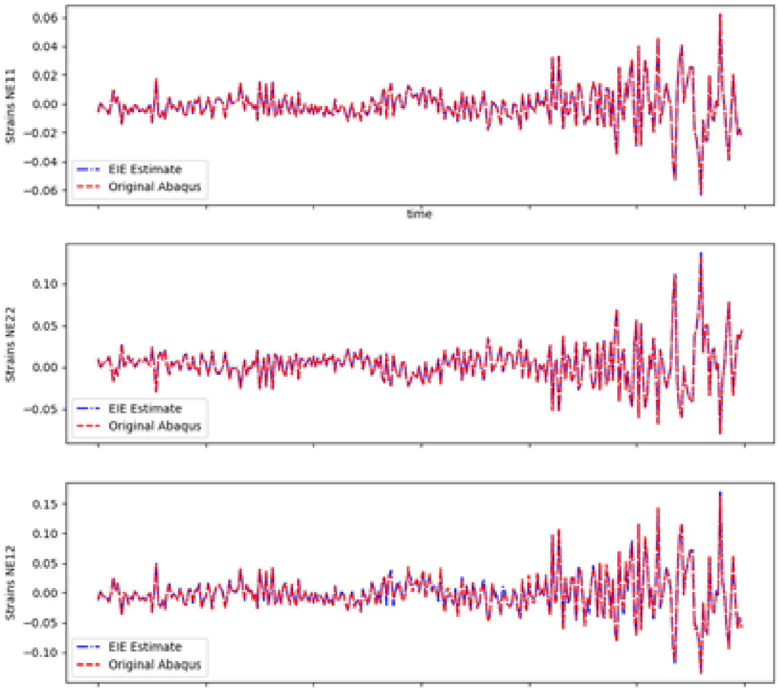


Fig.14. Comparison of EIE-interpolated strain components (blue) v. direct finite element solution (red) at the location of the most critical element.

The fatigue life for the interpolated history was 7.52E8 and for the directly solve history the fatigue life was 7.87E8. These results indicate a close agreement between the EIE and directly solved cases. Other validation cases were recently published elsewhere (Mars et al 2024).

Conclusion

Analysis of rubber components typically involves strong nonlinearities due to material behaviour, finite strain kinematics, and contact. The traditional linear superposition of unit load cases, widely used in metal fatigue analysis, is not effective in such cases. Fortunately, the Endurica EIE solver can generate strain histories efficiently and accurately in these cases. The EIE tools allow the analysis to precalculate a set of FE solutions for efficient discretization of the load space and accurate interpolation of signals within the load space. With sufficient discretization of the load space, it was shown that quite accurate results can be produced for cases where there are between one and six load input channels.

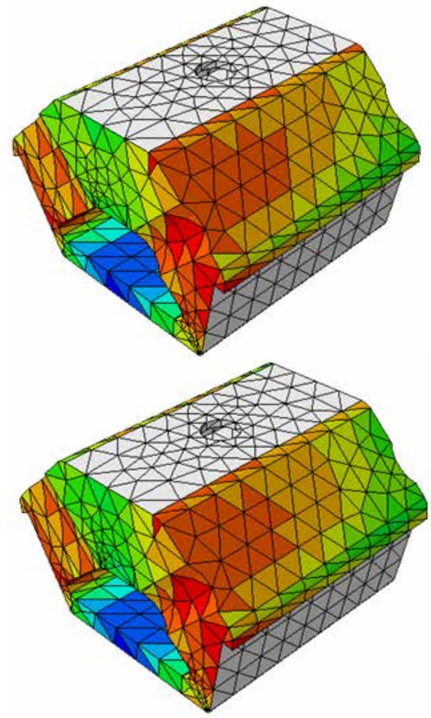


Fig.15. Comparison of fatigue life calculated from EIE-interpolated strain components (right) and direct finite element solution (left).

References

[1] R. W. Landgraf, "Applications of fatigue analyses: transportation", *Fatigue '87*, vol. 3, pp. 1593–1610, 1987

[2] Moon, Seong-In et al, "Fatigue life evaluation of mechanical components using vibration fatigue analysis technique", *Journal of Mechanical Science and Technology*, vol. 25, pp. 631–637, 2011.

[3] F. A. Conle and C. W. Mousseau, "Using vehicle dynamics simulations and finite-element results to generate fatigue life contours for chassis components", *International Journal of Fatigue,* vol. 13(3), pp. 195–205, 1991.

[4] K. P. Barbash and W. V. Mars, "Critical plane analysis of rubber bushing durability under road loads", *SAE Technical Paper* No. 2016-01-0393, 2016.

[5] W. V. Mars, "Interpolation engine for analysis of time-varying load data signals". U.S. Patent 9, 645, 041, May 9, 2017.

[6] W. Mars, K. Barbash et al, "Durability of Elastomeric Bushings Computed from Track-Recorded Multi-Channel Road Load Input", SAE Technical Paper No. 2024-01-2253, 2024.

For more information:
Alessio Trevisan – EnginSoft
a.trevisan@enginsoft.com

Data processing of injection moulding processes

by Kriti Goma, Nicolò Spiezia[1], Marco Barbetta[2], Giovanni Sperotto[3]
1. M3E- 2. MSquare Dynamics - 3. AzzurroDigitale

This article presents the preliminary results of the DIMO (DIgital MOulding) research project developed by AzzurroDigitale, M3E and MSquare Dynamics, with the external support of Casagrande, an Italian plastic moulding company. Plastic injection moulding is a widely used industrial manufacturing process capable of producing plastic objects with complex geometries with a high degree of precision and productivity [1].

There are four stages in the injection moulding process: plasticizing, injecting, packing, and cooling. These steps involve melting the polymer, injecting it into the mould, compressing it and finally cooling it. Process parameters are critical to moulding quality and correct process setup will improve cycle time and part quality. Consequently, many studies have attempted to predict product quality from the values of the production process parameters [1].

Injection moulding must reduce defects and improve quality to reduce scrap and rework costs. High-quality, defect-free components are required to meet strict industry standards, particularly in the automotive and medical sectors. Reliable products increase customer satisfaction and loyalty, reducing market competition. Quality production ensures on-time delivery and operational efficiency. Defect reduction is critical to cost-effectiveness, product reliability, and market competitiveness.

The aim of the DIMO project was to identify correlations between variations in the monitoring data and the amount of waste recorded in order to identify underlying relationships that have not previously been considered. This will contribute to a better understanding of the reasons for such variability. The aim is not only to better understand the production mechanisms, but also to optimize the production process and reduce waste.

The list of variables is described in Table 1 and Table 2. For example, we closely monitored the variables “hmdty_cbn” (i.e. the relative humidity in the press cabin); “temp_cbn” (i.e. the air temperature in the press cabin); “presN1” and “presN2” (i.e. the pressure measurements before the plastic is injected into the mould to create a vacuum in the plastic); “TempoCiclo (Cycle Time)” (i.e. the time it takes the machine to complete the entire injection cycle); “TempoRiempimento (Filling Time)” (i.e. the time it takes the machine to inject hot plastic to fill the mould); and “TempoMantenimento (Time Maintained)” (i.e. the time after filling during which the injection pressure is maintained to allow the plastic to stabilize).

Problem description

A data-driven approach is critical in the injection moulding process because of its ability to improve parameter optimization, reduce manual interpretation errors, and improve product quality.

Systematic data analysis, using a variety of methods and tools, can significantly support quality improvement of the injection moulding process in production. This approach improves the predictability, efficiency, and overall quality of the manufacturing process.

Data-driven monitoring and analysis can significantly improve efficiency and reduce costs, making it essential for modern factories. In addition, a data-driven approach can be useful in making real-time predictions about quality, energy consumption, and sustainability. The use of mixed regression models to evaluate time-series energy consumption data allows the identification of patterns and trends, providing insights into how to reduce the electrical consumption of industrial facilities.

Data acquisition

The first step was to digitize data collection, both from processes and operators.

As regards real-time process data, some was extracted from the machine’s PLC and some was collected using additional sensors.

S.No.	NAME	UNIT OF MEASURE	SOURCE	DATE OF ACQUISITION
1	presN1_mean	bar	SENSORS	02-08-2023
2	presN1_var	-	SENSORS	02-08-2023
3	presN1_min	bar	SENSORS	02-08-2023
4	presN1_max	bar	SENSORS	02-08-2023
5	presN2_mean	bar	SENSORS	02-08-2023
6	presN2_var	-	SENSORS	02-08-2023
7	presN2_min	bar	SENSORS	02-08-2023
8	presN2_max	bar	SENSORS	02-08-2023
9	hmdty_cbn	%	SENSORS	02-08-2023
10	temp_cbn	°C	SENSORS	02-08-2023
11	tempN	°C	SENSORS	02-08-2023
12	tempMoldStat	°C	SENSORS	02-08-2023
13	tempMoldMvng	°C	SENSORS	02-08-2023
14	tempDryer	°C	SENSORS	02-08-2023
15	TempoRaffreddamento	0.1s	SENSORS	02-08-2023

Table 1: List of data acquired from sensors installed on the machine.

S.No.	NAME	UNIT OF MEASURE	SOURCE	DATE OF ACQUISITION
1	ContaCicli	-	PLC	29-09-2023
2	TempoCiclo	0.1 s (tenths)	PLC	29-09-2023
3	StatoMacchina	-	PLC	29-09-2023
4	QuotaDosatura	0.1 mm (tenths)	PLC	29-09-2023
5	TempoRaffreddamento	0.1 s (tenths)	PLC	29-09-2023
6	TempoRiempimento	0.1 s (tenths)	PLC	29-09-2023
7	TempoMantenimento	0.1 s (tenths)	PLC	29-09-2023
8	QuotaCuscino	0.1 mm (tenths)	PLC	29-09-2023
9	MediaPressioneRiempimento	0.1 bar	PLC	29-09-2023
10	VarianzaPressioneRiempimento	-	PLC	29-09-2023
11	MediaPressioneMantenimento	0.1 bar	PLC	29-09-2023
12	VarianzaPressioneMantenimento	-	PLC	29-09-2023
13	MediaContropressione	0.1 bar	PLC	29-09-2023
14	VarianzaPressioneMantenimento	-	PLC	29-09-2023

Table 2: List of data acquired from PLC of the machine.

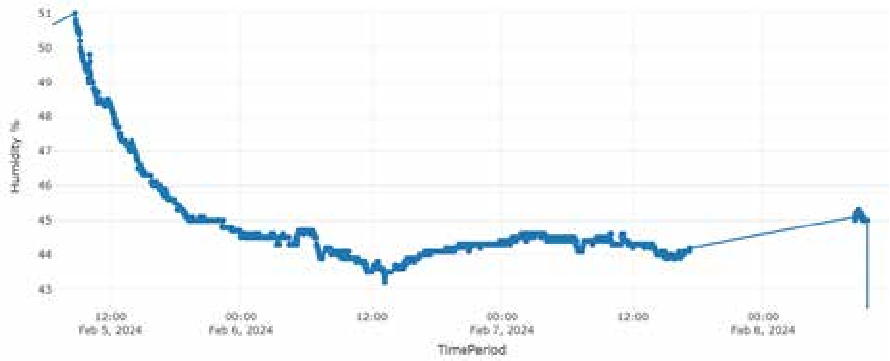


Fig.1. Time series analysis of humidity values during the injection moulding process.

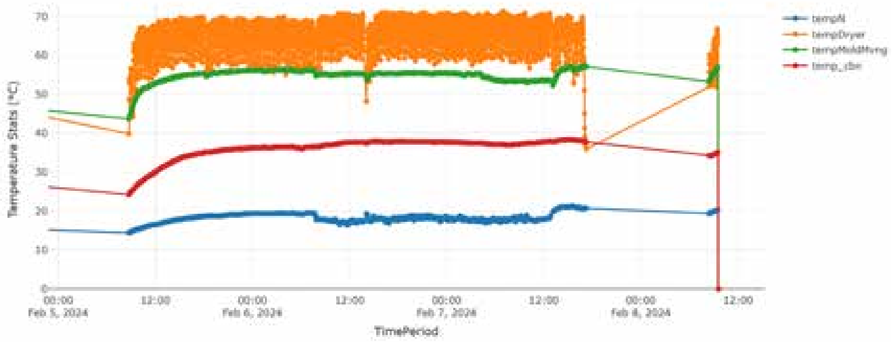


Fig.2. Trends of four different temperature variables.

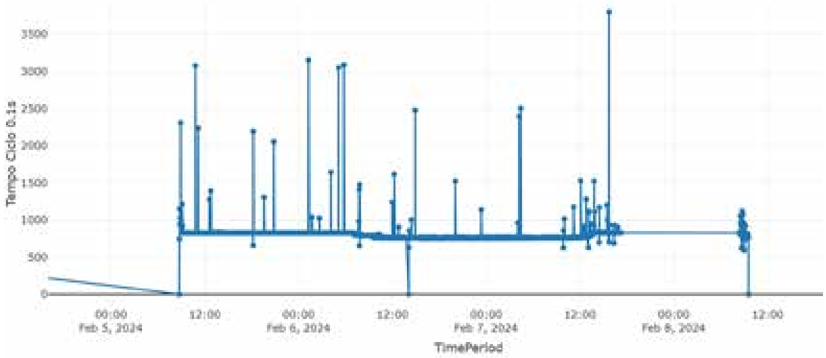


Fig.3. Cycle time (Tempo Ciclo) [0.1s] of the injection moulding process from 5–8 February 2024.

Regarding the quality gate data, at the beginning of the project most of the data was collected manually by the company's employees, so digitization was a crucial step. Digital data collection enables qualitative analysis of defects and defect quantities, together with defect descriptions.

Data visualization and analysis

Our analysis of the data collected aimed to identify opportunities for process improvements and to determine whether specific variables were influencing the process or causing defects. Specifically, we wanted to understand which variables were responsible for which defects.

Python script was used for data cleaning and produced a comprehensive table listing all variables along with their acquisition times. Time series analysis was performed on each variable to identify trends and patterns in the injection moulding process. Selected time series analysis graphs from our work are shown below.

Fig.1 shows the time series analysis of humidity values during the injection moulding process from 5–8 February 2024. It shows an initial sharp decrease followed by a period of stability. Minor fluctuations on 7 February fall within acceptable ranges, indicating the consistent conditions essential for high quality moulding. A sharp increase on 8 February suggests an anomaly, highlighting the need for continuous monitoring and rapid response. Overall, maintaining stable moisture levels ensures process efficiency and product quality.

Fig.2 shows the temperature trends of four different temperature variables, namely "temp_cbn" (i.e. the air temperature in the press cabin); "tempDryer" (i.e. the temperature of the air blown into the press dryer); "tempMoldMvng" (i.e. the temperature of the moving part of the mould); and tempN (i.e. the temperature of N2 just before it is injected into the mould). The temperature parameters show an overall stable and consistent trend, except for 8 February. A sudden drop followed by an increase was observed indicating an anomaly that may require further investigation.

The graph in Fig.3 shows the cycle time of the injection moulding process from 5–8 February 2024. It shows significant variability with several peaks indicating possible process disturbances. There are consistently lower cycle times, but outliers above 2,500 seconds indicate major inefficiencies. Potential causes include machine malfunction, maintenance issues, or operator error. Addressing these issues through root cause analysis, process optimization, preventive maintenance, and real-time monitoring can improve process stability and efficiency.

Fig.4 shows a correlation matrix between the variables described above. It shows the interdependencies of different process variables in the week from 5–8 February 2024. Many temperature- and pressure-related variables also show strong positive correlations: "tempMoldMovng" with "tempMoldStat" and "tempN" of "pres1" with "presN1_mean". The most relevant negative correlations are "tempMoldMvng" vs. "presN2_mean" and "presN1_mean" vs. "TempoRaffreddamento". Variables such as "TempoMantenimento", "Tempo-Raffreddamento", and "TempoRipremimento" are strongly correlated with each other — changes in one will strongly influence the other two.

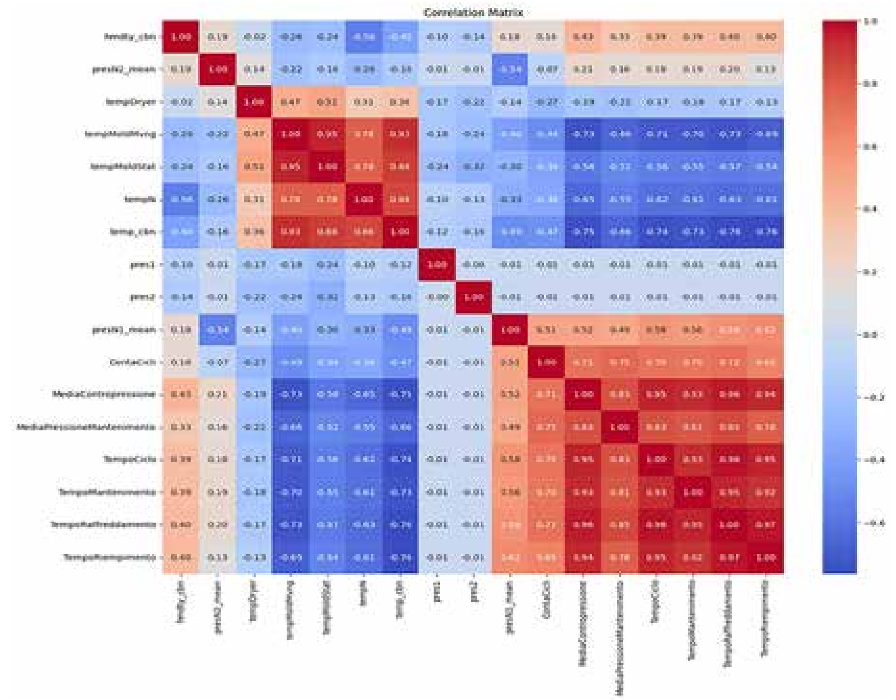


Fig.4. Correlation matrix between the variables.

These results indicate that proper temperature and pressure control as well as high maintenance rates and cycle times are critical to process stability. This matrix highlights the potential for improvement and the notion that these variables must be managed together to improve overall performance.

The quality gate analysis was performed using data on defects generated during the process, classified according to their descriptions. The aim of this analysis was to visualize the number of defects and to establish correlations between defect types.

By examining these variables through time series analysis we attempted to identify the underlying causes of the defects. Fig.5 shows a visualization of the defects and their types.

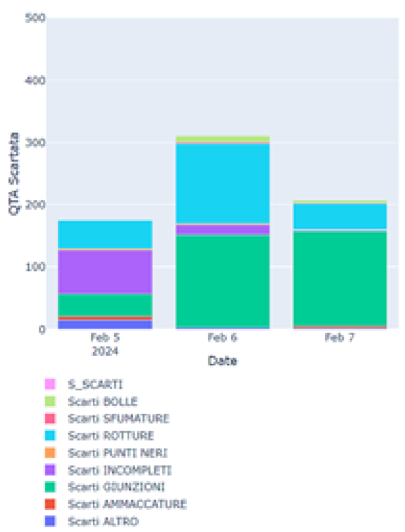


Fig.5. Distribution of defects according to the labelling system in production (QTY Rejected time for different defects: S_Rejects, Rejects BUBBLES, Rejects SHADES, Rejects BROKEN, Rejects BLACK SPOTS, Rejects INCOMPLETE, Rejects JUNCTIONS, Rejects DENTS, Rejects OTHER).

Conclusion and future work

Digital monitoring of the injection process and data-driven analysis are critical in today's industrial manufacturing processes and can provide insights into production.

Manual data collection can be digitized in a way that makes it easier for workers to do their jobs, which can help improve the company's production levels and, in particular, reduce defects and waste.

The DIMO project has laid the foundations for a more effective use of technology in monitoring and optimizing industrial processes.

Future work could include the integration of data-driven models to identify and address defects and establish some real-time monitoring.

Acknowledgments

M3E would like to thank Dr Kriti Goma for the data analysis, exploration and visualization tasks performed during her internship.

The DIMO project partners wish to thank Casagrande for providing the facilities, data and an insight into the process.

The DIMO project has received financial support from the Veneto Region as part of the "Piano Sviluppo e Coesione, sezione speciale, AREA TEMATICA PSC 1 - RICERCA E INNOVAZIONE - DGR n. 1800 del 15 dicembre 2021" or Development and Cohesion Plan (PSC), special section, THEMATIC AREA PSC 1 - RESEARCH AND INNOVATION - Regional Council Resolution No. 1800 of 15 December 2021.

References

[1] A. Polenta, S. Tomassini et al, "A Comparison of Machine Learning Techniques for the Quality Classification of Molded Products", *Information* vol. 13, pp. 272, 2022. https://doi.org/10.3390/info13060272

[2] S. Körber, K. Moser and J. Diemert, "Development of High Temperature Resistant Stereocomplex PLA for Injection Moulding", *Polymers* vol. 14 (3), pp. 384, 2022. https://doi.org/10.3390/polym14030384

[3] M. Kariminejad, D. Tormey et al, "Ultrasound Sensors for Process Monitoring in Injection Moulding", *Sensors* vol. 21 (15), pp. 5193, 2021. https://doi.org/10.3390/s21155193

For more information:

Giovanni Sperotto – AzzurroDigitale
giovanni.sperotto@azzurrodigitale.com

Or visit: www.azzurrodigitale.com/2024/07/23/monitoraggio-e-digitalizzazione-nello-stampaggio-plastico-il-progetto-dimo-digital-moulding

Capvidia: Transforming manufacturing with model-based workflows

by Jimmy Nguyen
Capvidia

Constant evolution: the shift to digital

Anything that can be digitalized, is being digitalized.
In the 1970s, major aerospace and automotive companies began using a cutting-edge digital technology called CAD (computer-aided design) to design complex parts.

The mainstream dismissed it as a fad: CAD systems could never replicate the feel and detail of hand drawing on paper and mylar sheets. The cost of introducing computers, software, and retraining engineers from pen and paper to keyboard and mouse would be too high and almost impossible. CAD would never happen.
In the 1980s, personal computers became mainstream. In the 1990s, CAD became standard.

Now in the 2020s, major aerospace and automotive companies are using model-based workflows, sometimes called MBD (model-based definition) or MBE (model-based enterprise), to design complex products.

Again, the mainstream is proclaiming it a fad: model-based workflows cannot compete with the ease and simplicity of 2D PDF drawings.

The cost of implementing MBD/MBE workflows, changing processes, and retraining engineers from a 2D to 3D workflow would be too high and almost impossible. Model-based workflows will never happen...

What are model-based workflows?

Traditional manufacturing is still a highly manual process. Design engineers design complex parts and assemblies in CAD.

However, to build and evaluate the part, design engineers capture all quantitative information (dimensions, tolerances, geometric dimensions, etc.), qualitative information (materials, surface treatments, surface roughness, etc.), and documentation requirements in a 2D drawing. Design engineers then pass the CAD file and the 2D drawing to quality engineers to check the feasibility of the design.

This is known in the industry as "throwing it over the wall" as the designer rarely understands the amount of work that quality and manufacturing engineers must go through to ensure a quality part or assembly.

Quality engineers take all the information conveyed in the 2D PDF drawing and manually re-enter data into quality workflows such as FAI (first article inspection), SPC (statistical process control), PPAP (production part approval process), CMM (coordinate measure machine), and more.

This process can take weeks or even months for complex parts and assemblies.

However, this process has many points of failure:

- Manual transcription increases the risk of error.
- Manual transcription increases the time required to perform a labour-intensive yet menial task.
- Manual transcription increases costs associated with rework and recalls.

All these setbacks associated with a 2D drawing-based workflow stem from a lack of interoperability. The design engineer has already put the manufacturing information into the 2D PDF drawing. Why do quality engineers have to re-digitalize the same information into their system? Shouldn't the information be automatically passed up and down the chain? The answer is model-based workflows.

With model-based definition, design engineers bring all the information needed to manufacture a product directly into CAD. One file, one source truth.

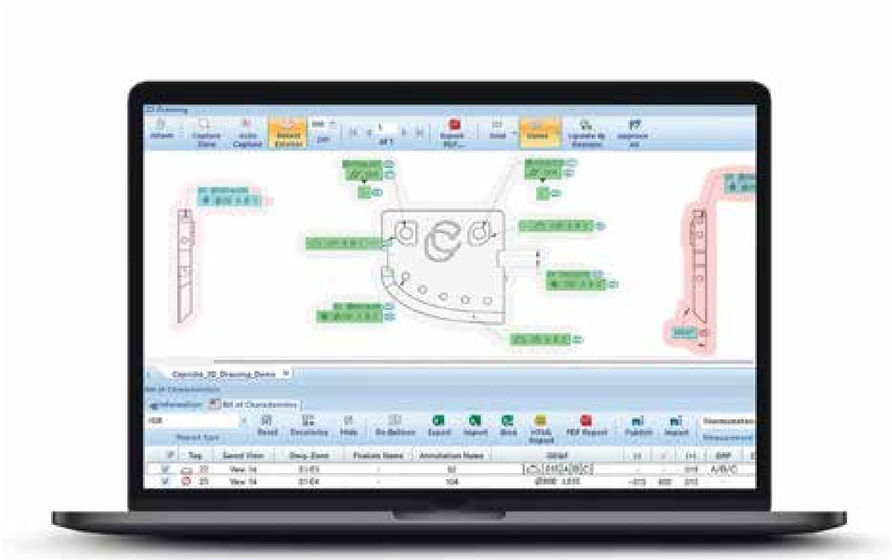
The CAD file is automatically used downstream by quality and manufacturing, providing a digital thread throughout the product life cycle, resulting in: automation, traceability, faster workflows, faster iteration, faster time to market, lower costs, and better products. And that is just the beginning.

In this new age of AI and big data, manufacturing leaders will draw insights from model-based workflows to beat the competition on speed, price, and quality. Better revenue. New revenues. All from data-driven insights.

QIF: The first step to model-based workflows

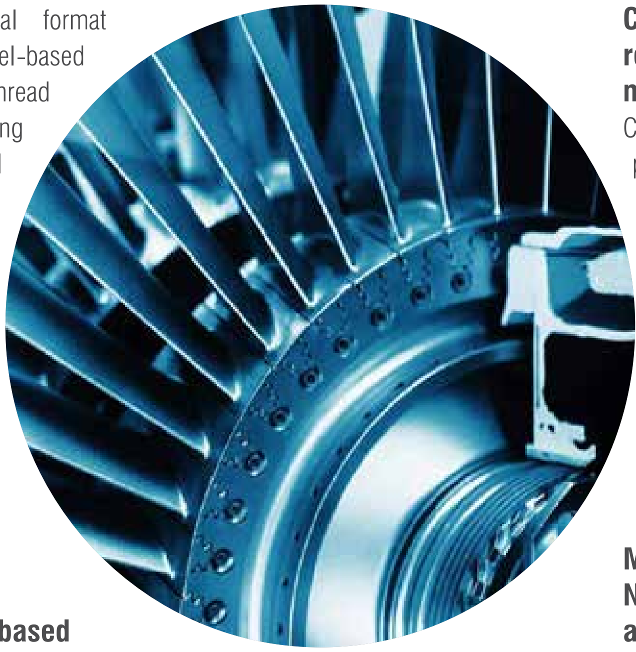
While it is easy in theory to incorporate manufacturing data into a CAD model, in practice it is hampered by interoperability issues, namely native CAD data that is locked into Creo, NX, SolidWorks, AutoCAD and other proprietary CAD software that needs to exchange reliable data with other software.

Neutral formats such as STEP and IGEs have been acceptable for geometry, but model-based workflows require a robust format that can handle product manufacturing information (GD&T, inspection plans, measurement results, etc.) and universally unique identifiers (UUIDs) for granular traceability, such as linking measurements to specific components. Enter QIF (Quality Information Framework).



QIF is an ISO CAD-neutral format designed specifically for model-based workflows and the digital thread in manufacturing, enabling traceability, collaboration, and automation from a single source of truth.

Capvidia software works with native CAD and QIF to provide seamless interoperability from design to inspection to manufacturing and beyond.



Capvidia provides solutions that power model-based workflows

MBDVidia: Deploy model-based workflows across the enterprise

MBDVidia is a model-based workflow productivity software that publishes native CAD models to QIF for downstream use.

Create a machine-readable bill of characteristics for automated FAI, PPAP, APQP, and other inspection reports. Publish inspection reports to Excel, PDF, HTML, and Net-Inspect.

MBDVidia also has an optional 2D workflow called Balloon 2D that converts 2D annotations into a machine-readable bill of characteristics.

Model-based workflows include quality inspection, welds, visual inspection, APQP, assembly, enterprise automation, and more.

CompareVidia: Manage CAD revisions and validate derivative models

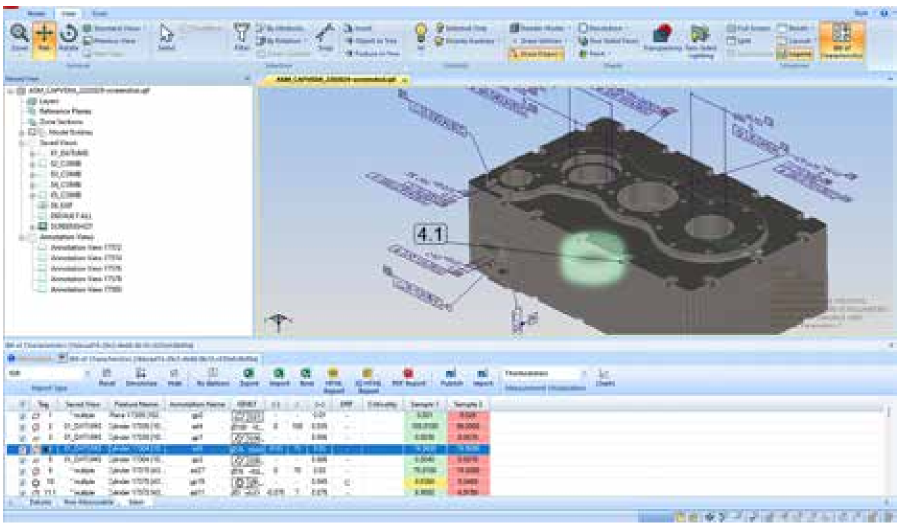
CompareVidia is a model-based workflow productivity software that validates customer production definition requirements such as Boeing DPD and other aerospace requirements.

Compare changes in derivatives (NX to QIF), revisions (Rev. 1 to Rev. 2), or versions (Creo 9 to Creo 10). Ensure consistency between native model and derivatives.

MBDConnect / FormatWorks: Native CAD plug-ins to export QIF and MBD data

MBDConnect/ FormatWorks is a model-based workflow productivity plug-in that exports native CAD files from Creo, NX or SolidWorks to a neutral MBD-ready CAD file such as QIF or STEP242.

Reuse CAD downstream for automated inspection reports and other model-based workflows including welding, visual inspection, APQP, assembly, and more.



Embracing the future

With AI and big data, manufacturing leaders will leverage insights from model-based workflows to outperform competitors in speed, cost, and quality, driving better revenues and new opportunities. Capvidia continues to lead this transformation, providing the tools to realize the full potential of model-based manufacturing.

For more information:
Enrico Boesso – EnginSoft
e.boesso@enginsoft.com

About Capvidia - Leading innovation

Founded in 1994, Capvidia has been at the forefront of emerging technologies in manufacturing. The company was the first to market with CAD translation in 2000 and first to market with CAD validation for Boeing validation in 2009.
In 2013, Capvidia saw the confluence of high-speed internet, fast computing, big data, and cyber-physical technologies to create conditions for a true quality-based digital thread throughout the product lifecycle. The company bet on model-based workflows as the future of manufacturing.

Changing the game for ADAS/ AV engineers: AnteMotion-Ansys partnership automates and improves simulation for testing of autonomous vehicles

by Luca Gasbarro
AnteMotion

Engineers working on simulation to design, test and validate autonomous vehicle systems can now automate the process of moving from HD maps to 3D simulation environments to physics-based sensor simulation – all at a new level of precision.

AnteMotion is a joint venture between EnginSoft, LHP Engineering Solutions, and V2R, three leading players in automotive industry R&D, bringing together a diverse range of skills and expertise to meet the growing demand for simulation in the field.

With a cross-functional team of mechatronics engineers, computer scientists, and 3D tech artists, AnteMotion is a reliable partner for vehicle simulation and R&D, offering a unique combination of expertise, continuous research and production capabilities.

The company offers a set of software and services that accommodate different workstyles to support simulation and testing operations, namely:

Maze: HD Maps to OpenDRIVE

Maze is a transcompiler tool that quickly and seamlessly converts between different road networks based on the modelling and simulation requirements, for instance, it can convert data from HERE HD Live Maps to ASAM OpenDRIVE. Maze has the following characteristics:

- Fully automatic OpenDRIVE Creation
- Simulation-ready data
- Automatic data enrichment
- Data fusion from multiple sources including HERE (and other) HD

Live Maps, Here SD Maps, and OpenStreetMaps

- Options to add road features like geometry, elevation, road markings, traffic signs, traffic lights, road links, lane links, junction connections, and more.
- Available both as a SaaS or an on-site solution for full flexibility of deployment

Procedural Worlds: automatic modelling of 3D environments

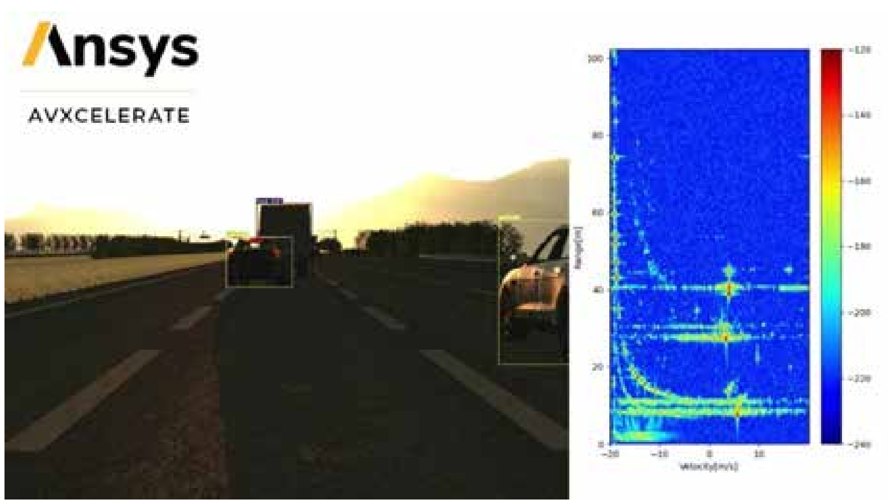
This powerful, procedural 3D environment generator for driving scenarios:

- Automatically forges OpenDRIVE into a 3D digital environment
- Fills the environment with buildings, parks, props, and features to make it realistic
- Allows the style of the scene (residential, industrial, countryside) to be set
- Ensures that the 3D environment generated perfectly matches the OpenDRIVE Road Network.

Midgard: open rendering engine framework developed on Unreal Engine 5.4

Midgard is designed to support the simulation, testing, and validation of ADAS and autonomous vehicles by aggregating simulation data and delivering it in the form of detailed, configurable interpretations of all collated information, thereby allowing engineers to make informed decisions with ease.

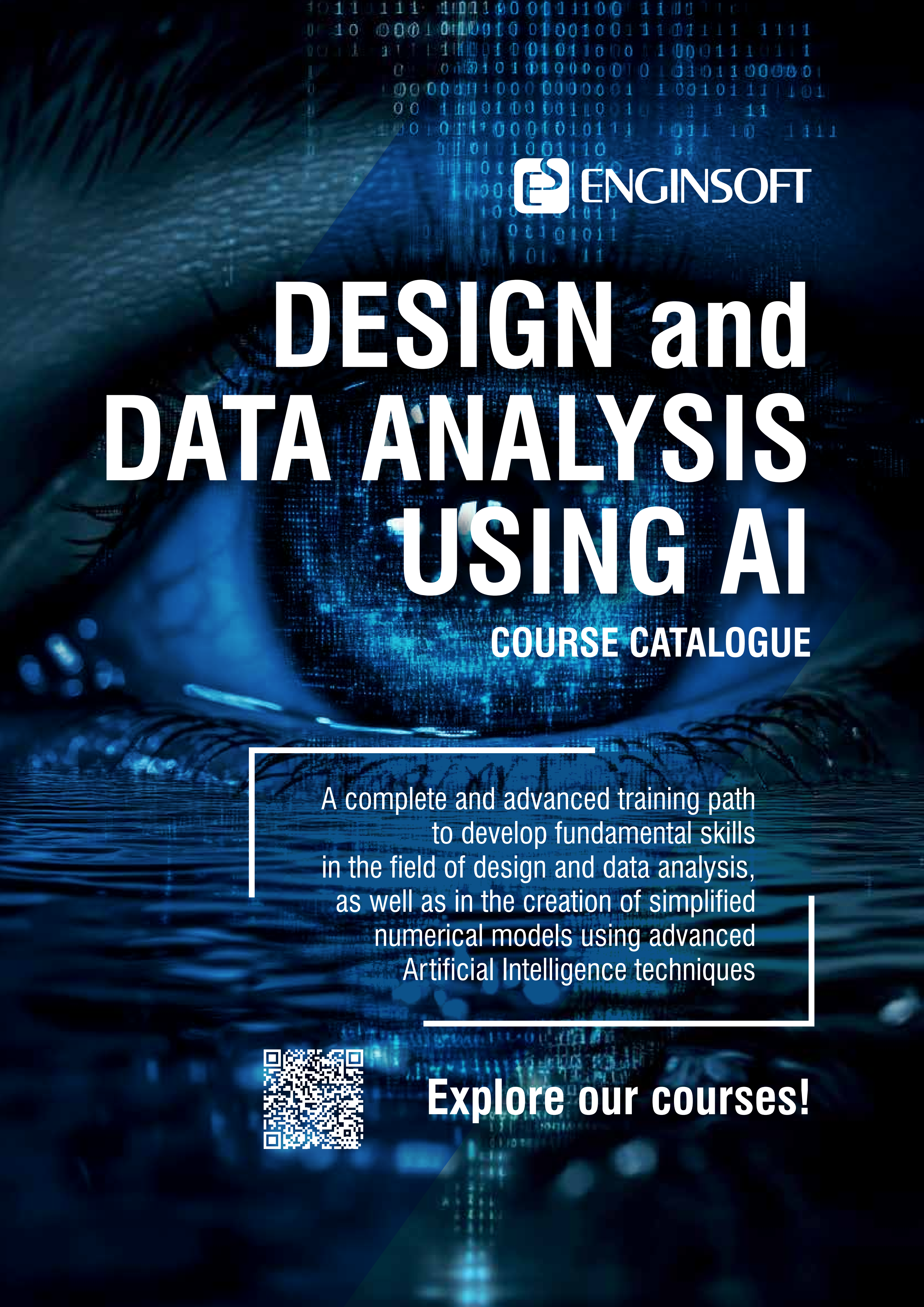
The framework extends the existing development pipeline without requiring significant changes, providing grey-box tools that integrate seamlessly with existing software and processes. Midgard provides a state-of-the-art rendering solution based on the powerful Unreal Engine 5.4 and enriched with ADAS/AV sensors and cameras based on complex physics, weather, day/night and runtime variability of the environment.



The software understands the complexity of specialized tools such as multi-body physics solvers or traffic simulators and provides the means to easily integrate any such tool into its framework, rather than limiting engineers to a specific implementation.

The great potential of these tools recently led to the formation of a cooperation agreement between Antemotion and Ansys in which AnteMotion's two flagship products, Maze and ProceduralWorlds, will be used to complement Ansys' ADAS technologies and bring a new level of automation and precision to simulation environments for autonomous vehicles, in particular with Ansys AVxcelerate suite.

For more information:
Luca Gasbarro – Antemotion
luca.gasbarro@antemotion.com


ENGINSOFT
DESIGN and DATA ANALYSIS USING AI
COURSE CATALOGUE
A complete and advanced training path to develop fundamental skills in the field of design and data analysis, as well as in the creation of simplified numerical models using advanced Artificial Intelligence techniques
Explore our courses!