White paper

Optimising gearbox performance: Romax and ODYSSEE combined for AI/ML-based transmission design

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Executive summary

As industry undergoes a significant shift, with sustainability a key objective driving the agenda, there is scope for drastic change in the way in which simulation is used for product development. The move to electrification, disrupting the automotive industry but also aerospace and beyond, together with the increased need to source energy in a renewable and sustainable way, places new demands on transmission designers, who also have to contend with ever-shortening development cycles and the need to innovate to keep ahead of the curve.

Computer-aided engineering (CAE) has been in existence for over half a century. The technology is now mature, and the growth is holding steady at around 10%. Artificial intelligence (AI) and machine learning (ML), however, are growing exponentially, and their value when applied to the field of transmission design is only now being explored. AI/ML have the potential to dramatically shorten the simulation lifecycle across multiple industries and also offer democratisation of advanced engineering processes as well as de-risking innovation. Indeed, we are on the verge of a fundamental shift from simulation validated by test to DoE-fed AI models validated by simulation and test.

The main objective of this paper is to introduce a solution for the current engineering challenges facing powertrain designers. This solution leverages the power of AI/ML technologies in the framework of transmission design. For this purpose, an evidence-based approach is adopted by presenting practical examples and use cases.

This study contains two main examples. The first is a small study conducted to validate the approach, focused on gear micro-geometry optimisation to reduce transmission error. This first study proves the accuracy and effectiveness of the method, after which a second, more comprehensive study is shown. This second study optimises a transmission design by varying a large number of parameters and evaluating the design's performance against a wide range of criteria. This second case study shows the potential power that can be leveraged using this solution, which combines physics-based CAE with AI/ML methods.

The methods described here have further applications for other transmission design and optimisation studies across multiple industries. There is potential to explore the full design space, to leverage more powerful ways to achieve multiphysics transmission optimisation, and to ensure the manufactured transmission will behave 'as-simulated'. Ultimately, this will improve product quality at far-reduced timescales, while democratising advanced technology and reducing reliance on engineering expertise and experience - thus removing some obstacles to innovation.

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Introduction

When designing transmissions for modern vehicles, OEMs and suppliers have to balance multiple conflicting demands. Electric vehicle powertrains must be light and efficient to increase range; they must be quiet in an environment where the lack of an engine makes other noises more apparent and more intrusive, and they must be durable to satisfy customer demands and create more sustainable manufacturing cycles. They must also be small, efficient, power-dense, and cost-effective to produce.

To achieve these criteria, the transmission must meet specific targets at various stages of development for gear and bearing durability, efficiency, NVH, cost, weight, and packaging, all while ensuring it fits other requirements for the transmission as a whole and the vehicle as a whole. These criteria are interdependent, and thus achieving optimal performance involves finding the best combination of these factors, even if that means compromising one to enhance another. Naturally, these criteria will be weighted differently in each application, and some will be prioritised over others. For wind turbine drivelines, durability may take priority over noise. In contrast, for high-performance luxury vehicles, the balance is more subtle, with a focus on durability, efficiency and NVH at the expense of greater cost.

The requirements are often extensive, and the inherent complexity of transmission systems means that finding the best way to achieve the required performance depends on many factors. From the early stages of developing a transmission, the designer must choose between innumerable different layouts and architectures. As the design progresses toward a greater level of detail at the component and transmission sub-system level, there are thousands of parameters that must be specified. Ultimately, a transmission is a very complex system with a large number of mutually interacting variables which affect the overall performance.

A complex system with complex interactions

Sub-system interactions in a transmission occur between the core components: shafts, gears, and bearings. The bearing stiffness (which is highly non-linear and depends on many factors) affects the shaft deflection, which causes the gears to misalign, shifting the contact from the centre of the gear to its edge. A tilting moment is then applied to the gear, which causes the shaft to deflect, which is reacted by the bearings, again changing their stiffness. This then propagates back through the system again and affects how the shafts deflect and how the gears contact. Additionally, the bearings are mounted inside a flexible housing, which interacts with the other components in complex ways. Simulating this behaviour correctly and accurately through capturing the system interactions, deflections, and misalignments requires modelling the whole system and analysing it iteratively and efficiently.

Using insight gained from each analysis run, the design can be updated and then the analysis rerun to understand the effect of various model adjustments on performance. However, while adjusting one parameter may achieve the best performance possible in terms of that component's durability, it may negatively impact NVH or the durability of another component. For this reason, it is very important to explore combinations of parameters simultaneously in order to end up with the optimum design.

This is even more important with the move to electrification. The desired performance parameters have changed, new noise environments lacking masking from the internal combustion engine place greater demands on reduced transmission noise and vibration, and range anxiety places more importance on designing efficient, power-dense, lightweight transmissions. As well as new performance criteria, the design parameters are changing too. The range of potential layouts and architectures is now different, and designers can no longer rely on experience and previous best practice. In addition, the impact of the

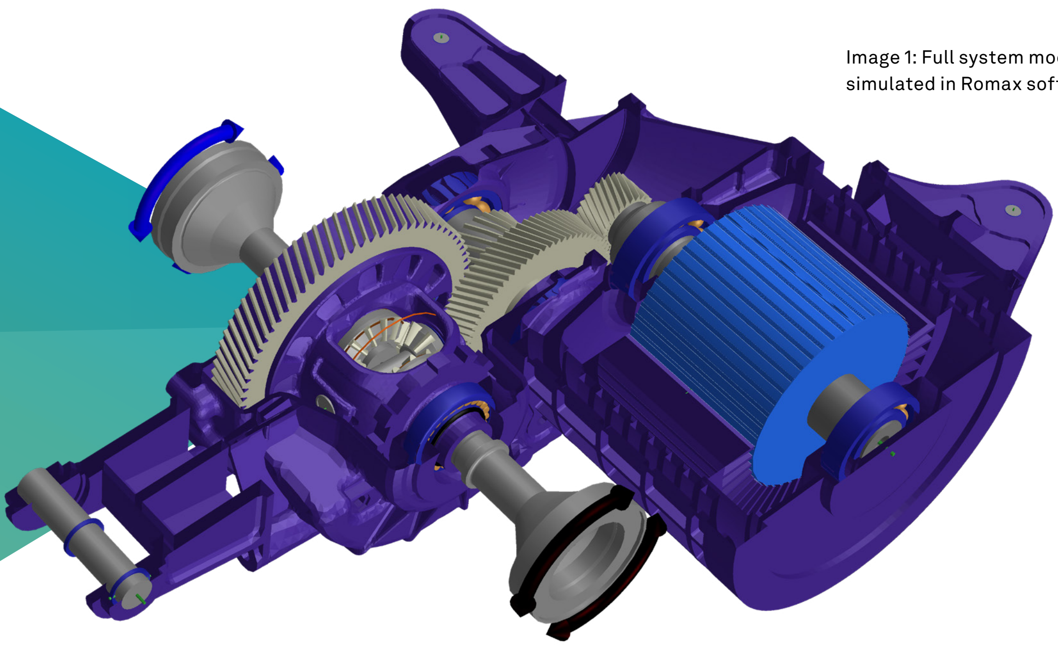


Image 1: Full system model simulated in Romax software

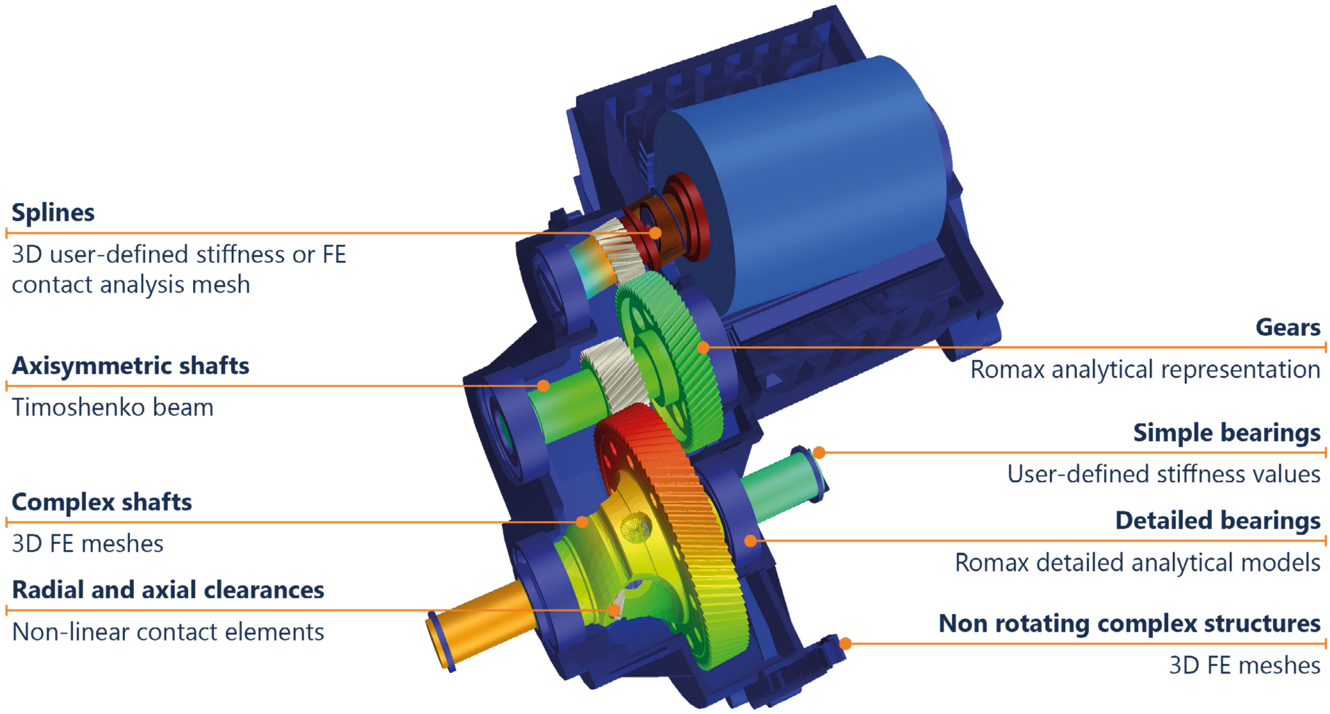


Image 2: Full system simulation approach in Romax software

electrical components brings new system interactions to consider. This places an even greater need for simulation-led design processes to drive optimisation.

Simulation-led design: reducing obstacles to innovation

With thousands of parameters to modify in order to find the optimum design, transmission designers face a great challenge, but also a significant opportunity to design the next 'big thing'. However, to add a further layer of complexity, it is not just a case of optimising the nominal design, but also using simulation-led design to understand variability in manufacturing. Some performance targets, for example those for NVH, can have a high degree of sensitivity to variation. Therefore, while it becomes even harder to find a design that is robust, it is simultaneously even more important to do so. Designers need tools to find the design space with the lowest sensitivity to manufacturing variation and with the best performance. As components and sub-systems are designed concurrently, ever-changing design parameters make it even harder to meet performance targets and even more important for departments to collaborate and communicate design changes.

Full system transmission simulation

This need for a full system approach has driven the Romax software philosophy. Romax tools provide a parametric environment for the design, analysis, and optimisation of transmission systems, considering system and component interactions. Even though this kind of simulation on the gearbox internals is highly complex, because Romax is optimised for this exact application, it can run this analysis very quickly. Rather than use FE for the whole system (which is hugely challenging, not wholly accurate, and almost impossible to use for a complete complex transmission system), Romax uses a hybrid approach, incorporating a combination of finite element, analytical, and empirical methods. Thus, it applies the most computationally-efficient and accurate method to every part and combines them together into a fully-coupled system simulation. This offers a blend of speed and accuracy, specifically optimised for powertrain simulation. For more on this topic, see Kouumdjieff (ref. [1]).

Complementing its fast runtimes, the fact that Romax models are parametric – and therefore the model's physical engineering properties can be easily varied – means that edits can be made and analyses rerun very quickly, multiple times. In Romax, making a change based on insights from advanced analyses does not just mean changing random numbers in a matrix or altering something abstract like the stiffness of a bearing, it means changing things that can actually be changed in the product specification – something concrete, like how much bearing preload to apply. Thus, users can understand how their system will perform and investigate the impact of making changes to the model – ultimately finding the optimal transmission design for a particular application.

Looking for even more power

By virtue of its parametric nature, Romax is ideally suited for use during the design phase, not simply as a computer-aided engineering (CAE) tool for validation. To complement this, Romax offers its own parametric sensitivity analysis optimisation methods; existing methods include full factorial, Monte Carlo, or genetic algorithms. These methods are proven, validated, and trusted but also have limitations. While Romax's genetic algorithm can be used for optimisation, the scalability of the approach does not lend itself well to situations where robustness to manufacturing variation also needs to be considered. Even though each evaluation of the model is fast, the total number required for robust optimisation is prohibitively computationally expensive for everyday use in a simulation-led development iteration. Typically, this study would have to be done in a separate analysis, with each parameter examined individually to keep the optimisation process manageable. When it comes to a full factorial study, it becomes even less feasible to consider all parameters simultaneously.

Indeed, this is a fault not with Romax's methods but with optimisation in general – it is almost impossible to look at changing everything at once, and some user direction is required to focus the study. You can define a cost function as a weighted sum of various targets, but the design of that cost function still requires human input and engineering expertise, which means there is risk of human error. Because looking at every parameter together is not feasible, the approach that Romax takes is to reduce the variables as much as possible by running sensitivity studies to determine which variables are most important to consider. However, because these parameters are interdependent and significantly impact whole-system interactions, this approach of changing parameters independently also leaves room for error. What if changing two things at once has a significant impact? The problem is, the only way to investigate this is to run Monte Carlo or full factorial studies, where you look at every possible combination of all parameters, but at the cost of unfeasibly long run times.

On top of its optimisation processes, Romax tools also offer automation procedures, with batch running capability allowing optimisation studies to be run from a third-party tool such as Excel, or from the command line, without even having to open Romax software. There are also established and well-used processes linking Romax to other optimisation tools, but these still don't address some inherent limitations of how the optimisation is run. These methods still require the Romax model to be constantly interrogated – the only part that's been replaced is the Romax optimisation engine. The ability to scale this to perform large-scale optimisations considering the full design space against many performance criteria, while accounting for manufacturing variability, requires a new solution.

With many parameters to optimise, it stands to reason that transmission development is an area where significant value can be realised from the application of Artificial Intelligence/Machine Learning (AI/ML) techniques throughout the design and development process. There is potential here to make sure the full design space is explored, to leverage more powerful ways to achieve transmission optimisation, to ensure the manufactured transmission will behave as the 'as-simulated'. Ultimately, there is a need to improve product quality at far reduced timescales while democratising advanced technology and reducing reliance on engineering expertise and past experience, thus removing some obstacles to innovation.

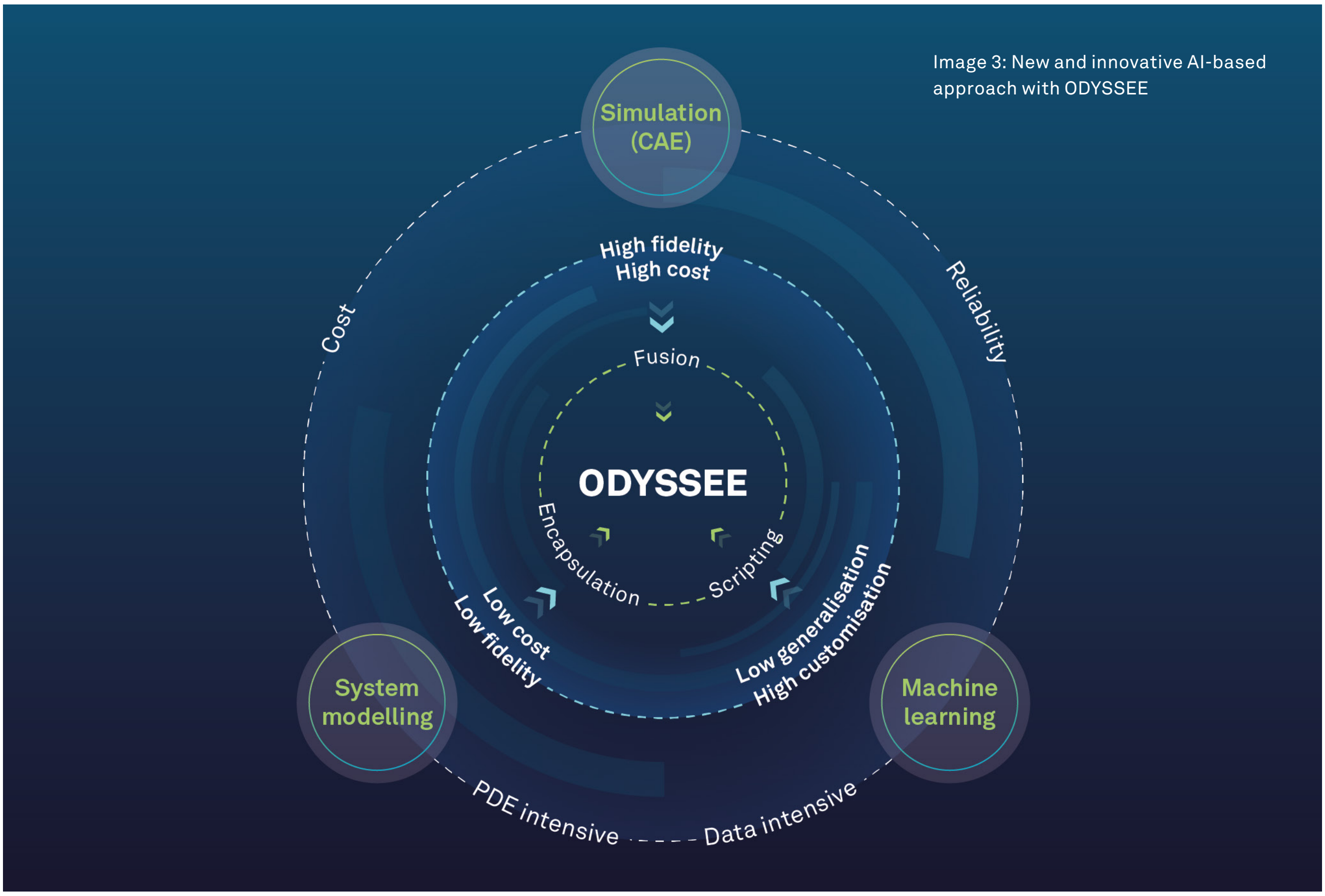


Image 3: New and innovative AI-based approach with ODYSSEE

Table 1. Physics-based modelling vs data-driven modelling

Physics-based modelling	Data-driven modelling
+ Solid foundation based on physics and reasoning + Generalises well to new problems with similar physics	+ Takes into account long term historical data and experiences + Once the model is trained, it is very stable and fast for making predictions
— Difficult consistent engineering judgment with increasing complexity — Can be too long and be too expensive — Difficult to assimilate very long-term historical data into the computational models without a Simulation Data Management System like SimManager — Sensitive to numerical instability when dealing with non-linearities and ill-conditioned problems	— So far most of the advanced algorithms work like black boxes — Bias in data is reflected in the model prediction — Poor generalisation on unseen problems

Using AI/ML to solve this problem

AI techniques can offer a smarter approach to design, as explored by Bouchiba, Kayvantash, Hanna (2020): "the mix of AI and physics-based approaches better addresses the increasingly complex problems confronting engineers today", while ML can be used to reduce the number of simulation runs during product design (ref. [2]). ML engines can leverage datasets from former simulations and test datasets and subsequently serve as a repository of know-how gained from running multiple simulation runs. This repository enables the democratisation of complex engineering tools and opens new possibilities for sharing data between companies and their supply chains.

In a recent report, PricewaterhouseCoopers observes that "AI could contribute up to $15.7 trillion to the global economy by 2030, more than the current output of China and India combined" (ref. [3]). Indeed, in the last few years, ML methods based on deep artificial neural networks (deep learning) have achieved tremendous success in many applications in many industries. These methods can provide accurate, data-driven process automation. In the context of CAE, AI has the potential to speed up the development of tools that allow non-experts to use sophisticated simulation capabilities, democratising the technology to increase productivity, optimise the computational resources required for the simulations, and improve the product design process through new insights. This powerful combination of AI and a physics-based simulation approach is well positioned to address the increasingly complex design problems confronting design engineers today.

One of the methods that ML can offer CAE is Reduced Order Modelling (ROM), a mathematical approach which aims to overcome the high computational costs of simulations via decomposition techniques employing already known past responses. This workflow can begin by using a co-simulation CAE model to create datasets that are used to train a ROM that provides sufficiently accurate results across the physical domain by identifying the most pertinent data from previous CAE runs to optimise the simulation's dataset before it is run. ROMs can be considered a simplification of a high-fidelity dynamical model that preserves essential behaviour and dominant effects to reduce solution time or storage capacity required for the more complex models. Combining ROM methods and more traditional ML techniques can overcome the challenge of achieving accurate real-time simulation.

Combining the power of ODYSSEE with Romax

Hexagon's ODYSSEE product was the first to offer AI-driven, real-time parametric simulations. ODYSSEE develops model reduction approaches for various engineering problems while remaining agnostic to the underlying physics type. By first identifying the most sensitive variables, ODYSSEE enables design optimisation using many fewer evaluations of the model. Ultimately, ODYSSEE can be used to find the best design space in the given packaging, to check any parameters and the sensitivity to manufacturing variation.

When used in conjunction with Romax, ODYSSEE can create its own version of Romax's parameters from a few experiments and then optimise its version of the model by performing much simpler and faster calculations, intelligently selecting sampling points based on analysis of sensitivity using Design of Experiments (DoE). There are consequently three reasons why it can perform this optimisation much more quickly: it performs the optimisation on a smaller model, it can do so by running fewer evaluations, and those evaluations will be much quicker to run. By training and using a ROM, the results obtained from an optimisation should be at least as good as those obtained from Romax, and they will definitely be much quicker.

ODYSSEE works by first learning from a set of initial experiments it runs on the Romax model, using a training dataset to build trends and sensitivities. The model which it builds is simple, abstract, and mathematical. While the inputs and outputs to the ODYSSEE model are real physical parameters, the ODYSSEE calculation itself knows nothing of the physics it is calculating – it is, in this way, a mathematical 'black box'. This means someone directly involved in the engineering workflow or tool setup must understand enough to ensure they are solving the right problem in the right way. Once this model has been built, ODYSSEE validates the model by running a few examples that it has not seen before to test its predictions. This is called the validation dataset and is independent of the training dataset. Once the validation has been done, you can use the model to perform experiments.

Combining the intelligent computing power of ODYSSEE with the domain-specialist physics of Romax offers an efficient solution to optimising transmission design parameters. ODYSSEE coupled with Romax helps designers optimise transmission performance faster than ever before – using Romax simulation to optimise conflicting multiphysics parameters.

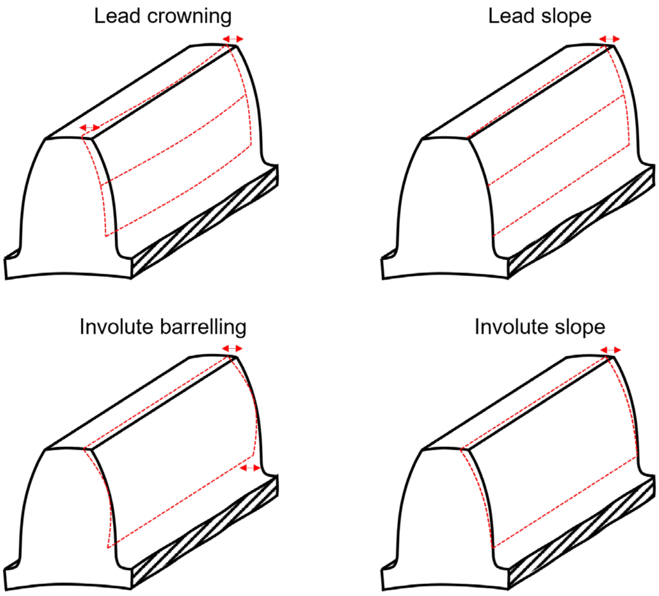


Image 4: Gear micro-geometry parameters

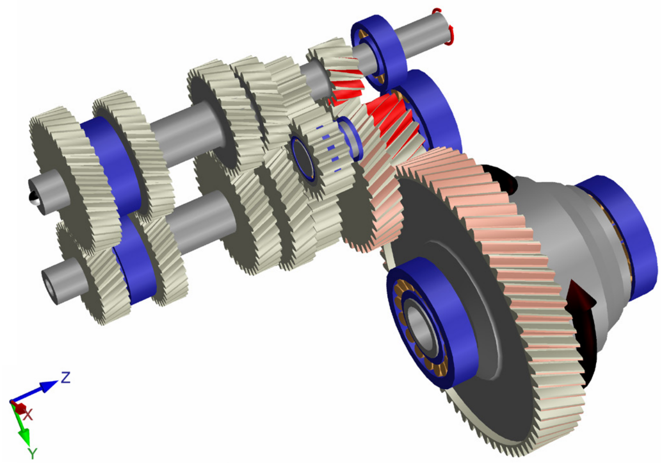


Image 5: Romax model used for initial test case study

Case Study 1: Validating the Romax and ODYSSEE DoE solution

To validate this approach combining Romax and ODYSSEE, an initial case study was done on a small scale. The study varied four parameters and investigated their effects on transmission error, an important metric for NVH performance.

The four parameters which were varied were all related to gear micro-geometry:

- Lead slope
- Lead crowning
- Involute slope
- Involute barrelling

Ultimately, the aim was to check the sensitivity of these parameters against transmission error and to optimise the system in such a way as to reduce transmission error by varying these four parameters. This type of micro-geometry study is a well-established, trusted process in Romax, which made it a good use case for validation.

The study was done using Romax optimisation methods (genetic algorithm) and then ODYSSEE to compare and validate the results. Such a simple example with a limited number of parameters would already run in Romax with a relatively fast run time. Therefore, the aim of this case study was not to prove the extent of time savings that were possible but rather to confirm that ODYSSEE would achieve the same or similar results – validating the method's accuracy so that it could be used to benchmark for speed and model evaluations. While the advantages for a small study like this are marginal, the real benefits would be seen when the same methods were applied to a more complex study.

Outcomes

For the five validation cases used, ODYSSEE was able to predict the TE of the model with various micro-geometry modifications to 99% accuracy. Romax and ODYSSEE had thus converged on the same or similar solution for the micro-geometry optimisation.

Even for this small-scale study, there was a marked difference in computation time. Each of Romax's runs takes around 1 second to complete. The Romax genetic algorithm required about 800 runs, and the full factorial method took over 6,500 runs just to vary these four input parameters. By contrast, ODYSSEE only required ten training runs to do the optimisation. During the training phase, ODYSSEE calls Romax for each of those runs; therefore, the training phase took 10 seconds. However, once the training phase is complete and the ROM is created, the analysis is instantaneous.

Good validation was achieved in this example, and it proved that the method was accurate and achieved similar results to Romax. So far, the method had only been applied to a small problem with a small number of variables. The next step, and the project where this would make a real difference to what Romax users could achieve, was to apply this to a bigger problem.

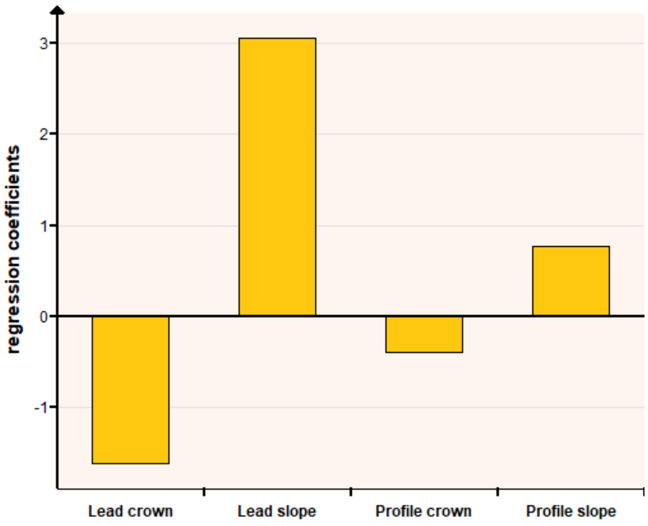


Image 6: Sensitivity plot for the validation case

Case Study 2: Scaling the problem, and the benefits

The validation study had only looked at gear micro-geometry – but what if you wanted to widen the optimisation to look at the whole system? Naturally, as the number of input parameters to explore increases, the number of runs required increases exponentially for full factorial and Monte Carlo studies. Eventually, it reaches a point where the design study is simply not feasible using these methods. While doing such a large study in Romax would typically have to be broken down – to look at gears, then bearings, etc., an optimisation-specific tool has ways to look at the results more economically. Additionally, while Romax is very strong at performing basic micro-geometry, the studies become longer and more complicated if you want to include robustness. Since there are so many interdependent parameters in a transmission, which have an impact on system interactions and the full system performance, harnessing the power of AI/ML and using ODYSSEE in combination with Romax becomes really valuable where many parameters can be investigated and optimised simultaneously – something which is not possible using traditional optimisation methods.

Therefore, a second study was set up which considered 22 input parameters. A sample study involving nominal plus min. and max. values for a set of 22 input parameters would give over 31 billion (31,381,059,609, to be precise) combinations. This number of combinations is not possible to analyse using current methods, which is why it is typical for a small number of (approx. 2-3) main parameters to be manually selected instead. However, this manual selection process means that the entire parameter set cannot be considered, and the resulting combinations are subject to human error.

As well as the pure numbers issue, the methods themselves come with limitations. The Monte Carlo method picks random samples and suggests the best candidate from the randomly selected sample set, while the genetic algorithm uses the theory of 'survival of the fittest' and requires a large sample size for more accurate results, which takes an extended amount of time to run. This study aimed to see how Romax's calculations and physics could be combined with the AI/ML power of ODYSSEE to make a more extensive investigation possible.

Leveraging AI/ML to optimise a full transmission

After the initial study had validated the method, the second study was set up. The first step was to run the Romax model to assess its baseline durability and efficiency performance in order to set the targets for the output of the experiment. After the durability and efficiency performance was recorded, the input and output parameter lists were defined. The input parameters had a nominal value as well as a min. and max., and the output parameters each had requirements such as to increase or decrease.

The input parameters selected were all related to bearing preload variation. When the system is manufactured, preload is applied to the bearings, where the outer race of the bearing is pressed inward or outward by some displacement/force. Although bearing preload is only set in the Z direction, variation in preload does also occur in the X and Y directions as a consequence of manufacturing variability. Therefore, in order to achieve a good understanding of the impact of manufacturing variation on the system's performance, this study varied the preload of all six bearings in all three directions (X, Y, and Z). Internal clearance in the radial direction was also considered in four out of the six bearings (not applicable for the two taper roller bearings), to account for the change from the manufactured to assembled state. Therefore, there were 22 input parameters in total.

The output parameters were selected to give good coverage of the conflicting demands on modern transmission performance. Naturally, efficiency is a top priority, while noise is important for high product quality perception. Durability is also integral, as designers aim to create transmissions that will last as long as the whole vehicle. Since the aim of the study was to optimise a transmission simultaneously for efficiency, durability and NVH, a range of output parameters were defined, from bearing life and power loss to mesh misalignment, gear bending and contact stress, transmission error, and overall efficiency: 33 output parameters in total. These output parameters would give a designer a good idea of the best design space as well as how the performance changes relative to variation in the input parameters. The fact that the input parameter being varied was bearing preload meant that this study would provide a good indication of manufacturing processes and variability rather than purely nominal design variation.

The workflow between Romax and ODYSSEE is very straightforward; Romax's batch running capability can be used to export an output file to Excel, which can then be fed directly into ODYSSEE to generate the DoE. ODYSSEE then takes one output parameter in turn and analyses its sensitivity to each input parameter. Once all of the sensitivities are provided, the top two sensitive parameters are pulled out. Then the exercise is repeated for the next output parameter and so on, until all 33 output parameters have been analysed, using a min., max. and nominal value for each input parameter. A matrix is then created from the ROM for each output parameter, to obtain machine learning predictions of the variation in the two most sensitive parameters out of the 22. This gives the user information about which area is the best to work in and gives them an indication of which parameters to vary before they know the optimised values. Additionally, the methods used here help the users define a parameter range, not just a minimum value, which can be used for tolerance setting to ensure robustness. Running through this process for this particular case study would have taken 81 runs in Romax but was done instantaneously in ODYSSEE.

The next stage of the project was to perform the optimisation. Out of the 33 output parameters, the first step was to optimise based on just four, running the optimisation and then finding the optimum input parameters for each output parameter. The output parameters were initially considered individually, independent of other parameters. Afterwards, multi-variant optimisation was performed for all bearing lives together (left and right bearings for three shafts – differential, input shaft, lay shaft). Next, another four output parameters were considered: total efficiency, TE, and bending and contact safety factors. Subsequently, these two sets of results were looked at together for another layer of multi-variant optimisation. This becomes impossible in Romax, since the number of runs would be too high.

This approach differs from traditional methods using a small parameter set created based on experiments or past experience. Design experiments for the whole system, or even for complex individual components such as gears, are costly and time-consuming. Using Romax and ODYSSEE together allows such a study to be applied to the design of cars, electric vehicles, trucks, or even aerospace transmissions. The designer can obtain a clear idea of the design space within which optimal performance can be achieved, as well as the probabilities of failure and durability values.

To confirm the accuracy of the study, a validation sensitivity study was generated in Romax using a subset of input parameters with random values. The 33 output parameters were analysed for this validation dataset. The same input parameters were tested on the ODYSSEE model created with the training dataset, and the results were correlated between the two programs to ensure they matched closely.

Romax batch running

To allow ODYSSEE to interface with Romax software, Romax's batch running capability was used for this study. Batch running allows Romax calculations to be run from the command line or a third-party tool such as Excel or ODYSSEE. Via batch running, it is possible to access all input parameters (including part dimensions, material properties, lubricant properties, operating loads etc.), action items and output parameters in a user-friendly manner. While the process requires a script to be written between ODYSSEE and Romax, the benefit is that the Romax model does not have to be run every time an optimisation run takes place. The ODYSSEE-generated DoE allows Romax to run the analysis and quickly generate results. Then, the optimised design from ODYSSEE can be quickly and easily tried out in Romax, since the Romax model is parametric. This means users can quickly go back into the Romax model and do more analyses to verify the optimised design candidate, bringing the model back to the physical engineering world from the "black box" of ML mathematical models.

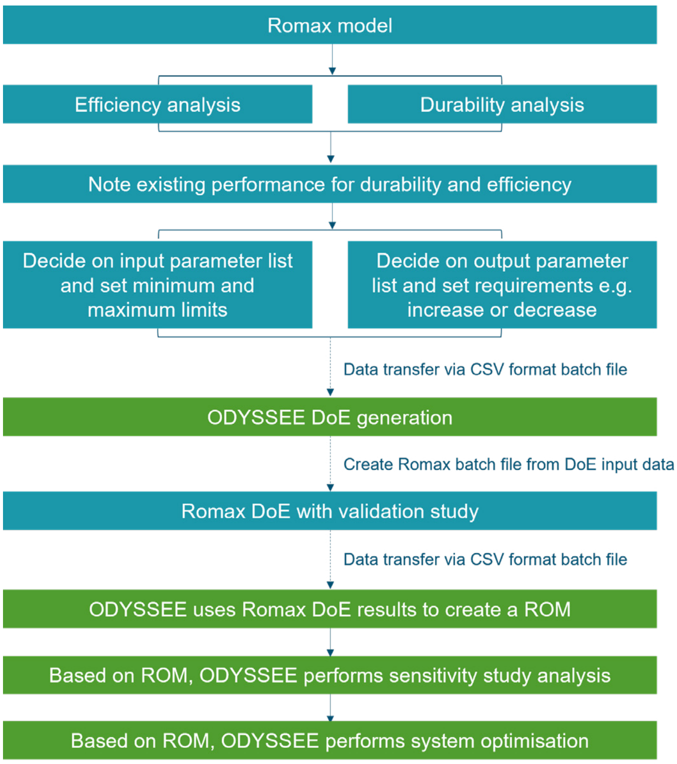


Image 7: Workflow between Romax and ODYSSEE

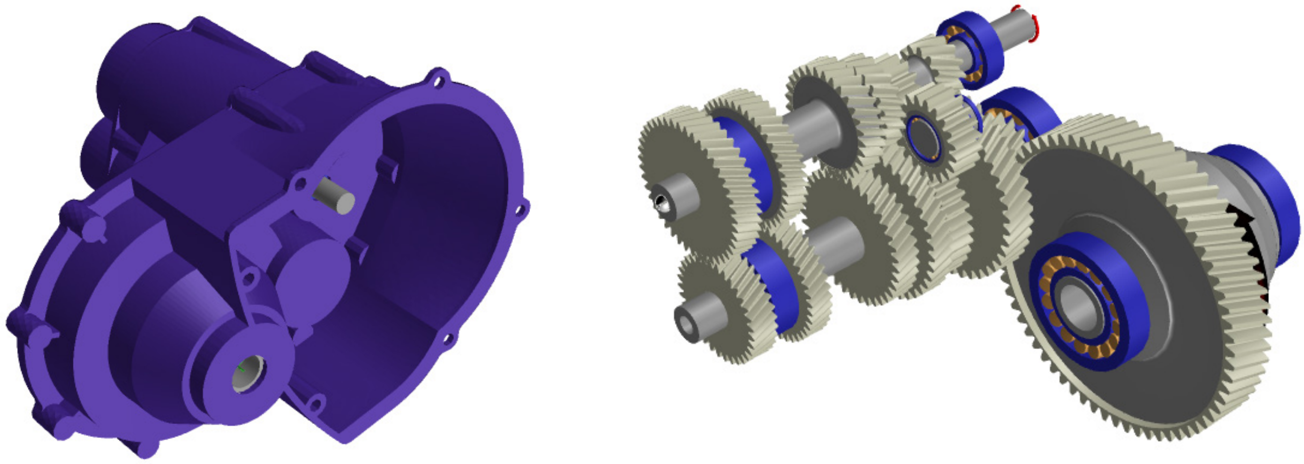


Image 8: Romax model used for second case study

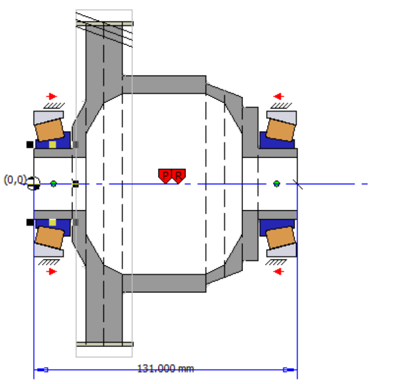
Outcomes

As a result of the study, bearing preload parameters were identified which achieved targets in all performance areas.

- NVH – the target was to keep TE as low as possible to ensure good NVH performance. Based on experience, it might be realistic to expect to reduce the TE by about 20% overall – during this study, a 17% reduction in TE was achieved purely due to varying the bearing preload.
- Durability –
  - Gears – gear safety factors were improved more than expected (except the 1st pinion contact safety factor, which was still better than the base design).
  - Bearings – all bearings showed an increase in safety factor (except the IP shaft left bearing – this could be dealt with by selecting a stronger bearing).
- Efficiency – the gearbox efficiency was already satisfactory in the initial studies. Therefore, the requirements from the optimisation study were that the efficiency would not fall below minimum expectations.

Ultimately, the sensitivity study looked at the effect of preload on various output parameters, and it was concluded that TE and pinion bending safety factor were particularly sensitive to variations in preload.

Because there are so many gearbox performance parameters, it is important to select the right ones to use as targets for such an optimisation study. It can be difficult to improve upon all design criteria, and there may be parameters worth sacrificing to a certain extent to improve others. Based upon the initial optimisation and input parameter variation study, certain design elements can be modified, such as, in this case, choosing a different bearing definition in one location. The input variation study helps provide guidelines regarding the ideal design space and shows if the output parameters are sensitive toward manufacturing variation.



		Diff Brg RH outer preload Z									
		-50	-37.5	-25	-18	-12.5	0	12.5	25	37.5	50
Diff Brg LH outer preload Z	-50	7072.69	6667.56	6262.39		5857.22	5452.06	5046.92	4641.75	4236.58	3831.42
	-37.5	7478.25	7073.08	6667.92		6262.78	5857.61	5452.44	5047.28	4642.14	4236.97
	-25	7883.81	7478.64	7073.47		6668.31	6263.14	5858.00	5452.83	5047.67	4642.50
	-12.5	8289.33	7884.17	7479.03		7073.86	6668.69	6263.53	5858.36	5453.22	5048.06
	0	8694.89	8289.72	7884.56		7479.39	7074.25	6669.08	6263.92	5858.75	5453.58
	12.5	9100.42	8695.25	8290.11		7884.94	7479.78	7074.61	6669.47	6264.31	5859.14
	25	9505.97	9100.81	8695.64		8290.47	7885.33	7480.17	7075.00	6669.83	6264.69
	37.5	9911.50	9506.36	9101.19		8696.03	8290.86	7885.69	7480.56	7075.39	6670.22
	38	existing life			**9082.00**						
	50	10317.06	9911.89	9506.72		9101.58	8696.42	8291.25	7886.08	7480.92	7075.78

Maximum life

Better design and manufacturing space

Base life

Minimum life

Image 9: Influence on bearing life due to mounting

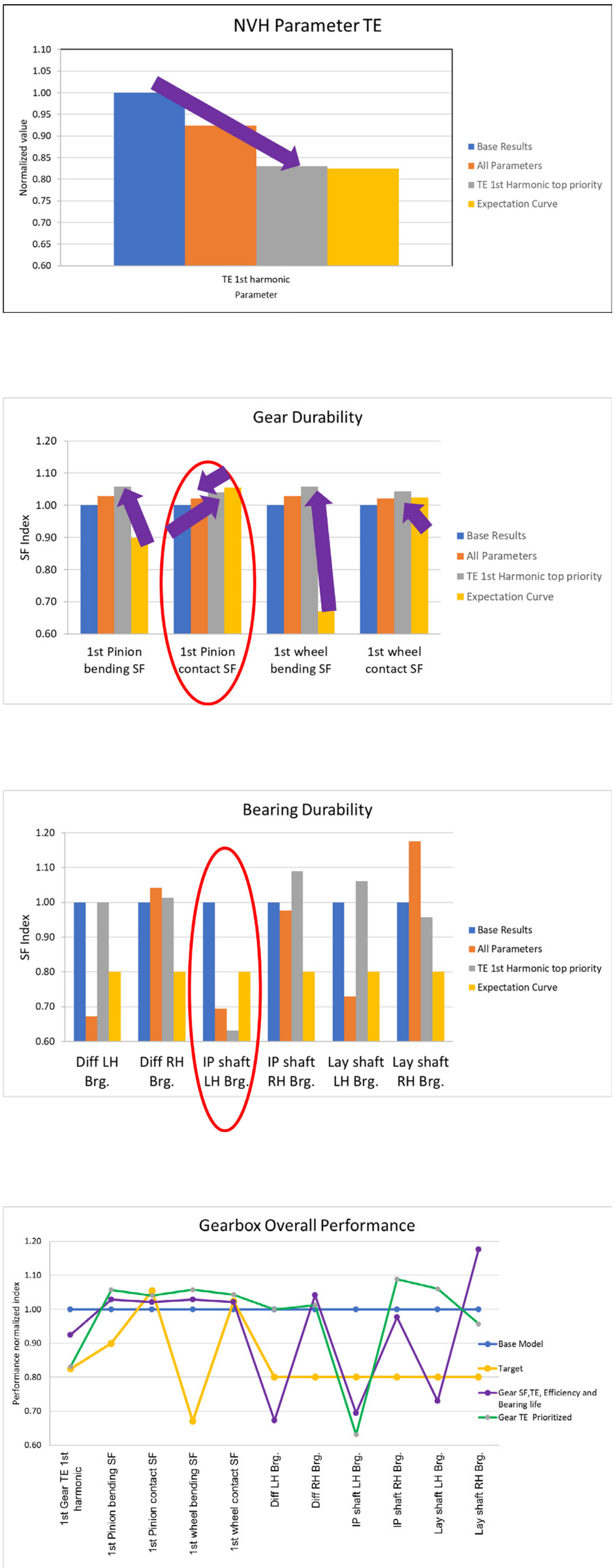


Image 10: Improvements were seen across performance criteria

Applying this process throughout development, not just at the end

The ideal way of using Romax and ODYSSEE together is to do so throughout the process. From the very early stage, optimisations can be carried out for design aspects including layout, gear ratio, and number of teeth. At this stage, it is important to consider indicative performance targets and look at varying macro-level parameters. As the design becomes more detailed and it is necessary to include consideration of manufacturing, procedures can be repeated for optimisation and robustness, bearing preloads, lead crowning on gears etc., to ensure that the final design specification meets performance targets. Romax provides the master model throughout the process and through varying levels of fidelity. All data is traceable back to the parametric model in Romax, and parameters can be changed to view the effect on results at any time. Ultimately, it is about adopting a process that enables simulation to be used efficiently so that you can do as much upfront as possible.

Conclusions and next steps

The usage of physics-based simulations will continue to increase nominally, but the growth of AI-based methods will increase even more rapidly. It is clear that AI will allow us to move from the traditional paradigm to a brand new one where CAE simulation is used for DoE (Design of Experiments) to feed AI models with data that will then be re-used for much faster runs, improving productivity and allowing for more optimisation of products. This is a fundamental shift from simulation validated by test to DoE-fed AI models validated by simulation and test.

In areas such as transmission design, where there is scope for many high-fidelity analyses to be run, varying many different parameters and considering manufacturing variation, the rewards that can be reaped using AI/ML-based methods are significant. Passenger vehicle transmissions have many input parameters with conflicting outputs. With the above-described approach, it is easy to find a robust design space which is less sensitive to manufacturing variation and robustly optimise the design. Using ODYSSEE allows designers to determine the most sensitive parameters first and then conduct a full factorial or genetic algorithm study, which would traditionally require billions of combinations and would be impractical using traditional methods. ODYSSEE gives the quickest and easiest way to explore the design space and make meaningful engineering decisions based on the generated results.

The study defined here uses a template method of selecting the input and output parameters, which means it can be easily implemented on similar models just by swapping the models or the parameters required. Investigations can also be extended – the next step for the example shown here might be to include consideration of upstream and downstream inertia and investigate the impact on contact pattern and NVH response.

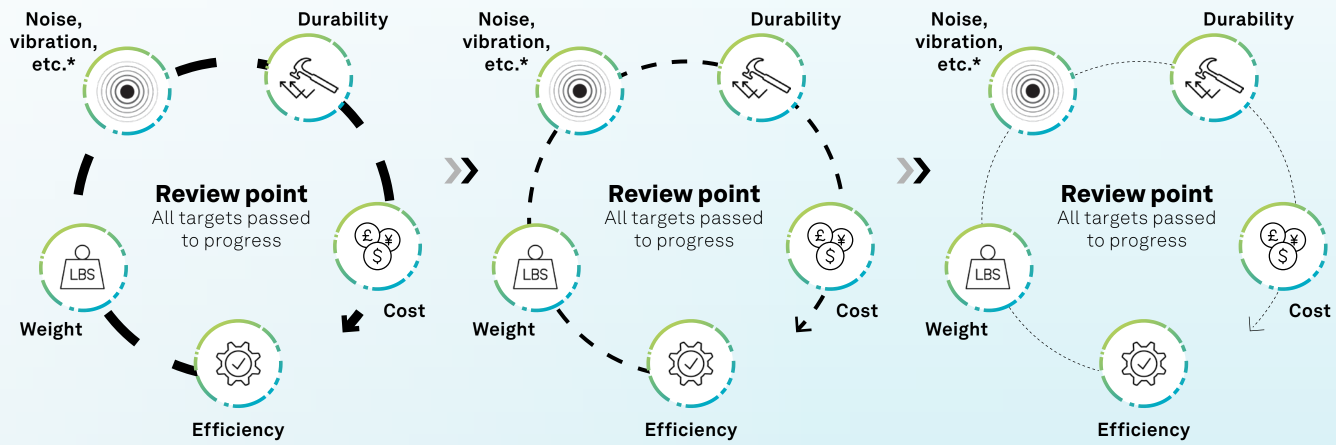
Combining the power of Romax and ODYSSEE has been seen here to enable a study to be performed considering many different transmission variables. The same power could be used in another way, to run hundreds of different load cases on a model, or in any application which requires running a high number of optimisation processes. Further integration is planned in the future between Romax and ODYSSEE. At the moment, the process requires ODYSSEE calling Romax, but the future might see ODYSSEE called from within Romax, to tie together further the technologies.

In addition, the use of ODYSSEE could be scaled to give the option to optimise across different products' physics, looking at aspects which can be analysed in Cradle (CFD), Actran (acoustics), and all leveraging the power of AI/ML. Thus, multiple software tools could be joined together for more advanced studies and to open up more possibilities, enabling true multiphysics optimisation.

In this way, the methods shown in this white paper have further applications for other transmission design and optimisation studies across multiple industries. There is potential here to explore the full design space, to leverage more powerful ways to achieve multiphysics transmission optimisation, to ensure the manufactured transmission will behave as the 'as-simulated' and ultimately improve product quality at far reduced timescales, while democratising advanced technology and reducing reliance on engineering expertise and past experience - and thus removing some obstacles to innovation.

Ideal way of using Romax-ODYSSEE

Using master model data throughout the process, for minimal data transfer and minimal errors

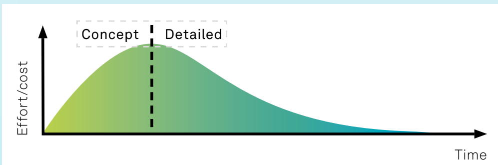


Categorise input parameters

- Indicative, broad targets
- Investigate small number of key parameters for bearing, gears, shafts, lubricants etc.

Late phases

- Narrower target focus
- Increase number of input and output parameters, with greater focus on micro-geometry



* Noise, vibration and other dynamic effects

Image 11. Using Romax and ODYSSEE throughout the design and development process

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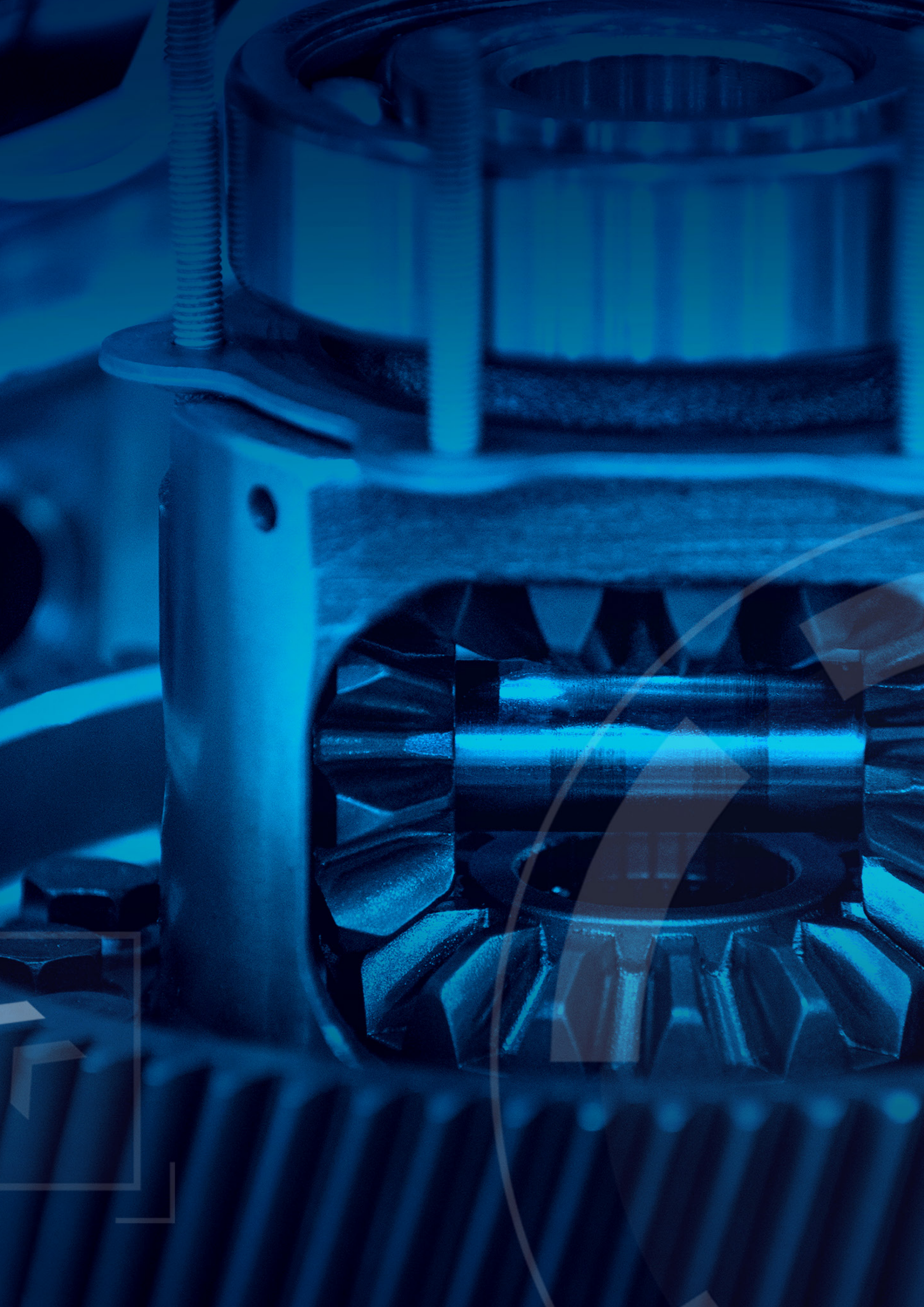

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