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Model Based System Testing approach for efficient testing of EPS systems

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Abstract: Model Based System Testing (MBST) can be defined as the discipline combining physical testing and simulation models with the aim to study, identify, validate and improve the behavior of multiphysical and mechatronic systems. One of its benefits is related to the use of simulation models to improve or accelerate the testing process, using well known procedures, such as optimal sensor and excitation placement, but also more recent methodologies, such as virtual testing or human-in-the-loop interactions. In this context, these MBST methodologies can be used for Electrical power steering (EPS) system testing, to allow for better characterization of the overall system and subsystems, and to better identify and model non-linearities. This paper presents a testing and simulation combined approach used to optimally define test conditions, such as sensor placement, test boundary conditions, excitation inputs and how they affect parameter identification.

Keywords: Model based system testing, virtual testing, electric power steering, nonlinearity, multiphysics

INTRODUCTION

The increasing challenges in product development, originating from the needs to decrease product development costs, while increasing overall performance and efficiency, have more and more led to the use of simulation methodologies in combination with testing. Physical prototypes are not only expensive and time-consuming to produce, but they are also only available late in the development cycle, when timing is even more critical. Improving testing conditions at this stage can lead to much more efficient test procedures, that not only spend less time and resources, but that can also provide data which is more useful for the validation and correlation of models, resulting in more well-performing systems, with shortened development times. However, such a combined virtual + physical approach can be less trivial when very complex, nonlinear multiphysical systems are taken in consideration. Such is the case in the automotive industry, where the increased use of mechatronics and controls also leads to higher complexity and higher needs to accurately identify system parameters in order to properly model and understand their behavior [1]. Moreover, most system components cannot be tested individually, as their behavior changes when they are integrated in the system. Therefore, parameters must be identified using system level tests, which can be very challenging, complex and costly. In this case, simulation and virtual testing can be used to improve test reliability, and lead to the right and efficient way to instrument and carry out the test campaign.

Experimental methodologies nowadays have shifted from purely test-only routines to simulation-aided methods. As test campaigns and their objectives grow in complexity, they make use more and more of virtual models to increase the knowledge of system behavior. Moreover, testing is no longer solely related to troubleshooting analysis, and the identified parameters and models can also be used for other purposes, such as force and load estimation, in the so-called virtual sensing applications [2]. Testing has also gone beyond the boundaries of purely mechanical systems, and its applications have expanded to other fields, such as electrical motor testing [3,4], electromechanical systems [5], multiphysical analyses [6] and mechatronic applications [7].

With the purpose of supporting the new paradigm that combines test and simulation, the model based system testing (MBST) framework was created [8]. The main purpose of MBST and its underlying methodologies is to support and improve testing and validation techniques, by using and/or combining test and simulation, with the aim to study, identify and validate multiphysical and mechatronic systems. MBST combines test and simulation into 3 categories: "Testing for Simulation", "Simulation for Testing" and "Testing with Simulation". The first two are cases in which both test and simulation are decoupled, and are carried out in different steps, while the last case involves test and simulation simultaneously. Figure 1 shows the MBST application tree and how the different domains are divided.

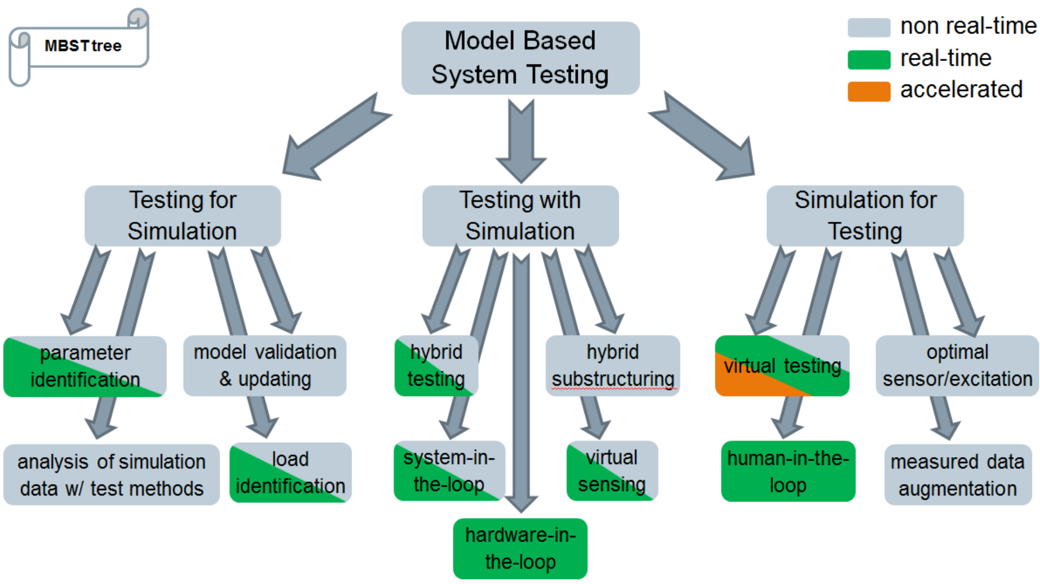

Figure 1 - MBST tree

This work will focus on the “Simulation for Testing” branch of the MBST application tree. This category has two already well known procedures, optimal sensor and excitation location, but also makes use of more recent methodologies, such as virtual testing, human-in-the-loop and measured data augmentation.

Electrical power steering has several advantages when compared to its concurrent technology in power steering, hydraulic actuation. It is more compact, has higher efficiency and reliability, and is easier to maintain [9]. However, there can be noise and vibration issues arising from this type of system, depending on the control strategy used to alleviate the required torque from the driver [10,11]. The EPS system can also undesirably isolate the feedback to the driver, reducing the driving feeling, which is an important sensorial feedback to the driver, giving them the right notion of the safe vehicle handling, especially with respect to unsafe conditions, such as vehicle side slip.
Model-based control strategies often prove to be an appropriate solution for EPS systems but they rely heavily on high fidelity models of the steering system which is by nature very complex, nonlinear and multiphysical. Nonlinearities such as friction and backlash are a common characteristic of the rack-pinion gear pair and also for the worm gear, some basic elements of the EPS system. Good models must include these physical properties to improve their prediction capabilities and allow for the model-based controller to properly drive the system [12].

A major portion of the mismatch between model and system behaviors arises of the poor characterization of the nonlinear components parameters. Experience from engineering projects within Siemens Industry Software dictates that the nonlinear behavior of the individual components is not the same as the behavior observed when they are interconnected. Therefore the parameters needed for the model needs to be identified at a system testing and not by a series of isolated measurements. This measurement campaign of an entire electromechanical system poses several challenges, in particular to isolate and determine the influence of individual parameter on the overall system behavior.

Electric power steering (EPS) and its functional model

Electric power steering (EPS) assistance systems provide auxiliary power to the steering mechanism of the vehicle to aid the driver in performing a desired maneuver, where part of the effort is frontloaded by an electric drive combined to the steering column of the mechanism. A common schematic used to generalize this type of device [12] is provided on Fig. 2(a) where the main components are shown: a steering wheel (where drivers apply their inputs); an electric motor and drive to provide auxiliary power; a reduction mechanism to transmit the electric motor power into the steering column; an electronic control unit (ECU) that reads the driver’s torque and commands the electric motor to assist the driver (reduce the torque required to perform a maneuver); a steering column that transmits torque to the rack and pinion; the rack and pinion that converts the rotary movement into a translation one; the tie-rods (left and right) which carry the translation motion and loads from the rack and pinion to the wheels; and finally the vehicle wheels that the driver desires to rotate around their axis to create a steering motion of the complete vehicle.

Figure 2(b) is a picture of an actual EPS mechanism where a few different components are named for ease of understanding how the real mechanism is conceived. It is possible to observe from this picture that several issues might arise from the actual construction of this mechanism, such as the use of joints in the steering column to redirect the direction of the rotational movement, the safe use and adjustment mechanism in the column, and more. The simplest way to model an EPS system is to relate the assist torque with the driver torque and steering rack displacement. Figure 3 show the diagram representing such a model, which is described by equations (1) and (2).

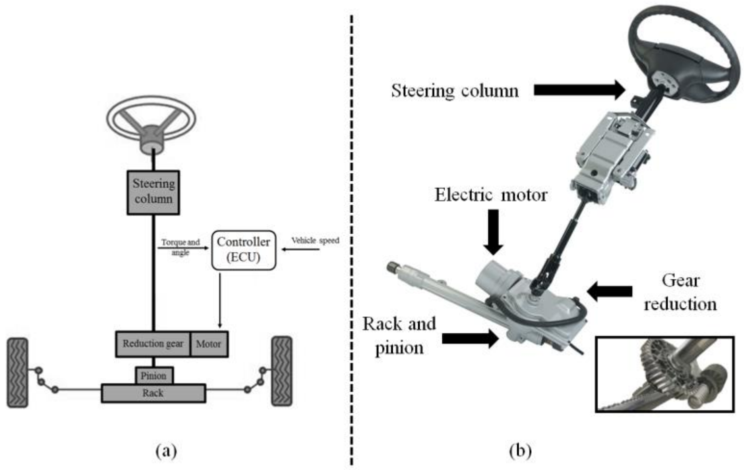

Figure 2– (a) Sketch of the working principle of and EPS system (b) Name of the components of and EPS system (source: internet)

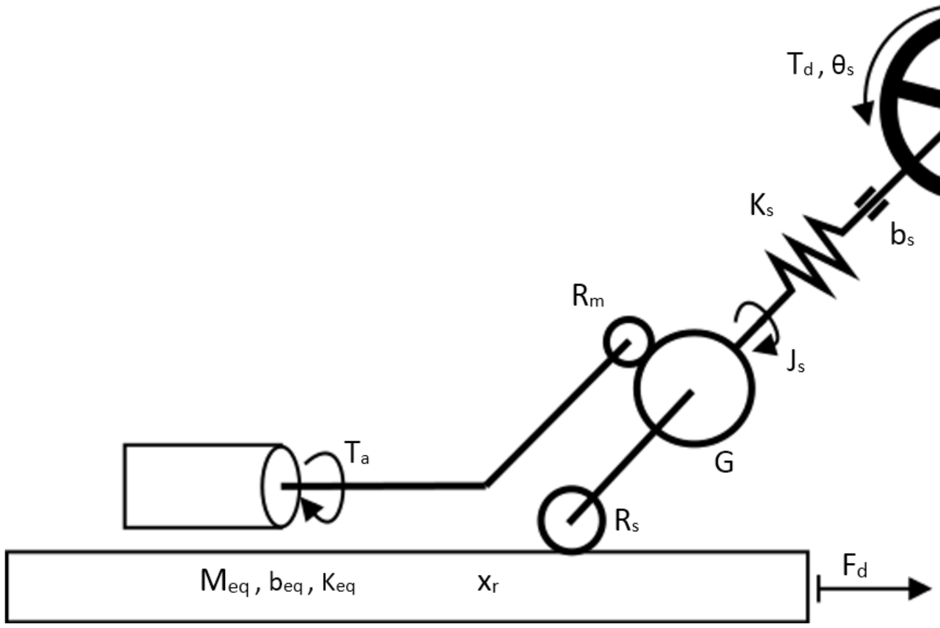

Figure 3 - Schematics for simple EPS model

$$J_s\ddot{\theta}_s + b_s\dot{\theta}_s + K_s\theta_s = T_d + \frac{K_s}{R_s}x_r \tag{1}$$

$$M_{eq}\ddot{x}_r + b_{eq}\dot{x}_r + K_{eq}x_r = \frac{T_m G}{R_m} + \frac{K_s}{R_s}\theta_s + F_d \tag{2}$$

Where J_s, b_s and K_s are the steering column inertia, friction and stiffness, θ_s is the steering column angle, T_d is the driver torque, R_s is the column pinion radius, x_r is the rack displacement, M_{eq}, b_{eq} and K_{eq} are the equivalent rack mass, friction and stiffness, T_a is the assistance torque, R_m is the assistance pinion radius, G is the gear ratio and F_d is the disturbance from the road. The realization of the EPS mechanism will lead to a system that has a more complex dynamic behavior than originally desired, with a series of nonlinearities, such as dry and viscous friction, backlash, hysteresis, etc. However, these phenomena are very hard to describe accurately, so the challenge from a modeling perspective is to idealize the system and define fundamental dynamics for each of its components that can adequately represent the behavior of the real system. For this purpose, functional models can be used instead, to aid in the modelling of important and complex dynamics, while still making it simple to describe the system. Functional models allocate physical systems to their (multiphysical) functionalities. In this sense, one can start from the simple electro-mechanical representation of the system by a combination of masses, springs, dampers, motors and converters (e.g. gears) of the system to reach a first functional iteration of the model.

As previously established in this paper, for disturbance rejection/control purposes a high fidelity model is desired, which imposes the inclusion of the nonlinear behavior present on the real system. One possible solution (followed in this paper) is to lump the nonlinearities at each component, meaning a set of specific nonlinear behavior for the: steering column, electric motor, gear reduction, rack-pinion pair and wheel.

For this paper a multi-physical model is constructed using LMS.Imagine AMESIM software, the sketch of the model is presented below by Fig. 4 together with a general classification used for the different subsystems considered. For each of the grouping presented a friction component is assigned (this is not the case for the control strategy – ECU) to lump all the nonlinear effects. The model takes as input the angular input provided by the driver at the steering wheel and calculates for a certain vehicle speed the torque perceived by the driver. If the control strategy is turned off (zero PI gains for example), the electrical drive reacts as a passive component with certain inertia associated to it. The driver's action is cascaded down to the tie-rods which push against the tire friction to create an angular motion at the spindle. The tire friction can also be written as a function of vehicle speed to take into account the rolling velocity in the side-slip of the tire. From a practical testing perspective it is interesting to characterize the EPS dynamics when the electric drive and control strategy is not activated, to define the response of the passive mechanical system, and also considering zero vehicle speed so the tire friction can be taken at its maximum state.

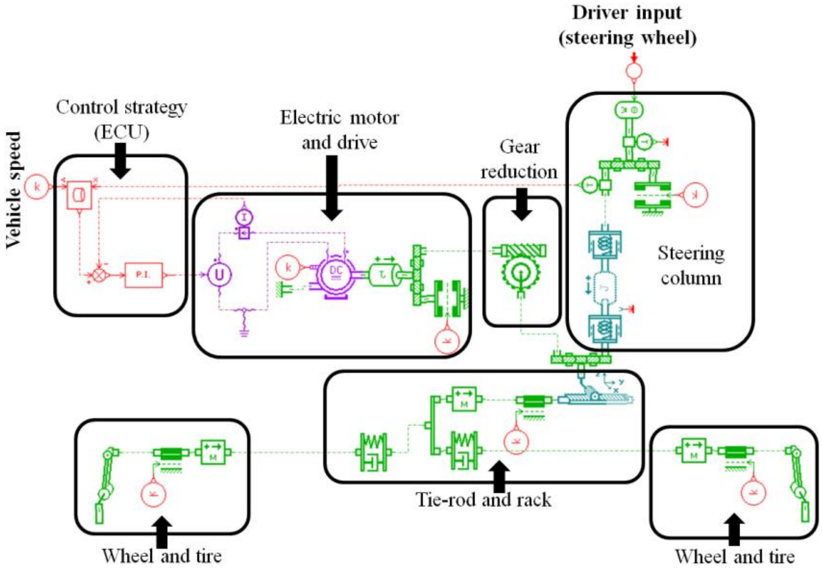

Figure 4 – EPS model realization in AMESIM

Several model parameters can be identifies a priory to reduce the number of unknowns in the system model. Geometrical and mechanical characteristics (mass and stiffness) can be determined a priory by the execution of simple tests and components inspection. Electrical quantities can also be directly measured at the electric motor. The largest uncertainty must be assigned to the nonlinear parameters, but a certain level of parameter freedom can also be assigned to these previously identified parameters for model fine tuning.

MBST approach applied to EPS

By applying the concepts of Model-Based System Testing (MBST), more specifically the subcategory of Simulation for Testing, one can generate a lot of insight on the testing activity by performing a series of simulations to explore the system response and help define testing configurations and methodologies that expose critical and key parameters of system of interest. To illustrate this concept the methodology is applied to the electric power steering (EPS) system in order to develop a testing procedure that allows for the composition of a high fidelity model that could later be used for control purposes.

The basic structure of the EPS model under consideration has been already introduced in the previous section of this paper where functional graphic modeling software (LMS.Imagine AMESIM) was used to sketch the structure taken for this physical system. This model can be used in a variety of ways to explore different aspects of the tests that will be carried out and to evaluate mechanism, configurations and conditions that would favor the later identification of the model parameters. A key remark is that this model already has reasonable (or even accurate) values for some of the linear dynamics components, such as masses, dimensions and stiffness. The challenge on developing an accurate model for this particular physical system lies on the characterization of the nonlinearities and viscous damping terms used.

The first exercise carried out here is to explore the behavior of smaller (called here cut-outs) of the system and subject those to different boundary condition to allow for the testing engineer to isolate the nonlinearities on a given component and precisely characterize them. It is important to recognize that not all cut-outs of the model presented in Fig. 3 can be executed in practice and also that imposing certain boundary condition might be unfeasible or too costly to be executed, therefore a subset of the possibilities are explored as an intersection of three different factors: utility of such a cut-out, the effort to implement it and the cost to execute it. As an example, Fig. 5 illustrates three EPS cut-outs exploring the behavior of a section of the system under a particular boundary condition. The cut-out from the left isolates the behavior of the column, where the configuration blocks the movement of the shaft at its base and allows for the evaluation of friction given that enough flexibility is present. The use of simulation of such a subset of the original developed model can help the test engineer evaluate if this cut-out can be useful or not for their parameter identification.

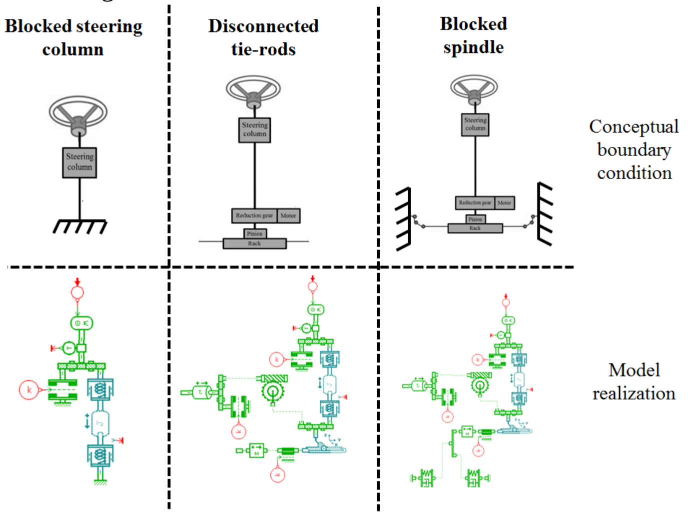

Figure 5 – Different possible boundary condition for the EPS mechanism and its model realization

The central cut-out shown in Fig. 5 consists of the disconnection of the tie rods from the wheel spindle which would allow the rack to move freely with no resistance. In this condition one can also disconnect the electric motor and have it as a free moving inertia in the system. Similar to the previous cut-out, in the one on the right side of Fig. 5, the tie-rods are blocked to create a zero displacement condition at the rack. The model realization for each cut-out can be used to evaluate and investigate in detail if it is a good candidate to excite and isolate a particular nonlinear behavior in each of the components.

Besides evaluating different model configurations (cut-outs) and boundary conditions, the virtual representation of the EPS system can be used to evaluate the usage of different inputs to the system and how they affect the response. Typical input profiles to be evaluated are: harmonic inputs (sine waves or sine sweep), used to evaluate cyclic behaviors; impact inputs (sharp or wide impacts), used to evaluate linear dynamic behavior; and also ramp inputs, used to identify transition points in the system dynamics.

Moreover, a combination of these inputs or different levels of the same input can be used to exploit the dominance of a given parameter in the response of the system. By developing this knowledge over several simulations, a set of unique input profiles can be derived such that the parameters are identified more accurately. One example is shown on Fig. 6, where the same cut-out model of the disconnected tie-rods is excited using a harmonic angular input (sine wave of 30 degrees of amplitude) using two different frequencies, one low (0.5 Hz) and another higher frequency (2 Hz). A significant response difference can be noticed between the two inputs applied to the system, where on the higher frequency sine input more inertial forces have to be overcome in order to start the motion and to reverse its direction, also the higher velocities make the viscous losses in the system more prominent.

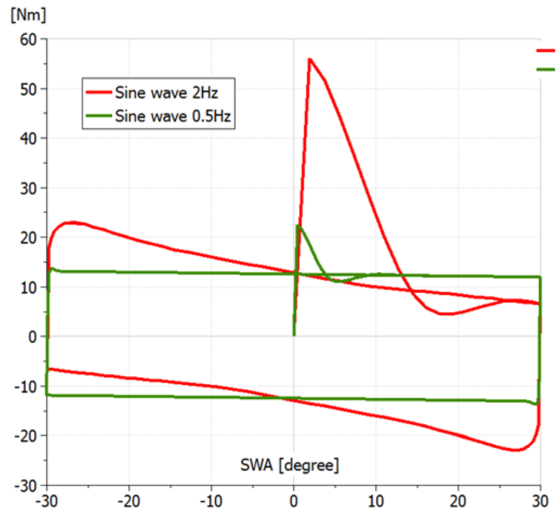

Figure 6 – Steering wheel angle by steering wheel torque plot for two different excitation harmonic inputs

As to be expected, the initial motion of the system with a higher frequency input will require a larger torque to move the rotational inertia, since the acceleration at this case is higher when compared to the 0.5 Hz input excitation. This allows the torque signal to go well beyond the noise floor level on the experimental setup and will make for a much more accurate identification of the system inertia. A similar logic can be applied to the viscous components since the system with a 2 Hz angular sinusoidal input will experience higher velocities and more viscous losses associated with it.

Another important use for the model, in order to enhance the testing of such a multi-physical system, is to evaluate how candidate sensor positions can help (or not) to detect the effect of a certain parameter on the measured system response at that location. In this situation, it is not feasible to carry out an exhaustive search of all the sensor locations and use observability criteria to determine if that measurement (or a set of measurements) can be used to identify all the parameters of interest of the system, since many of these locations and quantities cannot be instrumented due to effort, feasibility and cost related issues. Therefore, the use of experience in combination with the exploratory capabilities of the model can directly support the decision making process of the instrumentation to be installed in the EPS system.

Experimental setup and testing results

To validate the proposed MBST approach applied to an EPS, an experimental campaign was devised starting from the principles previously described in this paper and will be detailed in this section. In order to maximize the correlation between the experimental setup and an in-vehicle mechanism in operation, the measurements were chosen to be taken from an EPS installed in a vehicle (to guarantee the correct boundary conditions). Moreover, the mechanism of choice was from a world-wide commercially available vehicle of a large automotive company, which will not be named here for confidentiality issues. No previous data or knowledge on the system had been provided prior to the beginning of the MBST campaign and all the parameters of the system model (Fig. 4) were unknown.

A first inspection of the EPS under test shows that all the main components previously described in this paper are present and indeed the generic model can be used to represent the system. At this stage the same model parameters can be retrieved by direct inspection of the device, such as the dimensions of the gears, leverage arm of the tie-rod to tire, motor resistance and inductance, conversion mechanisms ratio and the mass of components (wheel, rack, etc). Some first estimates can also be calculated for the stiffness of the steering column and the tie-rod considering the geometry of the components and the constitutive material. No prior knowledge or estimates have been assigned to any friction parameters or even to the viscous losses present in the system, but they have been chosen to be within reasonable ranges (to allow for motion of the entire system).

By setting the functional model of the system, simulations were carried with ten candidate position of sensor locations, chosen based on the accessibility of the location and cost/time to instrument. The unknown model parameters were swept across a reasonable range of possible values and the responses of the sensors were evaluated whether they could capture a response change or not. From those candidate positions, three were selected as the minimal set of sensors needed to fully capture the system behavior. The driver steering angle was selected as the input to the system (to also be used in the simulations) and a sensor was also placed in that location.

Figure 7 is a schematic representation of the sensor positions selected for the MBST campaign, where a potentiometer is used to capture the angular input from the driver, a full-bridge of strain-gauges (062AK_350 from micro measurements) is used to measure the driver input torque and also to measure the force transmitted by the tie-rod to the wheel. A wire-draw displacement sensor (WDS-250-MPM-C-P_HG from micro-epsilon) records the displacement of the rack/tie-rod. A second force measurement of the force in the tie-rod is also done to verify the system symmetry.

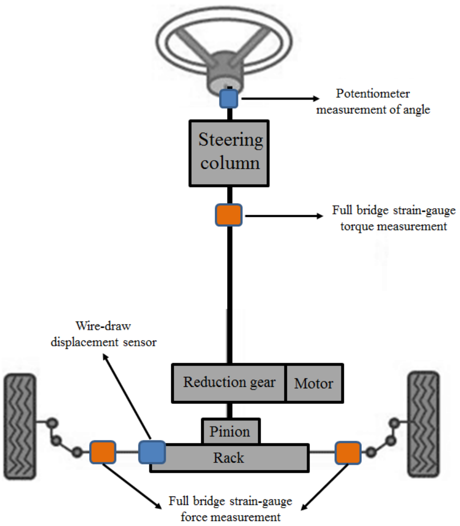

Figure 7 – Schematic representation of the test setup and instrumentation used

Data was collected by a SCADAS mobile hardware using VB8 family modules and the acquisition and post-processing using LMS Test.Lab software (Signature Acquisition module). Exponential filtering was used on the collected data to eliminate high frequency noise content of the data and since the same procedure is applied to all data phase delays should be even across the different data signals.

The models are used to evaluate possible test scenario of the EPS system considering different cut-outs and boundary conditions as explained in the previous section of this paper. In total, a combination of six different scenarios were investigated, five where the e-motor was a passive element in the system (blocked steering column, free tie-rods, blocked spindle, full system without tire friction – suspended vehicle – and full system with tires on the ground) and one scenario where the motor was actuated with a constant supply (free tie-rod). Based on the simulation results, three of these scenarios were chosen: (1) blocked steering column; (2) free tie-rods and; (3) full system with tires on the ground. These would, according to simulation results, enable the identification of all the unknown model parameters and were a good compromise between quality of the results and time/cost of the campaign.

The following step is to study how different inputs could be selected for each of the three test scenarios. For scenario (1), two sinusoidal inputs were selected, one fast (0.8 Hz) and one slow (0.2 Hz). Meanwhile, for (2) and (3), besides the two harmonic inputs, a slow ramp was also selected to allow for a clear definition of the transition points between different friction regimes in different components. At this stage, the simulations carried out provided full support to the test engineer to define the best practices for the EPS system and could then initiate the test procedure with high confidence.

The MBST procedure allowed for the execution of a fast and conscious instrumentation and testing of the EPS system given the insight provided by the simulation. The subsequent parameter identification procedure was carried out first at a model cut-out representing the test scenario (1), followed by (2) and (3) respectively. The parameters identified in the previous scenario were cascaded to the subsequent identification step and they were taken as constant to allow the algorithm to focus on the fitting based only on a subset of the model parameters. One of the results of the identification procedure is shown below by Fig. 8, where the simulated result for a control test on scenario (2) (not used in the parameter identification) is compared against the simulated result. As it turns out, this scenario has the poorest correlation between test and simulation, given that, on scenario (3), the tire friction dominates the system response (for zero vehicle speed) and hides most of the effects of the different components on the EPS.

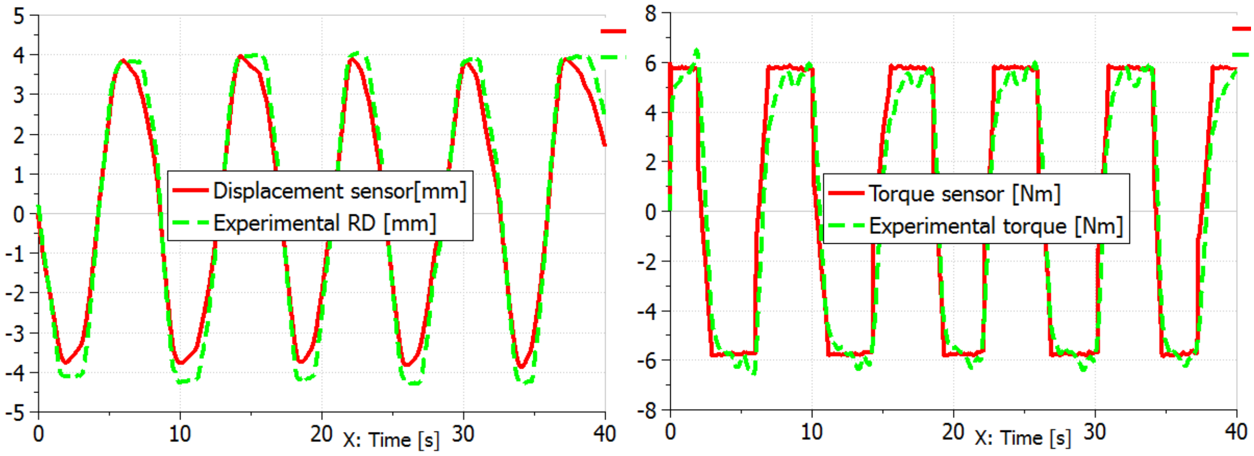

Figure 8 – Disconnected tie-rods results for the experimentally measured and simulated results after parameter identification is carried out.

As observed, the correlation between test and simulation obtained was quite good, nevertheless it is possible to see that some backlash on the experimental rack displacement (RD) measured is not captured by the model (flat top of the peak of experimental sinusoidal format). This is an interesting result since backlash is only present on the worm gear model and results in the identification of a physical phenomenon that is not included in the generic model developed.

Discussion and conclusions

This article presented the use of model based system testing applied to an electric power steering system. For that purpose, the concept of MBST was introduced, paying particular attention to the simulation for testing branch, where simulation and virtual models are used to aid in the testing procedure. Then, it was shown how it is possible to obtain a high fidelity model of an EPS system by breaking it down into different components and lumping the nonlinearities per component.

In this way, a full model with simple linear model parameters was used and divided in cutouts, with the objective of recreating boundary conditions for the test, in a way to identify the proper nonlinearities. Moreover, the model was used to determine the system input profiles that could be used to identify different types of parameters. Finally, sensor locations were evaluated taking into account ease of access, instrumentation efforts and observability.

Subsequently, a test campaign was carried out to validate the proposed methodology. By using simple geometrical and material properties, it was possible to concentrate the test efforts on identifying the nonlinear parameters, using the information obtained in the simulation model. The results showed good correlation between model and test, especially taking into account the complexity of the system.

In conclusion, it was observed that the combination of simulation and test (the MBST framework) can be very beneficial to aid in testing and parameter identification of complex systems. By using a model of the EPS system, it was possible to speed-up the testing procedure, reduce the number of used sensors and improve accuracy of the results. A next step could be to carry out automatic curve fitting to the nonlinear models to obtain the best possible nonlinear parameters. Such a step can be carried out with less effort, given that a model of the system under test has already been created.

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