PREDICTING USEFULNESS OF MEASURING STRUCTURES DURING LOAD TESTS

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ABSTRACT

This paper presents an approach for model identifiability that builds upon recent research into measurement data interpretation. The objective of this approach is to determine probabilistically to what degree the number of models able to explain a measured behaviour can be reduced in comparison to the initial solution space. The procedure is intended to be used prior to obtaining measurements from full-scale testing. The new methodology evaluates the probability of occurrence of two performance indices; the expected number of candidate models and the expected parameter range. It allows users, prior to taking measurements, to determine whether or not performing tests is likely to be useful. Since it does not require any intervention on the structure, this method may be used for a fraction of the cost required for full-scale testing. These features are illustrated through a case study, the Langensand Bridge (Switzerland). The methodology is the basis for a new generation of sensor placement techniques that determine to what extent particular sensor and load configurations are useful.

INTRODUCTION

With increasing availability of communication systems and the decreasing in cost of sensors, more structures will be measured in the future. However, the capacity for engineers to analyse sensor information has not adequately compensated the growth of data. System identification (SI) techniques have the potential to process such data. However, important challenges remain. Ljung (1994) stated that it is a fundamental problem of identification to be able, prior to analysis, to decide if all unknown values for parameters of a behaviour model can be uniquely identified. For most full-scale structures in civil engineering, unique identification of a model is unlikely. Goulet and Smith (2010) showed that it is possible to obtain several hundred candidate models. Therefore, a new methodology is required in order to determine to what extent a system is identifiable. This paper presents the expected identifiability methodology (eId) building upon the Candidate Model Search for System Identification Methodology (**CMS*4*SI**) proposed by Goulet and Smith (2010). The objective of this approach is to determine probabilistically to what degree a candidate model (CM) set can be reduced in comparison to the initial model instance set (IMS). The procedure is intended to be used prior to obtaining any measurement from full-scale testing.

Available System Identification Approaches

CMS*4*SI is based on the following *fundamental principle*:

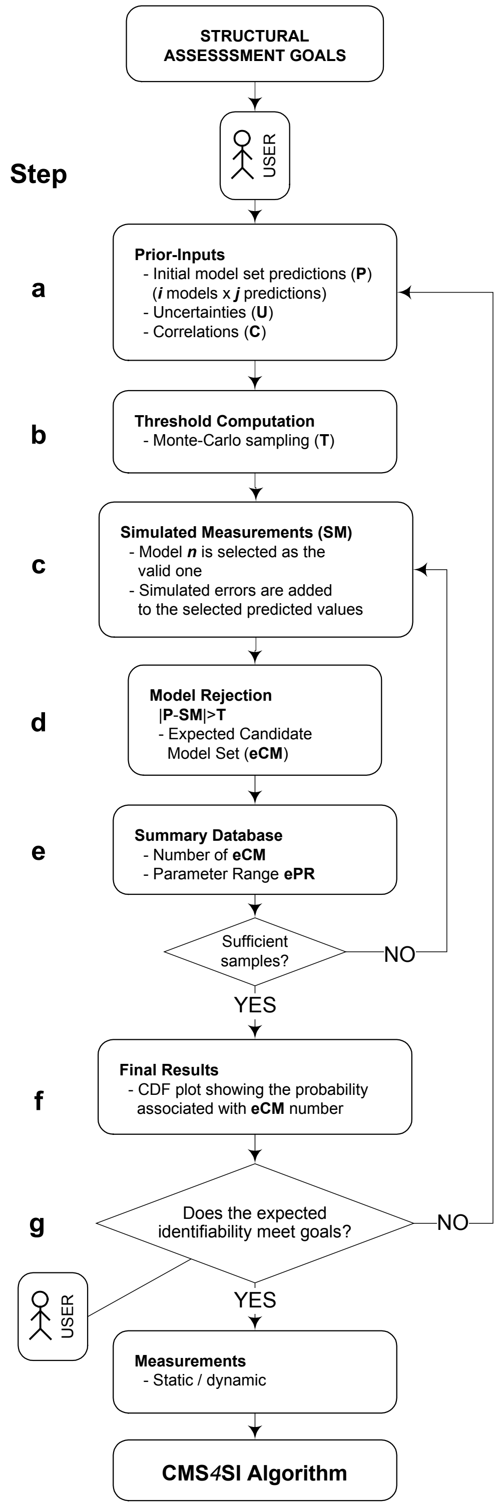

Figure 1 - Expected identifiability (eId) flowchart

When uncertainties are adequately evaluated and a right model[1] is present in the initial model set, this model should be included in the candidate model set 95 times out of 100[2].

This approach generates predictions for an initial population of model instances (IMS) which are the potential representations of the system. Once measurements are obtained from the real system, they are used to discard instances from the initial model set. For each instance, if the absolute difference between predicted and measured values at any location is larger than a predefined threshold (maximal plausible error), the model instance is discarded. The value for the threshold is based on the combination of uncertainties associated with both measurement and modelling tasks. The result of the filtering procedure is a Candidate Model (CM) set which contain the solutions able to explain the measured behaviour while considering uncertainties. This set may be further refined into clusters in order to allow for easier interpretation. It provides a tool to support decisions related to the behaviour of the structure.

Identifiability

Ljung (1999) described identifiability as a criterion which defines if an identification procedure would indicated unique values for parameters and whether or not the resulting model is the right system.

This paper describes the methodology proposed to predict the identifiability of a system prior to measurement. Building on **CMS*4*SI**, this approach quantifies in a probabilistic manner, the number of expected candidate models (CM). The objective is to provide a tool to define whether or not measuring a structure is useful. The paper is organized as follows: The first section presents the identification capability evaluation approach. The second presents applications of the new eId methodology on a full scale structure, the Langensand Bridge, Lucern (Switzerland).

EXPECTED IDENTIFIABILITY

The approach begins with the generation of the initial model set (IMS) that contains models having plausible values for

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[1] A model close enough to the real one for tasks in infrastructure management.
[2] A reliability of 95% is chosen due to its use elsewhere in structural engineering as an acceptable target.

parameters. Filtering the initial model set to obtain a candidate model set (CM) requires data to compare with model predictions. A small reduction in the initial model set indicates that measurements have not provided useful information related to the structural behaviour. On the other hand, a large reduction shows that the measurements improved the understanding of the structural behaviour. The expected identifiability (eId) is an evaluation of the probability that if measurements are taken, the candidate model set contains a number of individuals that is between one and the size of the initial model set. This procedure is intended to be performed prior to taking measurements. The flowchart of the methodology evaluating the eId is presented in Figure 1. The first step is to define goals in terms of what has to be identified. For example, a goal to reduce the initial model set (IMS) by more than 90% could be formulated. This goal is later used to define if whether or not, the expected identifiability is sufficient.

Prior Inputs & Threshold Computation (Steps a. & b.)

Users first have to provide the necessary inputs to the methodology. The inputs required are the model instance predictions, the uncertainties and the correlation associated with the identification process. Table 1 shows an example of model instance prediction inputs. Each row of the Table corresponds to a model instance, the first half of columns represents the template model free parameters, and the second half their predictions. In the case of structural identification, these may be obtained through using structural analysis simulations.

Table 1 – Example of initial model set

Model #	Param. 1 (GPa)	Param. 2 (GPa)	…	Param. n (kN/m)	Prediction 1 (mm)	Prediction 2 (μrad)	…	Prediction n ($\mu\varepsilon$)
1	32	200	…	150	-20	500	…	35
2	37	175	…	350	-24	425	…	40
3	25	96	…	100	-30	375	…	42
…	…	…	…	…	…	…	…	…
n	55	150	…	0	-19	600	…	22

The uncertainties sources to be evaluated are

Modelling

- Geometric model simplifications (geometry approximations, boundary conditions)
- Finite element method (FEM) simplifications (element choice, mesh discretization and numerical rounding)
- Fixed parameter values
- Temperature effects

Measurement

- Applied loading
- Repeatability
- Site conditions (signal noise and losses)
- Sensor resolution

Each of these uncertainties and their correlations may be evaluated prior to taking measurements. The uncertainties are used for two purposes. The first is to compute threshold values which are used to find candidate models. Threshold values represent the maximal plausible error occurring during the identification process. The second purpose is the generation of simulated measurements.

Simulated Measurements (Step c.)

As mentioned above, measurements, determine the size of the CM set. The expected identifiability (eId) methodology is consistent with the *fundamental principle*. Prior to analysing measurements, every model could be the right representation of the true system. Therefore, simulated measurements (SM) are derived from aleatory selection of one of these models. The values predicted by the right model would never exactly correspond to the one measured on the true system since errors are present in both modelling and measuring.

In order to account for these discrepancies, aleatory uncertainty samples are drawn from each source and then added to the predicted values of the *assumed right model*. Figure 2 shows an example of simulated measurement. In this figure, each point along the horizontal axis represents a model instance (from the initial model instance set (IMS)) and its vertical position is fixed by its predicted value. In the IMS, every instance is equally likely to be the right representation of the true system. Therefore any of these instances may be selected as an assumed right model. When a model instance is selected, errors from the sources mentioned above (modelling and measurement) are randomly generated and added to the model predictions.

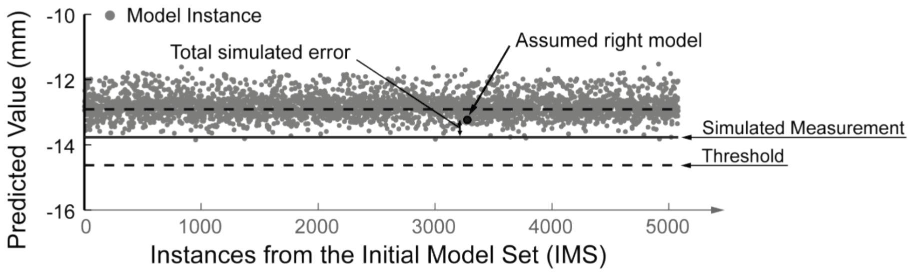

Figure 2 – Simulated-measurement generation process

This process results in simulated measurements (SMs). SMs may then be used in the same way as real measurements.

Model rejection & Results Database (Steps d. & e.)

In order to find an expected candidate model set (eCM), model instance predictions are compared to simulated measurements. For each model, if the absolute difference between a predicted and a SM value is larger than the threshold, then this model is rejected. The number of models and the free parameter ranges are extracted from the final expected CM set, and stored into a database. At this point, the eCM set may be discarded since it is no longer needed.

Iterative Process & final Results (Step f.)

The generation of simulated measurements and eCM instances need to be repeated several times in order to obtain a distribution representing the overall expected number of CM for several instances of simulated measurements. The convergence toward a steady solution is achievable by taking a enough samples to obtain a cumulative distribution function (CDF) similar to the solution obtained using an infinite amount of samples. This whole process is computationally inexpensive. A large number of samples (>10,000) can be created in a few minutes.

The results are presented as a CDF showing the probability of obtaining any number of expected candidate models (or the expected parameters range) if measurements are taken on the structure. An example of such a plot is showed in Figure 3. The two quantities of interest extracted from the CDF are the number of eCM (or the expected parameter range (ePR)) that should be obtained with a 95% (eCM(95%)) and 50% (eCM(50%)) certainty. The first represents, for example, a minimal expectation and the second, a maximal one. This latter corresponds to the limit in the number of expected models one has the most chances to obtain if measurements are taken.

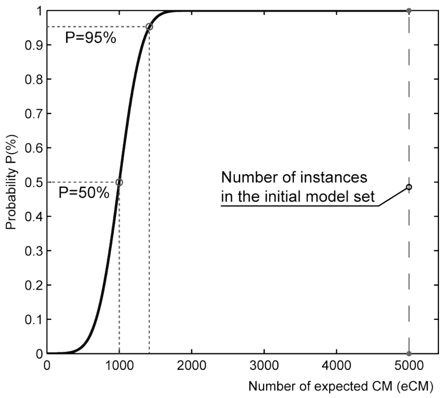

Figure 3 - Example of expected result

The numbers (eCM(95%) & eCM(50%)) are compared with the initial number of individuals in the IMS. Figure 3 shows an example where there is a 95% probability of reducing the IMS set by almost 75% and a 50% probability of reducing it by 80%. Therefore, taking measurements under such conditions is likely to contribute to understanding the system behaviour. In other words, if measurements are taken on the structure, there is a probability of 95% to obtain less than 1400 candidate models.

The same process may also be applied to the expected parameter range. However, this does not provide information about expected identifiability. Parameter compensation is inherent to inverse tasks. Therefore a small number of CM may be expected while large parameter ranges are still present. A reduced expected parameter range would indicate that values for this parameter are likely to be identified with more precision. When a limited reduction in parameter ranges is expected, local tests such as non-destructive testing can be used to guide determination of the right parameter value.

Decision making Step (g.)

Comparing the expected identifiability to the initial goals help decide whether uncertainties have to be reduced in order to achieve a better identification or whether eId is adequate and it is then possible to proceed with measurements. Once measurements are taken, data may directly be used in the **CMS*4*SI** methodology. If eId is unsatisfactory and initial uncertainties have to be reduced, assumptions may need to be revised. For example, the template model used may be improved in order to diminish the number of simplifications made in comparison with the real structure. Also many fixed parameter values such as element thickness variations, Poisson ratio, truck weight and temperature change may be determined by independent investigations in order to reduce their uncertainties.

The expected identifiability allows users to make efficient and useful measurements on full scale systems. Use of such methods help prioritize resources.

CASE-STUDY: LANGENSAND BRIDGE

The eId methodology is applied to a full-scale structure in order to evaluate the usefulness of measuring such a bridge. The structure studied is the Langensand Bridge, Lucerne, Switzerland.

Structure description

As described by Goulet et al (2010), this bridge is 80m long and shows an extremely slender profile (>L/30) , see Figure 4.

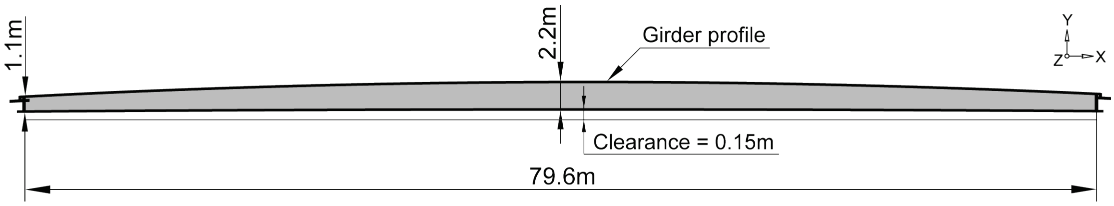

Figure 4 - Langensand Bridge elevation representation (Goulet et al. 2010)

Figure 5 shaded area represent the part of the bridge which is studied. It consists of a poured concrete deck on a steel girder. The central part of the bridge is used as roadway and its external parts as sidewalks.

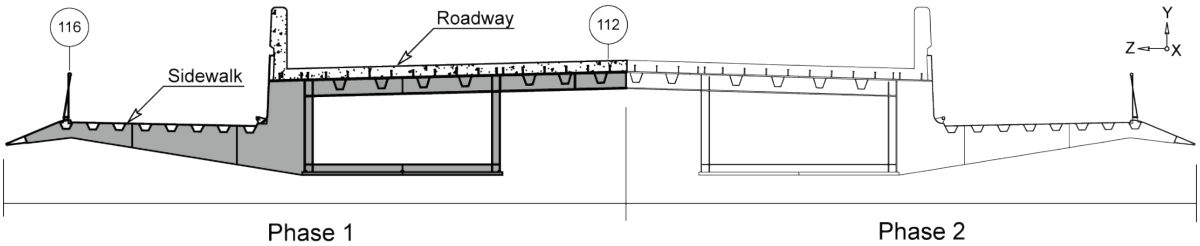

Figure 5 - Langensand cross section (Goulet et al. 2010)

Two of the load cases performed are presented in Figure 6. The measurement system used for the identification is composed of six displacements, two rotations and three strain measurements recorded for five load cases. The complete load configurations and sensor layout are detailed in (Goulet et al. 2010).

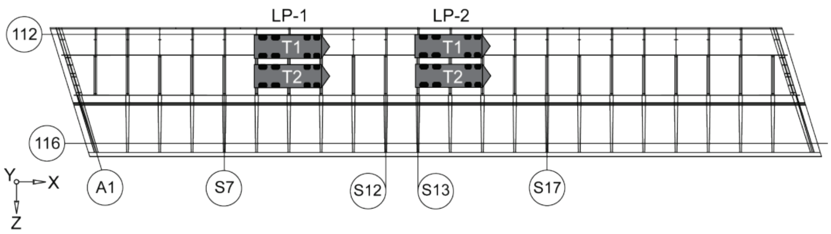

Figure 6 - Test truck layout (Goulet et al. 2010)

The finite element template model used in order to generate the initial model instance set is presented in Figure 7. Special care is necessary regarding the level of detail that needs to be included in the model. This figure shows in addition to the main steel girder and concrete slab, the secondary structural elements such as the deck stiffeners, the concrete barrier, the reinforcement and the road surface.

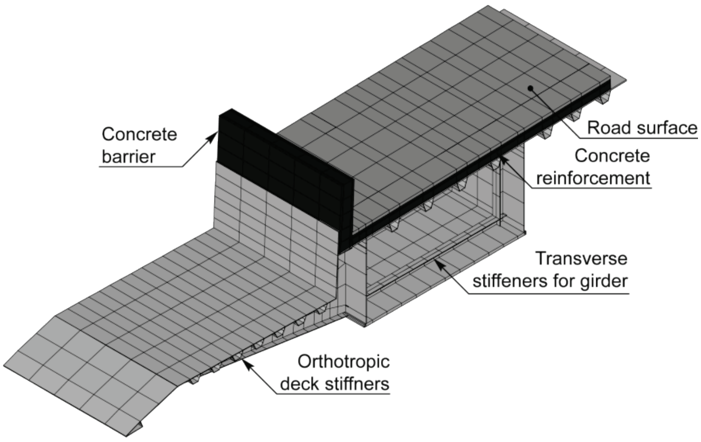

Figure 7 - Langensand Bridge FE template model (Goulet et al. 2010)

The IMS contains 5,000 models made of several sets of parameters. Each is evaluated for five load cases. Four parameters are to be identified: Young's modulus for concrete (E-CONC), steel (E-STEEL) and road surface (E-RS) and the stiffness of the horizontal restriction created by the bearing devices (U-STIFF).

<u>Uncertainties</u>

Uncertainties related to the identification are described in Table 2. Model simplification & FEM, mesh refinement and additional uncertainties are represented as extended uniform distributions. For these PDFs, the $\boldsymbol{\beta}$ parameter is taken to be 0.3. Sensor resolution as well as temperature variation are represented as uniform distributions. Model dependent uncertainties related to the geometry of the structure (variation in the thickness of the elements), the variation into the strain sensor positioning, Poisson's coefficient for concrete, truck weight as well as the measurement repeatability are represented as normal distributions.

Table 2 – Langensand Bridge uncertainties (Goulet and Smith 2010)

Uncertainty source	PDF	Displacement			Rotation			Strains		
		unit	min	max	unit	min	max	unit	min	max
Sensor resolution	Uniform	mm	-0.1	0.1	μrad	-0.4	0.4	με	-2	2
Model simplification & FEM	EUD	%	0	7	%	0	7	%	0	15
Mesh refinement	EUD	%	-1	0	%	-1	0	%	-2	0
Cable losses	Uniform	%	0	0	%	0	0	%	0	0
Additional uncertainties	EUD	%	-1	1	%	-1	1	%	-1	1
		unit			min			max		
Temperature variation	Uniform	°C			0			5		
		unit			Mean			STD		
$\Delta\nu$ concrete	Normal	-			0			0.025		
Truck weight	Normal	Ton			35			0.125		
Δt steel plates	Normal	%			0			1		
Δt pavement	Normal	%			0			5		
Δt concrete	Normal	%			0			2.5		
Strain sensor positioning	Normal	mm			0			5		
Measurement repeatability	Normal	mm/rad/με			0			Measurement dependent		

The dependencies between the displacement, rotation and strain are presented in Table 3. Uncertainty sources which are not mentioned in this table are taken to be independent. The correlation between errors associated with load cases is taken to be 0.95. Correlation values are used to generate random correlated uncertainties in order to compute the threshold value. Uncertainty generation is made out of 20,000,000 samples for each uncertainty source. This attains a usable coverage interval of more than 99.95%.

Table 3 - Langensand Bridge uncertainty correlations (Goulet and Smith 2010)

Prediction type	Disp.	Rotation	Strains	Uncertainty source
Disp.	0.9	-	-	
Rotation	0.8	0.9	-	Model simplification & FEM
Strains	0.7	0.7	0.8	
Disp.	0.9	-	-	
Rotation	0.8	0.9	-	Mesh refinement
Strains	0.7	0.7	0.8	
Disp.	0.5	-	-	
Rotation	0.5	0.5	-	Add. Uncertainties
Strains	0.5	0.5	0.5	
Measurement type	**Disp.**	**Rotation**	**Strains**	**Uncertainty source**
Displ.	0.9	-	-	
Rotation	0.8	0.9	-	Meas. Repeatability
Strains	0.7	0.7	0.8	

More details of uncertainties and correlation choices are presented in (Goulet and Smith 2010).

Reduction on the IMS

Figure 8 shows the process which directly evaluates the eId using uncertainties provided by the user. In this case, the expected identifiability is not good. The CDF showing the expected number of CM indicates that there is 95% of the chance to have a 5% reduction (eCM(95%)<4780) in the CM set and 50% of the chance to get a 22% reduction (eCM(50%)<3920). In such a case, even if possible, obtaining useful results from the measurements is probabilistically unlikely. The investigation performed on the structure using measurements identified a CM set containing approximately 2500 models. Therefore, prior to taking measurements, there was a probability of 22% of obtaining such results

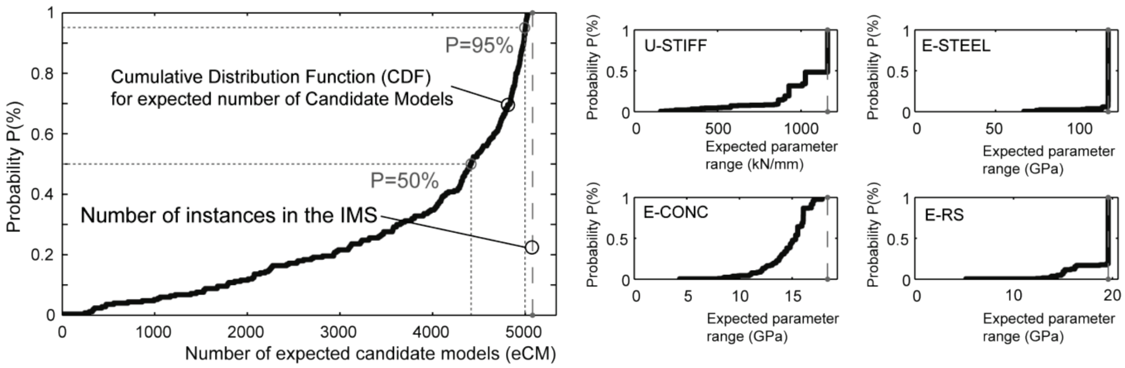

Figure 8 - Cumulative distribution functions (CDF) for Langensand expected results

The CDF for the free parameters enable to expect a small diminution in the ranges for U-STIFF and E-CONC. E-RS and E-STEEL. Because of their greater variability, E-RS and E-STEEL could be favoured if additional local investigation would be planned in order to further reduce the number of CM and address more precisely the value for these parameters.

Discussion

Future increases in computing power could reduce the amount of simplifications made in the template model (for example by using solid elements instead of shells), through reducing modelling uncertainties. Improvement in sensor technology and more sensors could reduce other sources of uncertainty.

The previous section shows that significantly reducing the eCM with a high probability (>50%) may be difficult in presence of uncertainties. Therefore, lowering uncertainties, especially those associated with the modelling process, could lead to a low number of candidate models in comparison with the initial model set. In addition to the uncertainties, other factors influence the performance of the identification. The quality of the measurement system, in this case the sensor locations, their types and the load configurations chosen for the test are also closely related to the expected identifiability of a structure. This topic is currently the object of further research into finding optimized measurement systems which minimize cost and the number of expected candidate models.

CONCLUSIONS

1- Using **CMS*4*SI** and eId, it is possible to study the usefulness of taking measurement on a structure (or on a system). The new methodology evaluates the probability of occurrence of two performance indices; the expected number of candidate models and the expected parameter range. It allows for users, prior to taking measurements, to determine whether or not performing tests is likely to be useful.
2- Since it does not require intervention on the structure, this method may be used for a fraction of the cost required for full-scale testing.
3- The eId methodology is the basis for a new generation of sensor placement techniques that determine to what extent particular sensor and load configurations are useful.

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