

RESEARCH CENTRE

Rennes - Bretagne Atlantique

IN PARTNERSHIP WITH:

Université Gustave Eiffel

2021

ACTIVITY REPORT

Project-Team

I4S

## Statistical Inference for Structural Health Monitoring

### DOMAIN

Applied Mathematics, Computation and  
Simulation

### THEME

Optimization and control of dynamic  
systems

# Contents

<b>Project-Team I4S</b>	<b>1</b>
<b>1 Team members, visitors, external collaborators</b>	<b>2</b>
<b>2 Overall objectives</b>	<b>3</b>
2.1 In Summary	3
2.2 Objectives	3
2.3 Introduction to physics driven dynamical models in the context of civil engineering elastic structures	4
2.4 Multi-fold thermal effects	4
2.5 Toward a multidisciplinary approach	5
2.6 Models for monitoring under environmental changes - scientific background	5
<b>3 Research program</b>	<b>7</b>
3.1 Vibration analysis	7
3.2 Identification	8
3.3 Detection	9
3.4 Diagnostics	10
3.5 Infrared thermography and heat transfer	10
3.5.1 Infrared radiation	11
3.5.2 Infrared Thermography	12
3.6 Heat transfer theory	12
3.7 Inverse model for parameter estimation	13
3.8 Reflectometry-based methods for electrical engineering and for civil engineering	14
3.8.1 Mathematical model of electric cables and networks	15
3.8.2 The inverse scattering theory applied to cables	15
<b>4 Application domains</b>	<b>16</b>
<b>5 Highlights of the year</b>	<b>17</b>
<b>6 New software and platforms</b>	<b>17</b>
6.1 New software	17
<b>7 New results</b>	<b>17</b>
7.1 System identification	17
7.1.1 Fast interval estimation for discrete-time linear systems	17
7.1.2 Uncertainty quantification for the Modal Phase Collinearity of complex mode shapes	17
7.1.3 Uncertainty quantification of the Modal Assurance Criterion in Operational Modal Analysis	18
7.1.4 Kalman filter-based subspace identification for operational modal analysis under unmeasured periodic excitation	18
7.2 Damage monitoring of civil engineering structures/fault detection and isolation	19
7.2.1 Subspace-based Mahalanobis damage detection robust to changes in excitation covariance	19
7.2.2 A reliability-based approach to determine the minimum detectable damage for statistical damage detection	19
7.2.3 Statistical model-based optimization for damage extent quantification	19
7.2.4 Dynamic System Fault Diagnosis under Sparseness Assumption	20
7.2.5 Damage Localization in Mechanical Systems by Lasso Regression	20
7.3 Analysis and monitoring of non-stationary systems	20
7.3.1 On the Optimality of the Kitanidis Filter for State Estimation Rejecting Unknown Inputs	20
7.3.2 Boundedness of the Kalman Filter Revisited	21

7.3.3	Estimation of local failure in tensegrity using Interacting Particle-Ensemble Kalman Filter	21
7.3.4	Structural health monitoring with non-linear sensor measurements robust to unknown non-stationary input forcing	21
7.3.5	Energy-efficient GPS synchronization for wireless nodes	22
7.4	Exploiting complex physical models for structural analysis and design	22
7.4.1	Advanced computational technique based on kriging and Polynomial Chaos Expansion for structural stability of mechanical systems with uncertainties	22
7.4.2	Advanced kriging-based surrogate modelling and sensitivity analysis for rotordynamics with uncertainties	22
7.4.3	Study of an optimal heating command law for structures with non-negligible thermal inertia in varying outdoor conditions	23
7.4.4	Lattice Boltzmann Method for Mathematical Morphology: Application to Porous Media	23
7.5	Exploiting new sensor technologies for structural analysis and monitoring	24
7.5.1	Characterization Shear Properties of PVC Foams Instrumented by Optical Fiber under Flexural Loading	24
7.5.2	A General Solution to Determine Strain Profile in the Core of Distributed Fiber Optic Sensors under Any Arbitrary Strain Fields	24
7.5.3	Analysis of Quadratic Surface Fitting for Subpixel Motion Extraction from Video Images	25
7.5.4	Experimental investigation of structural modal identification using pixels intensity and motion signals from video-based imaging devices	25
7.5.5	Investigation into the use of thermoelectric modules as an alternative to conventional fluxmeters	25
7.5.6	TeraHertz inspections of painted steel samples	26
<b>8</b>	<b>Bilateral contracts and grants with industry</b>	<b>26</b>
8.1	Bilateral contracts with industry	26
<b>9</b>	<b>Partnerships and cooperations</b>	<b>28</b>
9.1	International initiatives	28
9.1.1	Participation in other International Programs	28
9.2	European initiatives	29
9.2.1	FP7 & H2020 projects	29
9.2.2	Other European programs/initiatives	30
9.3	National initiatives	30
9.4	Regional initiatives	32
<b>10</b>	<b>Dissemination</b>	<b>32</b>
10.1	Promoting scientific activities	32
10.1.1	Scientific events: organisation	32
10.1.2	Scientific events: selection	32
10.1.3	Journal	34
10.1.4	Invited talks	34
10.1.5	Scientific expertise	34
10.1.6	Research administration	34
10.2	Teaching - Supervision - Juries	34
10.2.1	Teaching	34
10.2.2	Supervision	35
10.2.3	Juries	36
<b>11</b>	<b>Scientific production</b>	<b>36</b>
11.1	Major publications	36
11.2	Publications of the year	37
11.3	Cited publications	39

## Project-Team I4S

*Creation of the Project-Team: 2013 January 01*

### Keywords

#### Computer sciences and digital sciences

- A6.1.5. – Multiphysics modeling
- A6.2.1. – Numerical analysis of PDE and ODE
- A6.2.4. – Statistical methods
- A6.2.5. – Numerical Linear Algebra
- A6.2.6. – Optimization
- A6.3.1. – Inverse problems
- A6.3.3. – Data processing
- A6.3.4. – Model reduction
- A6.3.5. – Uncertainty Quantification
- A6.4.3. – Observability and Controlability

#### Other research topics and application domains

- B3.1. – Sustainable development
- B3.2. – Climate and meteorology
- B3.3.1. – Earth and subsoil
- B4.3.2. – Hydro-energy
- B4.3.3. – Wind energy
- B4.3.4. – Solar Energy
- B5.1. – Factory of the future
- B5.2. – Design and manufacturing
- B5.9. – Industrial maintenance
- B6.5. – Information systems
- B7.2.2. – Smart road
- B8.1. – Smart building/home
- B8.1.1. – Energy for smart buildings
- B8.1.2. – Sensor networks for smart buildings
- B8.2. – Connected city

## 1 Team members, visitors, external collaborators

### Research Scientists

- Laurent Mevel [Team leader, Inria, Senior Researcher, HDR]
- Xavier Chapeleau [Université Gustave Eiffel, Researcher]
- Enora Denimal [Inria, Researcher]
- Michael Doehler [Inria, Researcher]
- Christophe Droz [Inria, from Oct 2021, Starting Faculty Position]
- Jean Dumoulin [Université Gustave Eiffel, Researcher]
- Vincent Le Cam [Université Gustave Eiffel, Engineer]
- Romain Noel [Université Gustave Eiffel, Researcher]
- Qinghua Zhang [Inria, Senior Researcher, HDR]

### Post-Doctoral Fellows

- Swarup Mahato [Université Gustave Eiffel, Jan 2021]
- Boualem Merainani [Inria]

### PhD Students

- Ambroise Cadoret [IFPEN]
- Zhilei Luo [Inria, from Nov 2021]
- Cédric Nzouatchoua [IRT Jules Verne]
- Clément Rigal [Université de Strasbourg, From 12/2021]
- Quentin Sourisseau [ Université Gustave Eiffel]
- Eva Viefhues [BAM, Until September 2021]
- Bian Xiong [Inria]

### Technical Staff

- Ivan Guéguen [Université Gustave Eiffel, Engineer]
- David Pallier [UGE, Engineer, Until 10/2021]
- Thibaud Toullier [Université Gustave Eiffel, Engineer]

### Interns and Apprentices

- Raphael Chevalier [Inria, from May 2021 until Jul 2021]

### Administrative Assistant

- Hélène de La Ruée [Univ de Rennes I]

## External Collaborator

- Frédéric Gillot [Ecole Centrale de Lyon, From May 2021]

## 2 Overall objectives

### 2.1 In Summary

The objective of this team is the development of Structural Health Monitoring techniques by intrinsic coupling of statistics and thermo-aeroelastic mixing modeling for the development of robust and autonomous structural health monitoring solutions of mechanical structures. The emphasis of the team is the handling of very large systems such as the recent wind energy converters currently being installed in Europe, building on the expertise acquired by the team on bridges as an example of civil engineering structure, and for aircrafts and helicopters in the context of aero elastic instability monitoring. The necessity of system identification and damage detection systems robust to environmental variations and being designed to handle a very large model dimension motivates us. As examples, the explosion in the installed number of sensors and the robustness to temperature variation will be the main focus of the team. This implies new statistical and numerical technologies as well as improvements on the modeling of the underlying physical models. Many techniques and methods originate from the mechanical community and thus exhibit a very deep understanding of the underlying physics and mechanical behavior of the structure. On the other side, system identification techniques developed within the control community are more related to data modeling and take into account the underlying random nature of measurement noise. Bringing these two communities together is the objective of this joint team between Inria and IFSTTAR. It will results hopefully in methods numerically robust, statistically efficient and also mixing modeling of both the uncertainties related to the data and the associated complex physical models related to the laws of physics and finite element models.

Damage detection in civil structures has been a main focus over the last decade. Still, those techniques need to be matured to be operable and installed on structures in operation, and thus be robust to environmental nuisances. Then, damage localization, quantification and prognosis should be in that order addressed by the team. To be precise and efficient, it requires correct mixing between signal processing, statistical analysis, Finite Elements Models (FEM) updating and a yet to be available precise modeling of the environmental effects such as temperature through 3D field reconstruction.

Theoretical and practical questions are more and more complex. For example, in civil engineering, from handling hundreds of sensors automatically during some long period of time to localize and quantify damage with or without numerical models. Very large heavily instrumented structures are yet to come and they will ask for a paradigm in how we treat them from a renewed point of view. As the structures become large and complex, also the thermal and aeroelastic (among others) models become complex. Bridges and aircrafts are the main focus of our research. Opening our expertise on new applications topics such as helicopters and wind energy converters is also part of our priorities.

### 2.2 Objectives

The main objectives of the team are first to pursue current algorithmic research activities, in order to accommodate still-to-be-developed complex physical models. More precisely, we want successively

- To develop statistical algorithms robust to noise and variation in the environment
- To handle transient and highly varying systems under operational conditions
- To consider the impact of uncertainties on the currently available identification algorithms and develop efficient, robust and fast implementation of such quantities
- To consider relevant non trivial thermal models for usage in rejection based structural health monitoring and more generally to mix numerical models, physical modeling and data
- To develop theoretical and software tools for monitoring and localization of damages on civil structures or instability for aircrafts

- To explore new paradigms for handling very large and complex structures heavily instrumented (distributed computing)
- To study the characteristics of the monitored mechanic structures in terms of electromagnetic propagation, in order to develop monitoring methods based on electrical instrumentations.
- To consider society concerns (damage quantification and remaining life prognosis)

### 2.3 Introduction to physics driven dynamical models in the context of civil engineering elastic structures

The design and maintenance of flexible structures subject to noise and vibrations is an important topic in civil and mechanical engineering. It is an important component of comfort (cars and buildings) and contributes significantly to the safety related aspects of design and maintenance (aircrafts, aerospace vehicles and payloads, long-span bridges, high-rise towers... ). Requirements from these application areas are numerous and demanding.

Detailed physical models derived from first principles are developed as part of system design. These models involve the dynamics of vibrations, sometimes complemented by other physical aspects (fluid-structure interaction, aerodynamics, thermodynamics).

Laboratory and in-operation tests are performed on mock-up or real structures, in order to get so-called modal models, ie to extract the modes and damping factors (these correspond to system poles), the mode shapes (corresponding eigenvectors), and loads. These results are used for updating the design model for a better fit to data, and sometimes for certification purposes (e.g. in flight domain opening for new aircrafts, reception for large bridges).

The monitoring of structures is an important activity for the system maintenance and health assessment. This is particularly important for civil structures. Damaged structures would typically exhibit often very small changes in their stiffness due to the occurrence of cracks, loss of prestressing or post tensioning, chemical reactions, evolution of the bearing behavior and most importantly scour. A key difficulty is that such system characteristics are also sensitive to environmental conditions, such as temperature effects (for civil structures), or external loads (for aircrafts). In fact these environmental effects usually dominate the effect of damage. This is why, for very critical structures such as aircrafts, detailed active inspection of the structures is performed as part of the maintenance. Of course, whenever modal information is used to localize a damage, the localization of a damage should be expressed in terms of the physical model, not in terms of the modal model used in system identification. Consequently, the following elements are encountered and must be jointly dealt with when addressing these applications: design models from the system physics, modal models used in structural identification, and, of course, data from sensors. Corresponding characteristics are given now: Design models are Finite Element models, sometimes with tens or hundreds of thousands elements, depending on professional habits which may vary from one sector to another. These models are linear if only small vibrations are considered; still, these models can be large if medium-frequency spectrum of the load is significant. In addition, nonlinearities enter as soon as large vibrations or other physical effects (aerodynamics, thermodynamics, ..) are considered. Moreover stress-strain paths and therefore the response (and load) history comes into play.

Sensors can range from a handful of accelerometers or strain gauges, to thousands of them, if NEMS (Nano Electro Mechanical Structures), MEMS (Microelectromechanical systems) or optical fiber sensors are used. Moreover, the sensor output can be a two-dimensional matrix if electro magnet (IR (infrared), SAR, shearography ...) or other imaging technologies are used.

### 2.4 Multi-fold thermal effects

The temperature constitutes an often dominant load because it can generate a deflection as important as that due to the self-weight of a bridge. In addition, it sometimes provokes abrupt slips of bridge spans on their bearing devices, which can generate significant transient stresses as well as a permanent deformation, thus contributing to fatigue.

But it is also well-known that the dynamic behavior of structures under monitoring can vary under the influence of several factors, including the temperature variations, because they modify the stiffness and thus the modes of vibration. As a matter of fact, depending on the boundary conditions of the

structure, possibly uniform thermal variations can cause very important variations of the spectrum of the structure, up to 10%, because in particular of additional prestressing, not forgetting pre strain, but also because of the temperature dependence of the characteristics of materials. As an example, the stiffness of elastomeric bearing devices varies considerably in the range of extreme temperatures in some countries. Moreover, eigenfrequencies and modal shapes do not depend monotonically with temperature. Abrupt dynamical behavior may show up due to a change of boundary conditions e.g. due to limited expansion or frost bearing devices. The temperature can actually modify the number of contact points between the piles and the main span of the bridge. Thus the environmental effects can be several orders of magnitude more important than the effect of true structural damages. It will be noted that certain direct methods aiming at detecting local curvature variations stumble on the dominating impact of the thermal gradients. In the same way, the robustness and effectiveness of model-based structural control would suffer from any unidentified modification of the vibratory behavior of the structure of interest. Consequently, it is mandatory to cure dynamic sensor outputs from thermal effects before signal processing can help with a diagnostics on the structure itself, otherwise the possibility of reliable ambient vibration monitoring of civil structures remains questionable. Despite the paramount interest this question deserves, thermal elimination still appears to challenge the SHM community.

## 2.5 Toward a multidisciplinary approach

Unlike previously mentioned blind approaches, successful endeavours to eliminate the temperature from subspace-based damage detection algorithms prove the relevance of relying on predictive thermo-mechanical models yielding the prestress state and associated strains due to temperature variations. As part of the CONSTRUCTIF project supported by the Action Concertée Incitative Sécurité Informatique of the French Ministry for Education and Research, very encouraging results in this direction were obtained and published. They were substantiated by laboratory experiments of academic type on a simple beam subjected to a known uniform temperature. Considering the international pressure toward reliable methods for thermal elimination, these preliminary results pave the ground to a new SHM paradigm. Moreover, for one-dimensional problems, it was shown that real time temperature identification based on optimal control theory is possible provided the norm of the reconstructed heat flux is properly chosen. Finally, thermo-mechanical models of vibrating thin structures subject to thermal prestress, prestrain, geometric imperfection and damping have been extensively revisited. This project led by Inria involved IFSTTAR where the experiments were carried out. The project was over in July 2006. Note that thermo-mechanics of bridge piles combined with an *ad hoc* estimation of thermal gradients becomes of interest to practicing engineers. Thus, I4S's approach should suit advanced professional practice. Finite element analysis is also used to predict stresses and displacements of large bridges in Hong-Kong bay .

Temperature rejection is the primary focus and challenge for I4S's SHM projects in civil engineering, like SIMS project in Canada, ISMS in Danemark or SIPRIS in France.

A recent collaboration between Inria and IFSTTAR has demonstrated the efficiency of reflectometry-based methods for health monitoring of some civil engineering structures, notably external post-tensioned cables. Based on a mathematical model of electromagnetic propagation in mechanical structures, the measurement of reflected and transmitted electromagnetic waves by the monitored structures allows to detect structural failures. The interaction of such methods with those based on mechanical and thermal measurements will reinforce the multidisciplinary approach developed in our team.

## 2.6 Models for monitoring under environmental changes - scientific background

We will be interested in studying linear stochastic systems, more precisely, assume at hand a sequence of observations  $Y_n$  measured during time,

$$\begin{cases} X_{n+1} &= AX_n + V_n \\ Y_n &= HX_n + W_n \end{cases} \quad (1)$$

where  $V_n$  and  $W_n$  are zero mean random variables,  $A$  is the transition matrix of the system,  $H$  is the observation matrix between state and observation, and  $X_n$  the process describing the monitored system.  $X_n$  can be related to a physical process (for example, for a mechanical structure, the collection of displacements and velocities at different points). Different problems arise

1/ identify and characterize the structure of interest. It may be possible by matching a parametric model to the observed time series  $Y_n$  in order to minimize some given criterion, whose minimum will be the best approximation describing the system,

2/ decide if the measured data describe a system in a so called "reference" state (the term "reference" is used in the context of fault detection, where the reference is considered to be safe) and monitor its deviations with respect to its nominal reference state.

Both problems should be addressed differently if

1/ we consider that the allocated time to measurement is large enough, resulting in a sequence of  $Y_n$  whose length tends to infinity, a requirement for obtaining statistical convergence results. It corresponds to the identification and monitoring of a dynamical system with slow variations. For example, this description is well suited to the long-term monitoring of civil structures, where records can be measured during relatively (to sampling rate) large periods of time (typically many minutes or hours).

2/ we are interested in systems, whose dynamic is fast with respect to the sampling rate, most often asking for reaction in terms of seconds. It is, for example, the case for mission critical applications such as in-flight control or real-time security and safety assessment. Both aeronautics and transport or utilities infrastructures are concerned. In this case, fast algorithms with sample-by-sample reaction are necessary.

The monitoring of mechanical structures can not be addressed without taking into account the close environment of the considered system and their interactions. Typically, monitored structures of interest do not reside in laboratory but are considered in operational conditions, undergoing temperature, wind and humidity variations, as well as traffic, water flows and other natural or man-made loads. Those variations do imply a variation of the eigenproperties of the monitored structure, variations to be separated from the damage/instability induced variations.

For example, in civil engineering, an essential problem for in-operation health monitoring of civil structures is the variation of the environment itself. Unlike laboratory experiments, civil structure modal properties change during time as temperature and humidity vary. Traffic and comparable transient events also influence the structures. Thus, structural modal properties are modified by slow low variations, as well as fast transient non stationarities. From a damage detection point of view, the former has to be detected, whereas the latter has to be neglected and should not perturb the detection. Of course, from a structural health monitoring point of view the knowledge of the true load is itself of paramount importance.

In this context, the considered perturbations will be of two kinds, either

1/ the influence of the temperature on civil structures, such as bridges or wind energy converters : as we will notice, those induced variations can be modeled by a additive component on the system stiffness matrix depending on the current temperature, as

$$K = K_{struct} + K_T .$$

We will then have to monitor the variations in  $K_{struct}$  independently of the variations in  $K_T$ , based on some measurements generated from a system, whose stiffness matrix is  $K$ .

2/ the influence of the aeroelastic forces on aeronautical structures such as aircrafts or rockets and on flexible civil structures such as long-span bridges : we will see as well that this influence implies a modification of the classical mechanical equation (2)

$$M\ddot{Z} + C\dot{Z} + KZ = V \quad (2)$$

where  $(M, C, K)$  are the mass, damping and stiffness matrices of the system and  $Z$  the associated vector of displacements measured on the monitored structure. In a first approximation, those quantities are related by (2). Assuming  $U$  is the velocity of the system, adding  $U$  dependent aeroelasticity terms, as in (3), introduces a coupling between  $U$  and  $(M, C, K)$ .

$$M\ddot{Z} + C\dot{Z} + KZ = U^2 DZ + UE\dot{Z} + V \quad (3)$$

Most of the research at Inria for a decade has been devoted to the study of subspace methods and how they handle the problems described above.

Model (2) is characterized by the following property (we formulate it for the single sensor case, to simplify notations): Let  $y_{-N} \dots y_{+N}$  be the data set, where  $N$  is large, and let  $M, P$  sufficiently smaller

than  $N$  for the following objects to make sense: 1/ define the row vectors  $Y_k = (y_k \dots y_{k-M}), |k| \leq P$ ; 2/ stack the  $Y_k$  on top of each other for  $k = 0, 1, \dots, P$  to get the data matrix  $\mathcal{Y}_+$  and stack the column vectors  $Y_k^T$  for  $k = 0, -1, \dots, -P$  to get the data matrix  $\mathcal{Y}_-$ ; 3/ the product  $\mathcal{H} = \mathcal{Y}_+ \mathcal{Y}_-$  is a Hankel matrix. Then, matrix  $\mathcal{H}$  on the one hand, and the observability matrix  $\mathcal{O}(H, F)$  of system (2) on the other hand, possess almost identical left kernel spaces, asymptotically for  $M, N$  large. This property is the basis of subspace identification methods. Extracting  $\mathcal{O}(H, F)$  using some Singular Value Decomposition from  $\mathcal{H}$  then  $(H, F)$  from  $\mathcal{O}(H, F)$  using a Least Square approach has been the foundation of the academic work on subspace methods for many years. The team focused on the numerical efficiency and consistency of those methods and their applicability on solving the problems above.

There are numerous ways to implement those methods. This approach has seen a wide acceptance in the industry and benefits from a large background in the automatic control literature. Up to now, there was a discrepancy between the a priori efficiency of the method and some not so efficient implementations of this algorithm. In practice, for the last ten years, stabilization diagrams have been used to handle the instability and the weakness with respect to noise, as well as the poor capability of those methods to determine model orders from data. Those methods implied some engineering expertise and heavy post processing to discriminate between models and noise. This complexity has led the mechanical community to adopt preferably frequency domain methods such as Polyreference LSCE. Our focus has been on improving the numerical stability of the subspace algorithms by studying how to compute the least square solution step in this algorithm. This yields to a very efficient noise free algorithm, which has provided a renewed acceptance in the mechanical engineering community for the subspace algorithms. Now we focus on improving speed and robustness of those algorithms.

Subspace methods can also be used to test whether a given data set conforms a model: just check whether this property holds, for a given pair {data, model}. Since equality holds only asymptotically, equality must be tested against some threshold  $\varepsilon$ ; tuning  $\varepsilon$  relies on so-called *asymptotic local* approach for testing between close hypotheses on long data sets — this method was introduced by Le Cam in the 70s. By using the Jacobian between pair  $(H, F)$  and the modes and mode shapes, or the Finite Element Model parameters, one can localize and assess the damage.

In order to discriminate between damage and temperature variations, we need to monitor the variations in  $K_{struct}$  while being blind to the variations in  $K_T$ . In statistical terms, we must detect and diagnose changes in  $K_{struct}$  while rejecting nuisance parameter  $K_T$ . Several techniques were explored in the thesis of Houssein Nasser, from purely empirical approaches to (physical) model based approaches. Empirical approaches do work, but model based approaches are the most promising and constitute a focus of our future researches. This approach requires a physical model of how temperature affects stiffness in various materials. This is why a large part of our future research is devoted to the modeling of such environmental effect.

This approach has been used also for flutter monitoring in Rafik Zouari's PhD thesis for handling the aeroelastic effect.

## 3 Research program

### 3.1 Vibration analysis

In this section, the main features for the key monitoring issues, namely identification, detection, and diagnostics, are provided, and a particular instantiation relevant for vibration monitoring is described.

It should be stressed that the foundations for identification, detection, and diagnostics, are fairly general, if not generic. Handling high order linear dynamical systems, in connection with finite elements models, which call for using subspace-based methods, is specific to vibration-based SHM. Actually, one particular feature of model-based sensor information data processing as exercised in I4S, is the combined use of black-box or semi-physical models together with physical ones. Black-box and semi-physical models are, for example, eigenstructure parameterizations of linear MIMO systems, of interest for modal analysis and vibration-based SHM. Such models are intended to be identifiable. However, due to the large model orders that need to be considered, the issue of model order selection is really a challenge. Traditional advanced techniques from statistics such as the various forms of Akaike criteria (AIC, BIC, MDL, ...) do not work at all. This gives rise to new research activities specific to handling high order

models.

Our approach to monitoring assumes that a model of the monitored system is available. This is a reasonable assumption, especially within the SHM areas. The main feature of our monitoring method is its intrinsic ability to the early warning of small deviations of a system with respect to a reference (safe) behavior under usual operating conditions, namely without any artificial excitation or other external action. Such a normal behavior is summarized in a reference parameter vector  $\theta_0$ , for example a collection of modes and mode-shapes.

### 3.2 Identification

The behavior of the monitored continuous system is assumed to be described by a parametric model  $\{\mathbf{P}_\theta, \theta \in \Theta\}$ , where the distribution of the observations  $(Z_0, \dots, Z_N)$  is characterized by the parameter vector  $\theta \in \Theta$ .

For reasons closely related to the vibrations monitoring applications, we have been investigating subspace-based methods, for both the identification and the monitoring of the eigenstructure  $(\lambda, \phi_\lambda)$  of the state transition matrix  $F$  of a linear dynamical state-space system :

$$\begin{cases} X_{k+1} &= F X_k + V_{k+1} \\ Y_k &= H X_k + W_k \end{cases}, \quad (4)$$

namely the  $(\lambda, \phi_\lambda)$  defined by :

$$\det(F - \lambda I) = 0, \quad (F - \lambda I) \phi_\lambda = 0, \quad \varphi_\lambda \triangleq H \phi_\lambda \quad (5)$$

The (canonical) parameter vector in that case is :

$$\theta \triangleq \begin{pmatrix} \Lambda \\ \text{vec}\Phi \end{pmatrix} \quad (6)$$

where  $\Lambda$  is the vector whose elements are the eigenvalues  $\lambda$ ,  $\Phi$  is the matrix whose columns are the  $\phi_\lambda$ 's, and  $\text{vec}$  is the column stacking operator.

Subspace-based methods is the generic name for linear systems identification algorithms based on either time domain measurements or output covariance matrices, in which different subspaces of Gaussian random vectors play a key role [52].

Let  $R_i \triangleq \mathbf{E}(Y_k Y_{k-i}^T)$  and:

$$\mathcal{H}_{p+1,q} \triangleq \begin{pmatrix} R_1 & R_2 & \vdots & R_q \\ R_2 & R_3 & \vdots & R_{q+1} \\ \vdots & \vdots & \vdots & \vdots \\ R_{p+1} & R_{p+2} & \vdots & R_{p+q} \end{pmatrix} \triangleq \text{Hank}(R_i) \quad (7)$$

be the output covariance and Hankel matrices, respectively; and:  $G \triangleq \mathbf{E}(X_k Y_{k-1}^T)$ . Direct computations of the  $R_i$ 's from the equations (4) lead to the well known key factorizations :

$$R_i = H F^{i-1} G \quad (8)$$

$$\mathcal{H}_{p+1,q} = \mathcal{O}_{p+1}(H, F) \mathcal{C}_q(F, G) \quad (9)$$

where:

$$\mathcal{O}_{p+1}(H, F) \triangleq \begin{pmatrix} H \\ HF \\ \vdots \\ HF^p \end{pmatrix} \quad \text{and} \quad \mathcal{C}_q(F, G) \triangleq (G F G \dots F^{q-1} G) \quad (10)$$

are the observability and controllability matrices, respectively. The observation matrix  $H$  is then found in the first block-row of the observability matrix  $\mathcal{O}$ . The state-transition matrix  $F$  is obtained from the shift invariance property of  $\mathcal{O}$ . The eigenstructure  $(\lambda, \phi_\lambda)$  then results from (5).

Since the actual model order is generally not known, this procedure is run with increasing model orders.

### 3.3 Detection

Our approach to on-board detection is based on the so-called asymptotic statistical local approach. It is worth noticing that these investigations of ours have been initially motivated by a vibration monitoring application example. It should also be stressed that, as opposite to many monitoring approaches, our method does not require repeated identification for each newly collected data sample.

For achieving the early detection of small deviations with respect to the normal behavior, our approach generates, on the basis of the reference parameter vector  $\theta_0$  and a new data record, indicators which automatically perform :

- The early detection of a slight mismatch between the model and the data;
- A preliminary diagnostics and localization of the deviation(s);
- The tradeoff between the magnitude of the detected changes and the uncertainty resulting from the estimation error in the reference model and the measurement noise level.

These indicators are computationally cheap, and thus can be embedded. This is of particular interest in some applications, such as flutter monitoring.

Choosing the eigenvectors of matrix  $F$  as a basis for the state space of model (4) yields the following representation of the observability matrix:

$$\mathcal{O}_{p+1}(\theta) = \begin{pmatrix} \Phi \\ \Phi\Delta \\ \vdots \\ \Phi\Delta^p \end{pmatrix} \quad (11)$$

where  $\Delta \triangleq \text{diag}(\Lambda)$ , and  $\Lambda$  and  $\Phi$  are as in (6). Whether a nominal parameter  $\theta_0$  fits a given output covariance sequence  $(R_j)_j$  is characterized by:

$$\mathcal{O}_{p+1}(\theta_0) \text{ and } \mathcal{H}_{p+1,q} \text{ have the same left kernel space.} \quad (12)$$

This property can be checked as follows. From the nominal  $\theta_0$ , compute  $\mathcal{O}_{p+1}(\theta_0)$  using (11), and perform e.g. a singular value decomposition (SVD) of  $\mathcal{O}_{p+1}(\theta_0)$  for extracting a matrix  $U$  such that:

$$U^T U = I_s \text{ and } U^T \mathcal{O}_{p+1}(\theta_0) = 0 \quad (13)$$

Matrix  $U$  is not unique (two such matrices relate through a post-multiplication with an orthonormal matrix), but can be regarded as a function of  $\theta_0$ . Then the characterization writes:

$$U(\theta_0)^T \mathcal{H}_{p+1,q} = 0 \quad (14)$$

**Residual associated with subspace identification.** Assume now that *a reference  $\theta_0$  and a new sample  $Y_1, \dots, Y_N$  are available*. For checking whether the data agree with  $\theta_0$ , the idea is to compute the empirical Hankel matrix  $\widehat{\mathcal{H}}_{p+1,q}$ :

$$\widehat{\mathcal{H}}_{p+1,q} \triangleq \text{Hank}(\widehat{R}_i), \quad \widehat{R}_i \triangleq 1/(N-i) \sum_{k=i+1}^N Y_k Y_{k-i}^T \quad (15)$$

and to define the residual vector:

$$\zeta_N(\theta_0) \triangleq \sqrt{N} \text{vec} \left( U(\theta_0)^T \widehat{\mathcal{H}}_{p+1,q} \right) \quad (16)$$

Let  $\theta$  be the actual parameter value for the system which generated the new data sample, and  $\mathbf{E}_\theta$  be the expectation when the actual system parameter is  $\theta$ . From (14), we know that  $\zeta_N(\theta_0)$  has zero mean when no change occurs in  $\theta$ , and nonzero mean if a change occurs. Thus  $\zeta_N(\theta_0)$  plays the role of a residual.

As in most fault detection approaches, the key issue is to design a *residual*, which is ideally close to zero under normal operation, and has low sensitivity to noises and other nuisance perturbations, but high sensitivity to small deviations, before they develop into events to be avoided (damages, faults, ...). The originality of our approach is to :

- *Design* the residual basically as a *parameter estimating function*,
- *Evaluate* the residual thanks to a kind of central limit theorem, stating that the residual is asymptotically Gaussian and reflects the presence of a deviation in the parameter vector through a change in its own mean vector, which switches from zero in the reference situation to a non-zero value.

The central limit theorem shows [46] that the residual is asymptotically Gaussian :

$$\zeta_N \xrightarrow{N \rightarrow \infty} \begin{cases} \mathcal{N}(0, \Sigma) & \mathbf{P}_{\theta_0}, \\ \mathcal{N}(\mathcal{J}\eta, \Sigma) & \mathbf{P}_{\theta_0 + \eta/\sqrt{N}}, \end{cases} \quad (17)$$

where the asymptotic covariance matrix  $\Sigma$  can be estimated, and manifests the deviation in the parameter vector by a change in its own mean value. Then, deciding between  $\eta = 0$  and  $\eta \neq 0$  amounts to compute the following  $\chi^2$ -test, provided that  $\mathcal{J}$  is full rank and  $\Sigma$  is invertible :

$$\chi^2 = \bar{\zeta}^T \mathbf{F}^{-1} \bar{\zeta} \geq \lambda, \quad (18)$$

where

$$\bar{\zeta} \triangleq \mathcal{J}^T \Sigma^{-1} \zeta_N, \quad \mathbf{F} \triangleq \mathcal{J}^T \Sigma^{-1} \mathcal{J}. \quad (19)$$

### 3.4 Diagnostics

A further monitoring step, often called *fault isolation*, consists in determining which (subsets of) components of the parameter vector  $\theta$  have been affected by the change. Solutions for that are now described. How this relates to diagnostics is addressed afterwards.

The question: *which (subsets of) components of  $\theta$  have changed ?*, can be addressed using either nuisance parameters elimination methods or a multiple hypotheses testing approach [45].

In most SHM applications, a complex physical system, characterized by a generally non identifiable parameter vector  $\Phi$  has to be monitored using a simple (black-box) model characterized by an identifiable parameter vector  $\theta$ . A typical example is the vibration monitoring problem for which complex finite elements models are often available but not identifiable, whereas the small number of existing sensors calls for identifying only simplified input-output (black-box) representations. In such a situation, two different diagnosis problems may arise, namely diagnosis in terms of the black-box parameter  $\theta$  and diagnosis in terms of the parameter vector  $\Phi$  of the underlying physical model.

The isolation methods sketched above are possible solutions to the former. Our approach to the latter diagnosis problem is basically a detection approach again, and not a (generally ill-posed) inverse problem estimation approach.

The basic idea is to note that the physical sensitivity matrix writes  $\mathcal{J} \mathcal{J}_{\Phi\theta}$ , where  $\mathcal{J}_{\Phi\theta}$  is the Jacobian matrix at  $\Phi_0$  of the application  $\Phi \mapsto \theta(\Phi)$ , and to use the sensitivity test for the components of the parameter vector  $\Phi$ . Typically this results in the following type of directional test :

$$\chi_{\Phi}^2 = \zeta^T \Sigma^{-1} \mathcal{J} \mathcal{J}_{\Phi\theta} (\mathcal{J}_{\Phi\theta}^T \mathcal{J}^T \Sigma^{-1} \mathcal{J} \mathcal{J}_{\Phi\theta})^{-1} \mathcal{J}_{\Phi\theta}^T \mathcal{J}^T \Sigma^{-1} \zeta \geq \lambda. \quad (20)$$

It should be clear that the selection of a particular parameterization  $\Phi$  for the physical model may have a non-negligible influence on such type of tests, according to the numerical conditioning of the Jacobian matrices  $\mathcal{J}_{\Phi\theta}$ .

### 3.5 Infrared thermography and heat transfer

This section introduces the infrared radiation and its link with the temperature, in the next part different measurement methods based on that principle are presented.

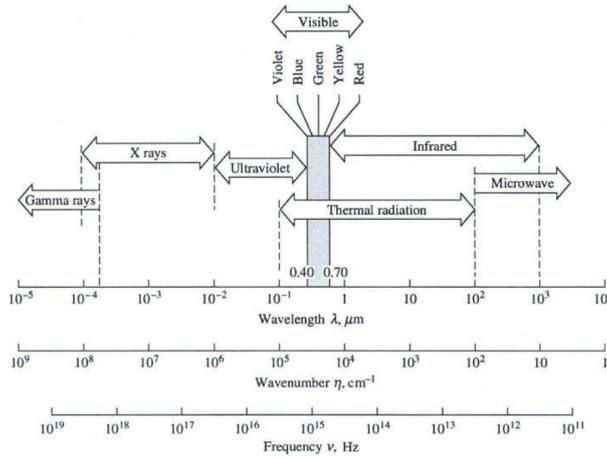


Figure 1: Electromagnetic spectrum - Credit MODEST, M.F. (1993). Radiative Heat Transfer. Academic Press.

Band name	wavelength	Uses \ definition
Near infrared (PIR, IR-A, NIR)	0.7 – 3μm	Reflected solar heat flux
Mid infrared (MIR, IR-B)	3 – 50μm	Thermal infrared
Far infrared (LIR, IR-C, FIR)	50 – 1000μm	Astronomy

Table 1: Wavelength bands in the infrared according to ISO 20473:2007

### 3.5.1 Infrared radiation

Infrared is an electromagnetic radiation having a wavelength between  $0.2 \mu\text{m}$  and  $1 \text{mm}$ , this range begins in uv spectrum and it ends on the microwaves domain, see Figure 1.

For scientific purposes, infrared can be divided in three ranges of wavelength in which the application varies, see Table 1.

Our work is concentrated in the mid infrared spectral band. Keep in mind that Table 1 represents the ISO 20473 division scheme, in the literature boundaries between bands can move slightly.

The Planck's law, proposed by Max Planck in 1901, allows to compute the black body emission spectrum for various temperatures (and only temperatures), see Figure 2 left. The black body is a theoretical construction, it represents perfect energy emitter at a given temperature, cf. Equation (21).

$$M_{\lambda,T}^o = \frac{C_1 \lambda^{-5}}{\exp \frac{C_2}{\lambda T} - 1} \quad (21)$$

With  $\lambda$  the wavelength in m and  $T$  as the temperature in Kelvin. The  $C_1$  and  $C_2$  constants, respectively in  $\text{W.m}^2$  and  $\text{m.K}$  are defined as follow:

$$\begin{aligned} C_1 &= 2hc^2\pi \\ C_2 &= h\frac{c}{k} \end{aligned}$$

with

- $c$ , the electromagnetic wave speed (in vacuum  $c$  is the light speed in  $\text{m.s}^{-1}$ ).
- $k = 1.381e^{-23} \text{J.K}^{-1}$  The Boltzmann (Entropy definition from Ludwig Boltzmann 1873). It can be seen as a proportionality factor between the temperature and the energy of a system.

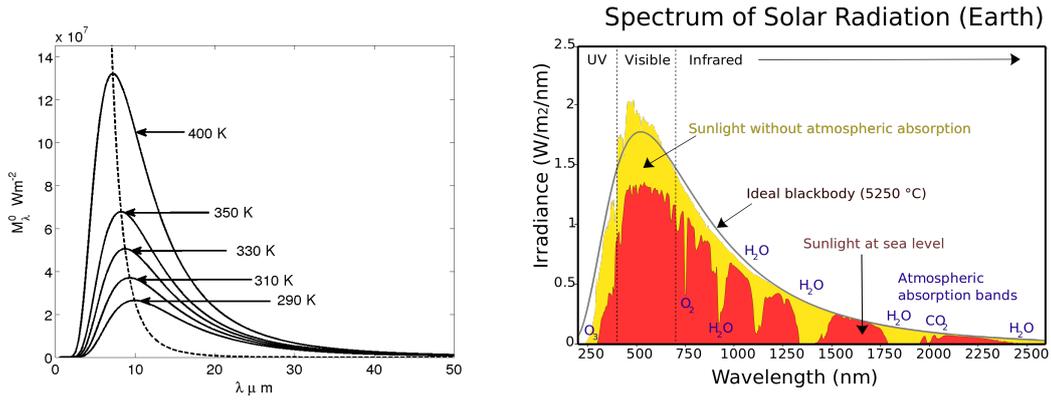


Figure 2: Left: Planck's law at various temperatures - Right: Energy spectrum of the atmosphere

- $h \approx 6,62606957e^{-34}$  J.s The Planck constant is the link between the photons energy and their frequency.

By generalizing the Planck's law with the Stefan Boltzmann law (proposed first in 1879 and then in 1884 by Joseph Stefan and Ludwig Boltzmann), it is possible to address mathematically the energy spectrum of real body at each wavelength depending on the temperature, the optical condition and the real body properties, which is the base of the infrared thermography.

For example, Figure 2 right presents the energy spectrum of the atmosphere at various levels, it can be seen that the various properties of the atmosphere affect the spectrum at various wavelengths. Other important point is that the infrared solar heat flux can be approximated by a black body at 5523,15 K.

### 3.5.2 Infrared Thermography

The infrared thermography is a way to measure the thermal radiation received from a medium. With that information about the electromagnetic flux, it is possible to estimate the surface temperature of the body, see section 3.5.1. Various types of detector can assure the measure of the electromagnetic radiation.

Those different detectors can take various forms and/or manufacturing process. For our research purposes, we use uncooled infrared camera using a matrix of microbolometers detectors. A microbolometer, as a lot of transducers, converts a radiation in electric current used to represent the physical quantity (here the heat flux).

This field of activity includes the use and the improvement of vision system, like in [7].

## 3.6 Heat transfer theory

Once the acquisition process is done, it is useful to model the heat conduction inside the cartesian domain  $\Omega$ . Note that in opaque solid medium the heat conduction is the only mode of heat transfer. Proposed by Jean Baptiste Biot in 1804 and experimentally demonstrated by Joseph Fourier in 1821, the Fourier Law describes the heat flux inside a solid, cf Equation (22).

$$\varphi = k\nabla T \quad X \in \Omega \quad (22)$$

Where  $k$  is the thermal conductivity in  $\text{W}\cdot\text{m}^{-1}\cdot\text{K}^{-1}$ ,  $\nabla$  is the gradient operator and  $\varphi$  is the heat flux density in  $\text{W}\cdot\text{m}^{-2}$ . This law illustrates the first principle of thermodynamic (law of conservation of energy) and implies the second principle (irreversibility of the phenomenon). From this law it can be seen that the heat flux always goes from hot area to cold area.

An energy balance with respect to the first principle yields to the expression of the heat conduction in all point of the domain  $\Omega$ , cf Equation (23). This equation has been proposed by Joseph Fourier in 1811.

$$\rho C \frac{\partial T(X, t)}{\partial t} = \nabla \cdot (k \nabla T) + P \quad X \in \Omega \quad (23)$$

With  $\nabla \cdot ()$  the divergence operator,  $C$  the specific heat capacity in  $\text{J.kg}^{-1}.\text{K}^{-1}$ ,  $\rho$  the volumetric mass density in  $\text{kg.m}^{-3}$ ,  $X$  the space variable  $X = \{x, y, z\}$  and  $P$  a possible internal heat production in  $\text{W.m}^{-3}$ .

To solve the system (23), it is necessary to express the boundaries conditions of the system. With the developments presented in section 3.5.1 and the Fourier's law, it is possible, for example, to express the thermal radiation and the convection phenomenon which can occur at  $\partial\Omega$  the system boundaries, cf Equation (24).

$$\varphi = k \nabla T \cdot n = \underbrace{h(T_{fluid} - T_{Boundary})}_{\text{Convection}} + \underbrace{\epsilon \sigma_s (T_{environment}^4 - T_{Boundary}^4)}_{\text{Radiation}} + \varphi_0 \quad X \in \partial\Omega \quad (24)$$

Equation (24) is the so called Robin condition on the boundary  $\partial\Omega$ , where  $n$  is the normal,  $h$  the convective heat transfer coefficient in  $\text{W.m}^{-2}.\text{K}^{-1}$  and  $\varphi_0$  an external energy contribution  $\text{W.m}^{-2}$ , in cases where the external energy contribution is artificial and controlled we call it active thermography (spotlight etc...), otherwise it is called passive thermography (direct solar heat flux).

The systems presented in the different sections above (3.5 to 3.6) are useful to build physical models in order to represents the measured quantity. To estimate key parameters, as the conductivity, model inversion is used, the next section will introduce that principle.

### 3.7 Inverse model for parameter estimation

Lets take any model  $A$  which can for example represent the conductive heat transfer in a medium, the model is solved for a parameter vector  $P$  and it yields another vector  $b$ , cf Equation (25). For example if  $A$  represents the heat transfer,  $b$  can be the temperature evolution.

$$AP = b \quad (25)$$

With  $A$  a matrix of size  $n \times m$ ,  $P$  a vector of size  $m$  and  $b$  of size  $n$ , preferentially  $n \gg m$ . This model is called direct model, the inverse model consist to find a vector  $P$  which satisfy the results  $b$  of the direct model. For that we need to inverse the matrix  $A$ , cf Equation (26).

$$P = A^{-1} b \quad (26)$$

Here we want to find the solution  $AP$  which is closest to the acquired measures  $M$ , Equation (27).

$$AP \approx \mathcal{M} \quad (27)$$

To do that it is important to respect the well posed condition established by Jacques Hadamard in 1902

- A solution exists.
- The solution is unique.
- The solution's behavior changes continuously with the initial conditions.

Unfortunately those condition are rarely respected in our field of study. That is why we dont solve directly the system (27) but we minimise the quadratic coast function (28) which represents the Legendre-Gauss least square algorithm for linear problems.

$$\min_P (\|AP - \mathcal{M}\|^2) = \min_P (\mathcal{F}) \quad (28)$$

Where  $\mathcal{F}$  can be a product of matrix.

$$\mathcal{F} = [AP - \mathcal{M}]^T [AP - \mathcal{M}]$$

In some cases the problem is still ill-posed and need to be regularized for example using the Tikhonov regularization. An elegant way to minimize the cost function  $\mathcal{F}$  is compute the gradient, Equation (29) and find where it is equal to zero.

$$\nabla \mathcal{F}(P) = 2 \left[ -\frac{\partial AP^T}{\partial P} \right] [AP - \mathcal{M}] = 2J(P)^T [AP - \mathcal{M}] \quad (29)$$

Where  $J$  is the sensitivity matrix of the model  $A$  with respect to the parameter vector  $P$ .

Until now the inverse method proposed is valid only when the model  $A$  is linearly dependent of its parameter  $P$ , for the heat equation it is the case when the external heat flux has to be estimated,  $\varphi_0$  in Equation (24). For all the other parameters, like the conductivity  $k$  the model is non-linearly dependant of its parameter  $P$ . For such case the use of iterative algorithm is needed, for example the Levenberg-Marquardt algorithm, cf Equation (30).

$$P^{k+1} = P^k + [(J^k)^T J^k + \mu^k \Omega^k]^{-1} (J^k)^T [\mathcal{M} - A(P^k)] \quad (30)$$

Equation (30) is solved iteratively at each loop  $k$ . Some of our results with such linear or non linear method can be seen in [8] or [2], more specifically [1] is a custom implementation of the Levenberg-Marquardt algorithm based on the adjoint method (developed by Jacques Louis Lions in 1968) coupled to the conjugate gradient algorithm to estimate wide properties field in a medium.

### 3.8 Reflectometry-based methods for electrical engineering and for civil engineering

The fast development of electronic devices in modern engineering systems involves more and more connections through cables, and consequently, with an increasing number of connection failures. Wires and connectors are subject to ageing and degradation, sometimes under severe environmental conditions. In many applications, the reliability of electrical connexions is related to the quality of production or service, whereas in critical applications reliability becomes also a safety issue. It is thus important to design smart diagnosis systems able to detect connection defects in real time. This fact has motivated research projects on methods for fault diagnosis in this field. Some of these projects are based on techniques of reflectometry, which consist in injecting waves into a cable or a network and in analyzing the reflections. Depending on the injected waveforms and on the methods of analysis, various techniques of reflectometry are available. They all have the common advantage of being non destructive.

At Inria the research activities on reflectometry started within the SISYPHE EPI several years ago and now continue in the I4S EPI. Our most notable contribution in this area is a method based on the *inverse scattering* theory for the computation of *distributed characteristic impedance* along a cable from reflectometry measurements [14, 11], [51]. It provides an efficient solution for the diagnosis of *soft* faults in electrical cables, like in the example illustrated in Figure 3. While most reflectometry methods for fault diagnosis are based on the detection and localization of impedance discontinuity, our method yielding the spatial profile of the characteristic impedance is particularly suitable for the diagnosis of *soft faults with no or weak impedance discontinuities*.

Fault diagnosis for wired networks have also been studied in Inria [53, 49]. The main results concern, on the one hand, simple star-shaped networks from measurements made at a single node, on the other hand, complex networks of arbitrary topological structure with complete node observations.

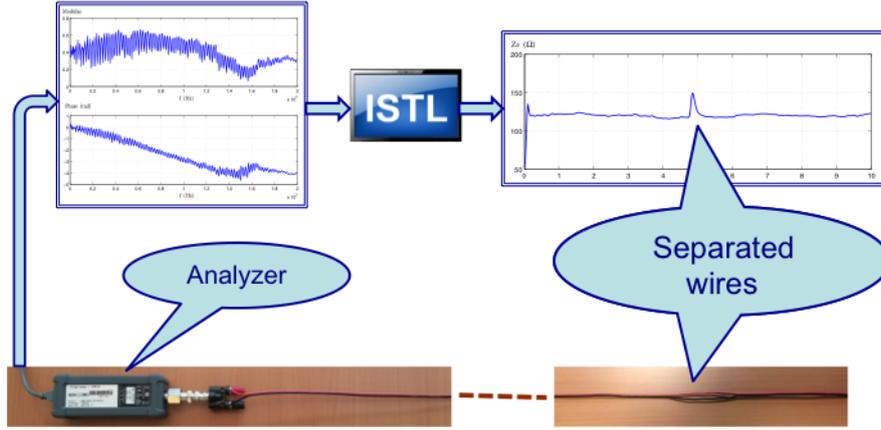


Figure 3: Inverse scattering software (ISTL) for cable soft fault diagnosis.

Though initially our studies on reflectometry were aiming at applications in electrical engineering, since the creation of the I4S team, we are also investigating applications in the field of civil engineering, by using electrical cables as sensors for monitoring changes in mechanical structures.

What follows is about some basic elements on mathematical equations of electric cables and networks, the main approach we follow in our study, and our future research directions.

### 3.8.1 Mathematical model of electric cables and networks

A cable excited by a signal generator can be characterized by the telegrapher's equations [50]

$$\frac{\partial}{\partial z} V(t, z) + L(z) \frac{\partial}{\partial t} I(t, z) + R(z) I(t, z) = 0 \quad (31)$$

$$\frac{\partial}{\partial z} I(t, z) + C(z) \frac{\partial}{\partial t} V(t, z) + G(z) V(t, z) = 0 \quad (32)$$

where  $t$  represents the time,  $z$  is the longitudinal coordinate along the cable,  $V(t, z)$  and  $I(t, z)$  are respectively the voltage and the current in the cable at the time instant  $t$  and at the position  $z$ ,  $R(z)$ ,  $L(z)$ ,  $C(z)$  and  $G(z)$  denote respectively the series resistance, the inductance, the capacitance and the shunt conductance per unit length of the cable at the position  $z$ . The left end of the cable (corresponding to  $z = a$ ) is connected to a voltage source  $V_s(t)$  with internal impedance  $R_s$ . The quantities  $V_s(t)$ ,  $R_s$ ,  $V(t, a)$  and  $I(t, a)$  are related by

$$V(t, a) = V_s(t) - R_s I(t, a). \quad (33)$$

At the right end of the cable (corresponding to  $z = b$ ), the cable is connected to a load of impedance  $R_L$ , such that

$$V(t, b) = R_L I(t, b). \quad (34)$$

One way for deriving the above model is to spatially discretize the cable and to characterize each small segment with 4 basic lumped parameter elements for the  $j$ -th segment: a resistance  $\Delta R_j$ , an inductance  $\Delta L_j$ , a capacitance  $\Delta C_j$  and a conductance  $\Delta G_j$ . The entire circuit is described by a system of ordinary differential equations. When the spatial discretization step size tends to zero, the limiting model leads to the telegrapher's equations.

A wired network is a set of cables connected at some nodes, where loads and sources can also be connected. Within each cable the current and voltage satisfy the telegrapher's equations, whereas at each node the current and voltage satisfy the Kirchhoff's laws, unless in case of connector failures.

### 3.8.2 The inverse scattering theory applied to cables

The inverse scattering transform was developed during the 1970s-1980s for the analysis of some nonlinear partial differential equations [48]. The visionary idea of applying this theory to solving the cable inverse

problem goes also back to the 1980s [47]. After having completed some theoretic results directly linked to practice [14], [51], we started to successfully apply the inverse scattering theory to cable soft fault diagnosis, in collaboration with GEEPS-SUPELEC [11].

To link electric cables to the inverse scattering theory, the telegrapher's equations are transformed in a few steps to fit into a particular form studied in the inverse scattering theory. The Fourier transform is first applied to obtain a frequency domain model, the spatial coordinate  $z$  is then replaced by the propagation time

$$x(z) = \int_0^z \sqrt{L(s)C(s)} ds$$

and the frequency domain variables  $V(\omega, x), I(\omega, x)$  are replaced by the pair

$$v_1(\omega, x) = \frac{1}{2} \left[ Z_0^{-\frac{1}{2}}(x)U(\omega, x) - Z_0^{\frac{1}{2}}(x)I(\omega, x) \right] \quad (35a)$$

$$v_2(\omega, x) = \frac{1}{2} \left[ Z_0^{-\frac{1}{2}}(x)U(\omega, x) + Z_0^{\frac{1}{2}}(x)I(\omega, x) \right] \quad (35b)$$

with

$$Z_0(x) = \sqrt{\frac{L(x)}{C(x)}}. \quad (36)$$

These transformations lead to the Zakharov-Shabat equations

$$\frac{dv_1(\omega, x)}{dx} + ikv_1(\omega, x) = q^*(x)v_1(\omega, x) + q^+(x)v_2(\omega, x) \quad (37a)$$

$$\frac{dv_2(\omega, x)}{dx} - ikv_2(\omega, x) = q^-(x)v_1(\omega, x) - q^*(x)v_2(\omega, x) \quad (37b)$$

with

$$\begin{aligned} q^\pm(x) &= -\frac{1}{4} \frac{d}{dx} \left[ \ln \frac{L(x)}{C(x)} \right] \mp \frac{1}{2} \left[ \frac{R(x)}{L(x)} - \frac{G(x)}{C(x)} \right] \\ &= -\frac{1}{2Z_0(x)} \frac{d}{dx} Z_0(x) \mp \frac{1}{2} \left[ \frac{R(x)}{L(x)} - \frac{G(x)}{C(x)} \right] \end{aligned} \quad (38a)$$

$$q^*(x) = \frac{1}{2} \left[ \frac{R(x)}{L(x)} + \frac{G(x)}{C(x)} \right]. \quad (38b)$$

These equations have been well studied in the inverse scattering theory, for the purpose of determining partly the “potential functions”  $q^\pm(x)$  and  $q^*(x)$  from the scattering data matrix, which turns out to correspond to the data typically collected with reflectometry instruments. For instance, it is possible to compute the function  $Z_0(x)$  defined in (36), often known as the characteristic impedance, from the reflection coefficient measured at one end of the cable. Such an example is illustrated in Figure 3. Any fault affecting the characteristic impedance, like in the example of Figure 3 caused by a slight geometric deformation, can thus be efficiently detected, localized and characterized.

## 4 Application domains

Civil engineering:

- Vibration-based damage diagnosis
- Thermal monitoring for non-destructive evaluation
- Energy assessment of buildings
- Railway monitoring

Aeronautics:

- In-flight monitoring - flutter detection
- Ground resonance detection for helicopters

Electrical cables and networks:

- Incipient fault detection

## 5 Highlights of the year

The team has organized the [ERNSI workshop](#) in October 2021.

## 6 New software and platforms

**DIARIT<sup>Sup</sup>** is a new software in development by I4S, developed during 2021, and will have an entry in BIL soon. The software follows the concept of "system of systems". It interconnects hardware and software dedicated to *in-situ* monitoring of structures or critical components. It embeds data assimilation capabilities combined with specific Physical or Statistical models like inverse thermal and/or mechanical ones up to the predictive ones. It aims at extracting and providing key parameters of interest for decision making tools. Its framework natively integrates data collection from local systems and/or also external systems, for instance the Météo-France Geoservice. DIARIT<sup>Sup</sup> is a Milestone in our roadmap for SHM Digital Twins research framework. Furthermore, it intends providing some useful information for Maintenance operations not only for surveyed targets but also for deployed sensors.

### 6.1 New software

## 7 New results

### 7.1 System identification

#### 7.1.1 Fast interval estimation for discrete-time linear systems

**Participants:** Qinghua Zhang.

This work studies interval estimation for discrete-time linear systems with unknown but bounded disturbances. Inspired by the parity space approach, we propose a point estimator with fixed-time convergence property. The estimator is combined with the zonotope-based interval analysis to achieve fast interval estimation. The parameter matrix in the estimator is optimized by minimizing the length of the edges of the outer box of the error zonotope. It is formulated as L1 optimization problem and can be efficiently solved by linear programming. Comparison studies illustrate the superiority of the proposed method over existing techniques. This work has been done in collaboration with Harbin Institute of Technology, China, and CNAM. The results have been published in [31].

#### 7.1.2 Uncertainty quantification for the Modal Phase Collinearity of complex mode shapes

**Participants:** Michael Doehler, Laurent Mevel.

The Modal Phase Collinearity (MPC) is a modal indicator designed to decide whether the mode shape used in its computation is a real or complex-valued vector. Its estimate inherits the statistical properties of the corresponding mode shape estimate. While the statistical framework for the uncertainty quantification of modal parameters is well-known and developed in the context of subspace-based system identification methods, uncertainty quantification for the MPC estimate has not been carried out yet. In this work, the uncertainty quantification of the MPC estimates is developed when the corresponding mode shapes are complex-valued vectors. In this case, the theoretical value of the MPC is strictly lower than 1 and it is shown that the distribution of the MPC estimate can be approximated as Gaussian. The computation of its variance and the resulting confidence intervals of the MPC estimate are developed. The proposed framework is validated in Monte Carlo simulations and illustrated on experimental data of an offshore structure. This work has been done in collaboration with Aalborg University and Structural Vibration Solutions, Denmark. The results have been published in [23].

### 7.1.3 Uncertainty quantification of the Modal Assurance Criterion in Operational Modal Analysis

**Participants:** Michael Doehler, Laurent Mevel.

The Modal Assurance Criterion (MAC) is a modal indicator designed to decide whether the mode shapes used in its computation are corresponding to the same mode. During structural monitoring, it can be applied to evaluate changes in the mode shapes. The evaluation of the statistical uncertainty of MAC estimates is particularly relevant when the estimate is close to 1, where 1 indicates equal mode shapes. A particular challenge for the statistical characterization of MAC is its boundedness in the interval between 0 and 1. In this work it is shown that this boundedness yields two different distributions of the MAC estimates. The MAC computed between estimates of different mode shapes is inside the interval (0, 1), and a Gaussian approximation of its distribution is obtained. When the MAC is computed between estimates of equal mode shapes, it is shown that the MAC estimate is linked to a quadratic form of the mode shapes, whose distribution can be approximated by a scaled and shifted chi2 distribution. For both cases, uncertainty bounds related to the MAC estimates are established. The proposed frameworks are validated by extensive Monte Carlo simulations and then applied to evaluate mode shape changes due to damage during monitoring of the S101 Bridge. This work has been done in collaboration with Aalborg University, Denmark. The results have been published in [25].

### 7.1.4 Kalman filter-based subspace identification for operational modal analysis under unmeasured periodic excitation

**Participants:** Michael Doehler, Laurent Mevel.

The modes of linear time invariant mechanical systems can be estimated from output-only vibration measurements under ambient excitation conditions with subspace-based system identification methods. In the presence of additional unmeasured periodic excitation, for example due to rotating machinery, the measurements can be described by a state-space model where the periodic input dynamics appear as a subsystem in addition to the structural system of interest. While subspace identification is still consistent in this case, the periodic input may render the modal parameter estimation difficult, and periodic modes often disturb the estimation of close structural modes. The aim of this work is to develop a subspace identification method for the estimation of the structural parameters while rejecting the influence of the periodic input. In the proposed approach, the periodic information is estimated from the data with a non-steady state Kalman filter, and then removed from the original output signal by an orthogonal projection. Consequently, the parameters of the periodic subsystem are rejected from the estimates, and it is shown that the modes of the structural system are consistently estimated. Furthermore, standard data analysis procedures, like the stabilization diagram, are easier to interpret. The proposed method is validated on Monte Carlo simulations and applied to both a laboratory example and a full-scale structure

in operation. This work has been done in collaboration with Aalborg University and Structural Vibration Solutions, Denmark. The results have been published in [21].

## 7.2 Damage monitoring of civil engineering structures/fault detection and isolation

### 7.2.1 Subspace-based Mahalanobis damage detection robust to changes in excitation covariance

**Participants:** Michael Doehler, Laurent Mevel.

In the context of detecting changes in structural systems, several vibration-based damage detection methods have been proposed and successfully applied to both mechanical and civil structures over the past years. These methods involve computing data-based features, which are then evaluated in statistical tests to detect damages. While being sensitive to damages, the data-based features are affected by changes in the ambient excitation properties that potentially lead to false alarms in the statistical tests, a characteristic that renders their use impractical for structural monitoring. In this work, a damage detection method is presented that is robust to changes in the covariance of the ambient excitation. The proposed approach is based on the Mahalanobis distance of output covariance Hankel matrices, which are normalized with respect to possibly changing excitation properties. The statistical properties of the developed damage feature are reported, and used for efficient hypothesis testing. Its robustness towards changes in the excitation covariance is illustrated on numerical simulations and successfully tested on a numerical offshore foundation model. This work has been done in collaboration with Aalborg University and Structural Vibration Solutions, Denmark. The work has been published in [22] and [36].

### 7.2.2 A reliability-based approach to determine the minimum detectable damage for statistical damage detection

**Participants:** Michael Doehler, Laurent Mevel, Alexander Mender.

In this work a formula is derived to determine the minimum detectable damage based on ambient vibration data. It is a key element to analyze which damage scenarios can be detected before a monitoring system is installed. For the analysis, vibration data from the reference structure as well as a finite element model are required. Minimum detectability is defined by adopting a code-based reliability concept that considers the probability of detection and the probability of false alarms. The results demonstrate that the minimum detectable damage depends on three elements: the uncertainty of the damage-sensitive feature (which decreases with increasing measurement duration), its sensitivity towards model-based design parameters, and the reliability requirements regarding the damage diagnosis results. The theory is developed for the stochastic subspace-based damage detection method but can be applied to any damage-sensitive feature provided its sensitivities and statistical properties can be characterized. For proof of concept, the minimum detectable change in stiffness and mass of a pin-supported beam are analyzed in a numerical and experimental study, respectively. Based on this work, the minimum localizable damage can be evaluated, and is presented in a case study in collaboration with GeM, Université de Nantes. The work has been published in [27], [38].

### 7.2.3 Statistical model-based optimization for damage extent quantification

**Participants:** Szymon Gres, Michael Doehler, Laurent Mevel.

A classical solution to damage localization and quantification is model updating, where the parameters of a finite element model of the possibly damaged structure are optimized to match with the

corresponding parameters estimated from its vibration responses. To avoid ill-posedness of the classical finite element updating problem, damage localization and quantification can be treated separately. First, the information about regions or clusters of possibly damaged elements in the structure is obtained by a damage localization method. Then, this information is used to reduce the number of parameters for damage quantification. A framework combining the advantages of methods for damage localization with model optimization is proposed in this work. For the exploration of the clustered physical model space, a stochastic optimization algorithm is coupled with the evaluation of the statistical properties of the MAC and frequency differences between the numerical model and the estimated modes for an adequate treatment of the data-based uncertainties. Herein, the development of the statistical properties of the MAC estimate is an important step, which is based on a recent quadratic framework that is adapted to the context of the inner product between an estimated mode shape and a numerical mode shape. This statistical information is used in the formulation of the objective function as well as in a data-driven stopping criterion for the optimization search. Another approach is developed based on the minimization of the Hankel matrix difference related to the data and the model. The proposed framework is validated on numerical simulations of a beam model, where damage at multiple locations is quantified up to the clustering precision. The work has been published in [24] and [37].

#### 7.2.4 Dynamic System Fault Diagnosis under Sparseness Assumption

**Participants:** Qinghua Zhang.

Dynamic system fault diagnosis is often faced with a large number of possible faults. The purpose of this paper is to propose an efficient method for such situations. To avoid intractable combinatorial problems, sparse estimation techniques appear to be a powerful tool for isolating faults, under the assumption that only a small number of possible faults can be simultaneously active. However, sparse estimation is often studied in the framework of linear algebraic equations, whereas model-based fault diagnosis is usually investigated for dynamic systems modeled with state equations involving internal states. The main contribution of this work is a link between these two formalisms through efficient and reliable algorithms, mainly relying on advanced analyses of residuals generated with the Kalman and Kitanidis filters. Based on these results, it becomes straightforward to solve fault diagnosis problems by applying well known sparse estimation techniques, in the framework of general time varying state-space systems involving unknown inputs. The work has been published in [32].

#### 7.2.5 Damage Localization in Mechanical Systems by Lasso Regression

**Participants:** Michael Doehler, Qinghua Zhang, Laurent Mevel.

Due to the complexity of civil, mechanical or aeronautical structures, SHM is often faced with high dimensional mechanical characteristics together with limited sensor instrumentation. In this work, Lasso regression is applied to address this complexity issue, based on its ability for solving large regression problems. The mechanical vibration model is first appropriately transformed into a linear regression model, with its parameters corresponding to small changes in the monitored mechanical characteristics, then these parameters are estimated from mechanical sensor signals under the assumption that most of the parameters are zeros. The performance of the proposed method is illustrated with a simulated truss structure. The work has been published in [35].

### 7.3 Analysis and monitoring of non-stationary systems

#### 7.3.1 On the Optimality of the Kitanidis Filter for State Estimation Rejecting Unknown Inputs

**Participants:** Qinghua Zhang.

As a natural extension of the Kalman filter to systems subject to arbitrary unknown inputs, the Kitanidis filter has been designed by one-step minimization of the trace of the state estimation error covariance matrix. In this technical communiqué, it is shown that the Kitanidis filter is also optimal for the whole gain sequence in the sense of matrix positive definiteness, which notably implies that the Kitanidis filter minimizes not only the trace criterion, but also the matrix spectral norm criterion. The work has been published in [18].

### 7.3.2 Boundedness of the Kalman Filter Revisited

**Participants:** Qinghua Zhang.

The boundedness of the Kalman filter, as the first cornerstone of its stability analysis, has been proved in the classical literature through upper bounds of non-recursive filters in the sense of the trace of the state estimation error covariance. In this paper, an upper bound of the Kalman filter prediction error covariance is established in the sense of matrix positive definiteness, based on a bounded recursive non-optimal filter. The boundedness of the error covariance is a prerequisite for the definition of a Lyapunov function involved in the state estimation error dynamics stability analysis. The work has been published in [44].

### 7.3.3 Estimation of local failure in tensegrity using Interacting Particle-Ensemble Kalman Filter

**Participants:** Laurent Mevel.

Tensegrities form a special case of truss, wherein compression members (struts/bars) float within a network of tension members (cables). Present study proposes an output-only time-domain method that makes use of tensegrity vibrational responses within a Bayesian filtering-based approach to monitor the tensegrity health in the presence of uncertainties due to ambient force, model inaccuracy, and measurement noise. For this, an interacting strategy combining Particle Filter (PF) and Ensemble Kalman Filter (EnKF) has been adopted (Interacting particle-Ensemble Kalman Filter, IP-EnKF) in which the EnKF estimates the response states as ensembles while running within a PF envelop that estimates a set of location-based health parameters as particles. Furthermore, for a cheaper damage detection procedure, strain responses are used as measurements. The efficiency of the proposed methodology in terms of accuracy, computational cost, and robustness against noise contamination has been demonstrated using numerical experiments performed on two tensegrity modules: a simplex tensegrity and an extended-octahedron tensegrity. The work is in collaboration with IIT Mandi, and has been published in [15].

### 7.3.4 Structural health monitoring with non-linear sensor measurements robust to unknown non-stationary input forcing

**Participants:** Qinghua Zhang, Laurent Mevel.

Bayesian filtering based structural health monitoring algorithms typically assume stationary white Gaussian noise models to represent an unknown input forcing. However, typical structural damages occur mostly under the action of extreme loading conditions, like earthquake or high wind/waves, which are characteristically non-stationary and non-Gaussian. Clearly, this invalidates this basic assumption, causing these algorithms to perform poorly under non-stationary noise conditions. This paper extends

an existing interacting filtering algorithm to efficiently estimate structural damages while being robust to unknown non-stationary non-Gaussian input forcing. Furthermore, this approach is generalized beyond linear measurements to encompass the case of non-linear measurements such as strains. The joint estimation of state and parameters is performed by combining Ensemble Kalman filtering, for non-linear system state estimation, and Particle filtering to estimate changes in the structural parameters. The robustness against input forcing is achieved through an output injection approach embedded in the state filter equation. Numerical simulations for two kinds of response measurements (acceleration and strain) are performed on a 3D frame structure under different damage location and severity scenarios. The sensitivity with respect to noise and the impact of different sensor combinations have also been investigated. The work is in collaboration with IIT Mandi, and has been published in [30] and [33].

### 7.3.5 Energy-efficient GPS synchronization for wireless nodes

**Participants:** David Pallier, Vincent Le Cam.

Synchronization is a challenging problem for wireless nodes, especially for applications demanding good synchronization accuracy over wide areas. In that case, the GPS is a valuable solution as the nodes can independently synchronize to UTC. However, the energy consumption of a GPS receiver (over 100 mW when switched on) is not sustainable on a wireless node. Therefore, in this work, we developed a synchronization scheme based on periodic extinctions of the GPS receiver. The goal is to study the GPS power switching effect on the synchronization accuracy. This work has been published in [29].

## 7.4 Exploiting complex physical models for structural analysis and design

### 7.4.1 Advanced computational technique based on kriging and Polynomial Chaos Expansion for structural stability of mechanical systems with uncertainties

**Participants:** Enora Denimal.

In this work, a numerical strategy based on the combination of the kriging approach and the Polynomial Chaos Expansion (PCE) is proposed for the prediction of buckling loads due to random geometric imperfections and fluctuations in material properties of a mechanical system. The original computational approach is applied on a beam simply supported at both ends by rigid supports and by one punctual spring whose location and stiffness vary. The beam is subjected to a deterministic axial compression load. The PCE-kriging meta-modelling approach is employed to efficiently perform a parametric analysis with random geometrical and material properties. The approach proved to be computationally efficient in terms of number of model evaluations and in terms of computational time to predict accurately the buckling loads of a beam system. It is demonstrated that the buckling loads are substantially impacted not only by both the location and the stiffness of the spring, but also by the random parameters. The work is in collaboration with Ecole Centrale Lyon, and has been published in [19].

### 7.4.2 Advanced kriging-based surrogate modelling and sensitivity analysis for rotordynamics with uncertainties

**Participants:** Enora Denimal.

Rotating machinery are present in many engineering applications. Such rotor systems often subjected to high vibration loads that can be at the origin of noise or failure. For these reasons, it is of main importance to predict with accuracy the critical speeds and the dynamic response amplitude of such structures. However, they are often subjected to many potential uncertainties that may rise from

environmental variations or manufacturing tolerances. These uncertain parameters, often described as random, are often numerous and must be taken into consideration during the design stage. For this, some design parameters are usually adjusted to propose a robust design of the rotor, considering the possible variation of the random parameters. Performing such studies require to be able to deal with a high number of uncertain parameters and with parameters of different nature, namely parametric and random. This work proposes to illustrate the efficiency of advanced kriging-based surrogate modelling in order to achieve such a goal. The proposed hybrid surrogate-model combines polynomial chaos expansion and kriging to deal with both parameter natures, to consider nine varying parameters of a full finite element model of the rotating system under study. For the first time, this hybrid surrogate model is applied to perform rotordynamics analysis and more specifically the prediction of critical speeds and the associated unbalance responses for a complex rotor system with uncertainties. Compared to previous works, the kriging performances are significantly increased by integrating some physical properties of the rotor directly in its construction. Finally, the hybrid surrogate model gives a direct access to the Sobol indices which makes it possible to carry out without additional computation costs an extensive sensitivity analysis. The work is in collaboration with Ecole Centrale Lyon, and has been published in [20].

#### 7.4.3 Study of an optimal heating command law for structures with non-negligible thermal inertia in varying outdoor conditions

**Participants:** Thibaud Toullier, Jean Dumoulin.

In this numerical study, an optimal energetic control model applied to local heating sources to prevent black-ice occurrence at transport infrastructure surface is addressed. The heat transfer Finite Element Model developed and boundary conditions hypothesis considered are firstly presented. Several heat powering strategies, in time and space, are then introduced. Secondly, control laws are presented with the objective of preventing ice formation while avoiding excessive energy consumption by taking also into account weather forecast information. In particular, the adjoint state method is adapted for the case of an operation without some continuous properties (discontinuous time heat sources). In such case, a projection from the space of continuous time functions to a piecewise constant one is proposed. To perform optimal control, the adjoint state method is addressed and discussed for the different powering solutions. To preserve some specific technical components and maintain their lifetime, operational constraints are considered and different formulations for the control law are proposed. Time dependent convecto-radiative boundary conditions are introduced in the model by extracting information from existing weather databases. Extension to updated inline weather forecast services is also presented and discussed. The final minimization problem considered has to act on both energy consumption and non-freezing surface temperature by integrating these specific constraints. As a consequence, the final optimal solution is estimated by an algorithm relying on the combination of adjoint state method and gradient descent that fits mathematical constraints. Results obtained by numerical simulations for different operative conditions with various weather conditions are presented and discussed. Finally, conclusion and perspectives are proposed. The work is in collaboration with CEA, and has been published in [26].

#### 7.4.4 Lattice Boltzmann Method for Mathematical Morphology: Application to Porous Media

**Participants:** Romain Noel.

The LBM (Lattice Boltzmann Method) is often used in CFD (Computational Fluid Dynamics) for efficient fluid flow simulations. Computation of the permeability of a porous media from direct simulations is a common application which benefits from the ability of the LBM (Lattice Boltzmann Method) to embed porosity parameters. The MM (Mathematical Morphology) is widely used in image processing as the theoretical aspects guaranty robust algorithms for geometrical characterization of shapes appearing

in images. The MM is commonly used to compute porosity from porous media images. The union of these two methods has been recently done through the LB3M (Lattice Boltzmann Method for Mathematical Morphology). The present work extends the LB3M to the extraction of porosity and pores segmentation from images. In order to benefit from the full capacity of the LB3M, it is necessary to reformulate and adjust the algorithms in a new paradigm. Thus, the underlying concept and algorithms required for computing the different previous information are detailed. Moreover, a comparison is provided between the permeability resulting from the CFD and MM both implemented by using the LBM. To sum up, this work emphasizes the full capacity of the LB3M to obtain complex transformations and operations issued from the MM theory through completely new and innovative algorithms. The herein challenge is to highlight the abilities of the LB3M to match with physical phenomenon. Indeed, the LB3M keeps the advantages from the MM such as a complete theory, fast convergence, scalability, robustness, etc. while adding the power of the LBM: statistical physics origins, partial differential equation solver, intrinsic properties of parallelization, efficiency, etc. The work is in collaboration with Ecole des Mines and INSA Lyon, and has been published in [40].

## 7.5 Exploiting new sensor technologies for structural analysis and monitoring

### 7.5.1 Characterization Shear Properties of PVC Foams Instrumented by Optical Fiber under Flexural Loading

**Participants:** Xavier Chapeleau.

The bending behavior of foam core sandwich composites has increasingly attracted attention and application in industries such as shipbuilding, aircraft, and wind turbine industries. The main objective of this research work is the assessment of shear strain in a foam core beam by means of optical fiber sensors during a bending test. Experimental studies were conducted on a polyvinyl chloride (PVC) foam beam in which three optical fibers were embedded in a longitudinal plane across the thickness of the foam core; straight optical fibers measure strains due to the tension/compression load, whereas the sinusoidal fibers catch strains due to the shear load. A finite element model was used to predict strain levels in order to validate and explain optical fiber sensor measurements from three- and four-point bending tests. The concordance of the shear properties identified by optical fiber sensor results and obtained by finite element simulation was evaluated to validate the newly developed technique of characterization. Results shows good agreement between the experimental and numerical responses. The work is in collaboration with Centrale Nantes and University of Sfax, Tunisia, and has been published in [28].

### 7.5.2 A General Solution to Determine Strain Profile in the Core of Distributed Fiber Optic Sensors under Any Arbitrary Strain Fields

**Participants:** Xavier Chapeleau.

Despite recent publications, the strain transfer in distributed optical fiber sensors is still often overlooked and poorly understood. In the first part of this paper, strain transfer is shown to be driven by a second-order differential equation, whether the optical fiber is embedded into the host material or surface-mounted. In this governing equation, only the value of a key parameter, called strain lag parameter, varies according to the attachment configuration and the type of optical fiber used as a sensor. Then, a general solution of the governing equation is proposed. It is an analytical expression established from new boundary conditions that are more adequate than those used previously in the literature and allows the determination of the strain profile in the core of a distributed optical fiber sensor under any arbitrary strain fields. This general solution has been validated by two experiments presented in the third part of the paper. A very good agreement between the analytical solutions and measured strain profiles using a high spatial resolution optical interrogator for both uniform and non-uniform strain fields has been obtained. These results highlight the importance of the strain lag parameter which must be taken into

account for a correct interpretation of measurements, especially in the case of important strain gradients. The work is in collaboration with Quadric, and has been published in [17].

### 7.5.3 Analysis of Quadratic Surface Fitting for Subpixel Motion Extraction from Video Images

**Participants:** Bian Xiong, Qinghua Zhang.

Digital image correlation is a popular method for estimating object displacement in successive images. At the pixel level, displacement is estimated by maximizing the crosscorrelation between two images. To achieve subpixel accuracy, displacement estimation can be refined in the vicinity of the crosscorrelation peak. Among existing refinement methods, quadratic surface fitting provides a good trade-off between accuracy and computational burden. The purpose of this paper is to analyze the quadratic surface fitting method. It is shown that the quadratic surface fitted to the cross-correlation values in the vicinity of the cross-correlation peak does not always have a maximum. Then the conditions ensuring the existence of a maximum are analyzed. The reported results consolidate the theoretic basis of the quadratic surface fitting method for subpixel motion extraction. The work has been published in [43].

### 7.5.4 Experimental investigation of structural modal identification using pixels intensity and motion signals from video-based imaging devices

**Participants:** Boualem Merainani, Bian Xiong, Qinghua Zhang, Michael Doehler, Jean Dumoulin.

This work aims to experimentally evaluate a simplified vision-based method for structural health monitoring (SHM). Contrary to conventional solutions that rely on extracting motions through image processing, this paper proposes to conduct the SHM analysis by the direct processing of pixel brightness without extracting the motion signals beforehand. After some pre-processing steps, it is shown that the brightness data reveal essential information about the dynamic characteristics of the monitored vibrating structure. Furthermore, the low-level information of the pixel is compensated by an efficient selection of the so called "active pixels" throughout the image time flow. Finally, a subspace system identification-based method is applied to the brightness data, so that the modal parameters with uncertainty bounds are estimated. The experiment database consists of image time flows of a cantilever beam excited by a shake table driven by a band limited random noise. The work has been published in [39].

### 7.5.5 Investigation into the use of thermoelectric modules as an alternative to conventional fluxmeters

**Participants:** Jean Dumoulin.

The present work aims to propose the use of Peltier modules for the superficial heat flux measurement, as an alternative to conventional heat flux sensors. In this study, the function of Peltier modules (TEM) as heat flux sensors is compared to the Captec heat flux sensors (FGT), based on the premise that conventional heat flux sensors such as Captec have been proven to have acceptable performance for the heat flux measurement, i.e., conduction, convection and radiation. A simple measurement device and a simple general formulation for decoupling the convective and radiative parts from the heat flux measurement are proposed. The latter are implemented in an experimental case presenting weak convective and radiative heat fluxes, using a black-shiny couple of Peltier modules and a black-shiny couple of Captec. The radiative part was found to be the same when comparing FGT and TEM measurements. However, the convective part when using TEM measurements was found to be around two times larger than when using FGT measurement. It has been encountered that this difference is better explained by

the geometrical and thermal properties of both sensors. The work is in collaboration with Université de Bordeaux, University of Panama and University of Shanghai for Science and Technology, and has been published in [16].

### 7.5.6 TeraHertz inspections of painted steel samples

**Participants:** Thibaud Toullier, Jean Dumoulin.

Aerospace industry needs accurate coating thickness measurement as well as adhesion testing for preventing the corrosion of wear of metal substrates. In this frame, a constant attention is towards the potentialities offered by non-invasive sensing techniques and their technological advancements. This communication deals with THz surveys of painted steel samples. Specifically, we account for time of flight THz imaging, enhanced by a noise filtering procedure based on the Singular Value Decomposition of the data matrix. This analysis allowed for detecting paint coating layers and providing images of them and of the probed face of the steel substrate. The work is in collaboration with CNR Italy, and has been published in XXX

## 8 Bilateral contracts and grants with industry

### 8.1 Bilateral contracts with industry

#### SNCF Réseau

**Participants:** Vincent Le Cam, Arthur Bouché.

SNCF Réseau has commissioned water level sensors adapted to the conditions of nozzles and waterways in the rail network. From a technological point of view the sensor is of small size and very weak consumption, communicating according to the LORA network. Total amount: 33 k€.

#### SNCF: Hot boxes detection

**Participants:** Jean Dumoulin, Thibaud Toullier.

The main strategic issue is the maintenance in operational condition of the Hot Box Detectors (DBC). The removal of the DBC from the track is part of Tech4Rail's ambition: reducing equipment to the track. The innovation aimed at in this project is to study and develop a measurement solution to be deployed at the edge of a lane out of danger zone and independent of track equipment. Among the scientific obstacles identified are the following three:

- the behavior of the measurement system in deteriorated meteorological conditions in a real site
- the design and implementation of an automated prototype for in-situ deployment (connection to an existing announcement system, hardware packaging of the system, study and design of a scalable software solution allowing pre-processing data).
- the development of automatic processing tools for the analysis of massive data generated by in-situ measurement systems

**Siemens: Proof of concept monitoring coupled with prediction model for de-icing metro lane surface**

**Participants:** Jean Dumoulin, Thibaud Toullier.

A proof of concept study aims at combining real site monitoring solutions with adjoint state FE thermal model approach to predict optimal heating required to preserve surface from icing in winter conditions. Furthermore, we introduced in our prediction model connection with in-line weather forecast provided by Meteo France Geoservice at different time horizons and spatial scales. Total amount: 124 k€.

**SDEL-CC Vinci: Lightning localization**

**Participants:** Vincent Le Cam.

After the two previous direct collaborations between the company SDEL-CC and I4S, a third contract is currently running. This new collaboration includes two objectives: industrial transfer for better performance in the "lightning localization" system, and to add new algorithms enabling the product of detecting other defects than lightnings like short-circuit and disphasing. This collaboration is based on an "Action 4" of ANR France Relance, where an SDEL-CC engineer works 4 days per week at the I4S laboratories for the industrial transfer. Total amount: Engineer 2 years at 80% 10/2021–09/2023, plus 30 k€ for equipments.

**Bureau Veritas: FPSO structures monitoring**

**Participants:** Xavier Chapeleau, Quentin Sourisseau.

The maintenance of steel structure installed in harsh offshore environment (like tropical areas), is a great challenge. Vessels and mobile offshore units can be maintained and repaired onshore in shipyards but, fixed units, such as platforms or FPSO (Floating Production, Storage and Offloading) structures, do not come back in dry dock and shall be maintained at sea. On FPSO units/structures, the corrosion is a permanent threat due to high temperature and high humidity conditions. The development of new techniques to repair those decks are actually in development, more particularly bonded repair solution which presents several advantages (short down-time and non-intrusively process). For this reason, the JIP StrengthBond Offshore project initiated by Bureau Veritas Marine and Offshore (BV) has been launched in March 2019 with the partners Total, Petrobras, Naval Group, Siemens, Infra-core and Coldpad. The project aims to achieve the following main objectives:

- Enable a better evaluation of the margin between the actual strength of a repair and the design load,
- Validate the characterization procedure for strength prediction of bonded assembly,
- Define a robust strength prediction method,
- Standardize the qualification process for offshore composite bonded repairs.

In this project involving the laboratories UGE/MAST/SMC and UGE/COSYS/SII-I4S, the PhD student (Quentin Sourisseau) studies different characterization strategies for composite reinforcements bonded to metal structures focusing on fracture mechanics methods. On the basis of experimental and modelling works, it should enable to improve current methodologies. During the first year of the PhD student, innovative methods of monitoring based on DIC (Digital Image Correlation) and DFOS (Distributed Fiber Optic Sensors) were used to estimate the crack length during the tests.

### Sercel: Vibration monitoring

**Participants:** Michael Doehler, Laurent Mevel.

With the goal of providing a complete SHM system for vibration monitoring with their high-end sensors, we have transferred modal analysis and damage detection algorithms in a technology transfer in two contracts to Sercel, involving technical development and support. Amount for I4S: 15k€.

### Quadric: Distributed Acoustic Sensors

**Participants:** Xavier Chapeleau.

A new concept of detection of wires breakage in post-tensioning strands of bridges is assessed in the framework of research partnership with the SME Quadric (Funding from CCI Seine-Estuaire). It is based on a relative recent distributed measurement technology by optical fiber called Distributed Acoustic Sensor (DAS). The results obtained in laboratory tests have demonstrated the feasibility and the efficiency of the concept. To validate the solution in real condition, a test is planned on a post-tensioning cables of the Normandy bridge. Amount for UGE MAST/SMC and I4S: 77k€.

## 9 Partnerships and cooperations

### 9.1 International initiatives

#### 9.1.1 Participation in other International Programs

##### UNYFI: RSE Saltire Facilitation Workshop Awards

**Participants:** Enora Denimal.

The project UNYFI has been funded by the Royal Society of Edinburgh (RSE) between Strathclyde University and the I4S team to engage an international collaboration and initiate a research project to develop a European network and aim for European fundings.

##### ASTI

**Participants:** Jean Dumoulin, Laurent Mevel, Michael Doehler.

The joint lab ASTI between Inria, University Gustave Eiffel and CNR has been approved and the letters of intent have been signed by all partners. The kick off meeting of this collaborating tri-party research lab has been postponed due to COVID.

##### Collaboration with Imperial College London

**Participants:** Enora Denimal.

E. Denimal collaborates with Imperial College London on the topic of structural optimisation for non-linear vibrations. She is a visiting researcher in the Dynamics group, has co-supervised and is currently co-supervising Msc students:

- MSc: Vincent Barreau, Imperial College London, Optimisation topologique et impression 3D d'aubes de turbine. E. Denimal and L. Salles, 09/2020-06/2021.
- MSc: Daniel Wickens, Imperial College London, 3D printing and test of topologically optimised blades, E. Denimal and L. Renson, 09/2021-06/2022.
- MSc: Jeremy Videau, Imperial College London, 3D printing and experimental validation of topologically optimal UPD, E. Denimal and L. Renson, 09/2021-06/2022.

Internal fundings have been secured to perform 3D printing and experimental validation of numerical works. Applications for larger calls and for the creation of an associate team are in progress.

## 9.2 European initiatives

### 9.2.1 FP7 & H2020 projects

#### DESDEMONA (DEtection of Steel Defects by Enhanced MONitoring and Automated procedure for self-inspection and maintenance)

**Participants:** Jean Dumoulin, Laurent Mevel, Michael Doehler, Xavier Chapeleau, Qinghua Zhang, Boualem Merainani, Thibaud Toullier, Bian Xiong.

- Call: RFCS-2017 (Call of the research programme of the Research Fund for Coal and Steel - 2017)
- Type of Action: RFCS-RPJ (Research project)
- Objective: DESDEMONA objective is the development of novel design methods, systems, procedure and technical solution, to integrate sensing and automation technologies for the purpose of self-inspection and self-monitoring of steel structures.
- Duration: 2018–2021
- Coordinator: Pr. Vincenzo Gatulli (La Sapienza University of Rome)
- Academic and industrial Partners: Sapienza Università di Roma (Italy), Universidad de Castilla – La Mancha, (Spain), Universidade do Porto (Portugal), Università di Pisa (Italy), UGE (France), Aiviewgroup srl (Italy), Sixense systems (France), Ecisa compania general de construcciones sa (Spain), Università di Cassino e del Lazio Meridionale (Italy), Universidad de Alicante (Spain), Inria (France).
- Inria contact: J. Dumoulin and L. Mevel
- Abstract: DESDEMONA objective is the development of novel design methods, systems, procedure and technical solution, to integrate sensing and automation technologies for the purpose of self-inspection and self-monitoring of steel structures. The approach will lead to an increment of the service life of existing and new steel civil and industrial infrastructure and to a decrease in the cost associated to inspections, improving human activities performed in difficult conditions, safety and workers' potential by the use of advanced tools. The research aims to expand beyond the current state-of-the-art new high-quality standard and practices for steel structure inspection and maintenance through the interrelated development of the following actions: i) steel structure geometry and condition virtualization through data fusion of image processing, thermography and vibration measurements; ii) developing a procedure for steel defect detection by robotic and automatic systems such as Unmanned Aerial Vehicles (UAV) and ground mobile robots iii) embedding sensor systems to revalorize and transform steel elements and structures into self-diagnostic (smart) elements and materials even through nanotechnologies, iv) realizing an experimental lab-based apparatus and a series of case studies inspected by intelligent and robotic systems. The project outcome will have an impact on the reduction of the cost of steel structures inspection and maintenance and on the increase of user safety and comfort in industrial and civil environment. The proposal with a multidisciplinary approach fulfils the objectives of the Strategic Research Agenda of the European Steel Technology Platform.

### 9.2.2 Other European programs/initiatives

#### ERA-NET MarTERA Flow-Cam

**Participants:** Qinghua Zhang.

- Date/duration: 2020-2023
- Project partners: CEA LIST (coordinator), UGE, DESISTEK, TEKNOPAR, MEDYSYS.
- Abstract: The FLoating Offshore Wind turbine CAble Monitoring project aims at studying new methods for the inspection, detection and monitoring of structural defects in the interconnection system of floating offshore wind farms. Based on multi-physics models linking damage mechanisms of conductive wires to electrical and thermal properties, new structural health monitoring methods studied in the project involve multi-sensor data processing and an underwater remotely operated vehicle.

### 9.3 National initiatives

#### IFPEN

**Participants:** Laurent Mevel, Enora Denimal.

Collaboration with IFPEN leading to the thesis of A. Cadoret on applying OMA techniques on wind turbines.

#### CEA List ONDULA2

**Participants:** Vincent Le Cam.

With CEA-LIST and Alstom-Rail, this project (until June 2022) focuses on NDT ultrasonic testing methods for rails. The goal is to deploy several complete rail-sensors in real railway application test benches; another aspect consists in transferring the common knowledge to the final customer Alstom.

#### MTE DGITM CASC: Acoustic Wave for Wirebreak in cables Monitoring

**Participants:** Vincent Le Cam, David Pallier.

This governmental project (until 2022) aims at testing new algorithms in the CASC platform for detecting and localizing wire breaks in cables of suspended bridges by means of acoustic waves time difference of arrival (TDOA), with the objective to provide a better "time of arrival" time-stamping (by means of the maximum of likelihood for instance). Another objective is the implementation of a good time-synchronization in wireless sensors while keeping the GPS-energy lower as possible. This was done in the context of the PhD of D. Pallier.

### ANR SCaNING

**Participants:** Vincent Le Cam.

- Duration: 2021 – 2024
- Partners: UGE (Coordinator), Université de Toulouse, Aix-Marseille Université, Université de Bordeaux, Andra, EDF
- Inria contact: Vincent Le Cam
- Abstract: Using embedded sensors which will provide information similar to that used in NDE while allowing to continuously evaluate performance indicators (compressive strength and Young's modulus) and the concrete conditions (porosity and water content) to improve indicator reliability and optimize diagnosis and communicating sensors through fully autonomous, low-power networks makes it possible to consider systems with low installation and operation costs. The project is lead by MAST LAMES laboratory of UGE. The full instrumentation part is ensured by I4S common team.

### ANR Convincés

**Participants:** Jean Dumoulin, Romain Noël.

- Duration: 11/2021 – 11/2025
- Partners: Univ. Lorraine (coordinator), CERTES (UPEC), Univ. Strasbourg, UGE, Cerema.
- Abstract: The ANR project CONVINCÉS is investigating the influence of convection in suspensions of micro-encapsulated phase change material (mPCM) in urban civil engineering applications. This project will include LBM (Lattice Boltzmann Method) and DEM (Discrete Element Method) in multi-scale simulations plus series of experiments at different scales to study the thermal impact of such mPCM suspensions in porous media. The final objective is the thermal regulation of pavements.

### ANR Resbati

**Participants:** Jean Dumoulin.

- Objectif: In-situ measurements of thermal wall resistance
- Duration: 10/2016 to 10/2020 extended to 03/2021
- Coordinator: Laurent Ibos
- Partners: UGE, CERTES, CEREMA, CSTB, LNE, THEMACS, AFNOR
- Abstract: RESBATI is an applied research project whose objective is to develop a field measurement device that meets precise specifications to systematically measure the level of thermal insulation of building walls. The preferred metrological tool is infrared thermography. A smart logger and a prototype have been developed and presented. A full autonomous system has been studied and developed for in-situ measurement on existing building envelope. In parallel, thermal resistance estimation method was studied. First experiments were carried out with a first generation prototype in 2019. For this purpose different instrumented building walls were built and qualified at CSTB before carrying out in-situ evaluations of the prototype.

## 9.4 Regional initiatives

### RFI Wise Musiwind

**Participants:** Xavier Chapeleau, Laurent Mevel, Michael Doehler, Swarup Mahato.

- Duration: 1/2020 to 2/2021
- Coordinator: Xavier Chapeleau
- Partners: VALOREM/VALEMO, Sercel
- Abstract: Structural health monitoring of wind turbines is becoming a real economic issue for the stakeholders of these structures. Indeed, they are more and more demanding of new structural health control techniques that enable the implementation of an automated and planned monitoring strategy to ensure the structural integrity of their wind turbines throughout their lifetime. Through a multi-sensor approach, the project integrates in particular the new QuietSeis™ low-noise accelerometer (developed by SERCEL) with a generic data acquisition card Pegase 3 on which is embedded innovative signal processing (data analysis).

During the year 2020, the monitoring system has been developed and tested in laboratory. It is composed of three modules. Each module is formed by the association of a QS3 card (containing the QuietSeis accelerometer) with a Raspberry Pi used as pilot card. To ensure accurate synchronization and timestamping, the card Pegase3 is used as NTP server in combination with a PPS signal delivered natively by this card. In 2021, the system has been deployed on the wind turbine, and the monitoring algorithms have been tested in-situ.

### AIS Rennes

**Participants:** Enora Denimal.

The city of Rennes has allocated 10k€ to E. Denimal to facilitate her installation and engage collaborations.

## 10 Dissemination

### 10.1 Promoting scientific activities

#### 10.1.1 Scientific events: organisation

##### General chair, scientific chair

- Q. Zhang was head of the local organizing committee of the ERNSI 2021 workshop.

##### Member of organizing committee

- E. Denimal and M. Doehler were members of the local organizing committee of the ERNSI 2021 workshop.

#### 10.1.2 Scientific events: selection

##### Chair of conference program committees

- V. Le Cam
  - head and general secretary of the EWSHM scientific committee
  - co-chair of SHM@COFREND and member of its scientific committee: each year a *SHM by Cofrend day* is organized grouping around 100 leaders in France in SHM techniques

**Member of the conference program committees**

- J. Dumoulin
  - member of the scientific committee of the GI Division (Geosciences Instrumentation and Data Systems) of EGU (European Geosciences Union) for infrastructure instrumentation and monitoring since 2013
  - member of the scientific committee of QIRT (quantitative Infrared Thermography) since 2014
  - chairman of session Multimodal Images for Remote Sensing at SPIE EOM21: 11785 (OM104)
- Q. Zhang
  - member of the IFAC Symposium on System Identification (SYSID) 2021 scientific committee
  - member of the IEEE International Conference on Systems and Control (ICSC) 2021 scientific committee
  - member of the IFAC Symposium on Fault Detection, Supervision and Safety for Technical Processes (SAFEPROCESS) 2022 scientific committee
  - member of the IFAC Workshop on Adaptive and Learning Control Systems (ALCOS) 2022 scientific committee
  - member of IFAC Technical Committee on Modelling, Identification and Signal Processing (TC 1.1)
  - member of IFAC Technical Committee on Adaptive and Learning Systems (TC 1.2)
  - member of IFAC Technical Committee on Fault Detection, Supervision and Safety of Technical Processes (TC 6.4)
- L. Mevel
  - member of the EWSHM scientific committee
  - member of the SHM-10 scientific committee
  - chairman of 2 sessions at SYSID 2021
- V. Le Cam
  - member of the IWSHM scientific committee
  - member of the Asian Pacific Workshop scientific committee
- M. Doehler
  - member of IFAC Technical Committee on Modelling, Identification, and Signal Processing (TC 1.1)
  - member of the IOMAC scientific committee
  - member of the SHM@COFREND scientific committee
  - chairman of session at ERNSI 2021

**Reviewer**

- M. Doehler was reviewer for CSHM-6, SYSID 2021.  
Q. Zhang was reviewer for SYSID 2021 and CDC 2021.  
L. Mevel was reviewer for SYSID 2021.

### 10.1.3 Journal

#### Member of the editorial boards

L. Mevel is member of the editorial board of the journal of Mechanical Systems and Signal Processing, the journal Mathematical Problems in Engineering, and of the journal Shock and Vibration.

Q. Zhang is member of the editorial board of the journal of Intelligent Industrial Systems.

J. Dumoulin is member of the editorial board of the journal Quantitative Infrared Thermography, and Executive Editor for the journal Geoscientific Instrumentation and Data Systems.

E. Denimal is a guest editor for a special review in Applied Mechanics.

#### Reviewer - reviewing activities

L. Mevel was reviewer for Mechanical Systems and Signal Processing, Engineering Structures, Structural Control and Health Monitoring.

M. Doehler was reviewer for Mechanical Systems and Signal Processing, Engineering Structures, Control Engineering Practice, Wind Energy, International Journal for Uncertainty Quantification

J. Dumoulin was reviewer for Structural Health Monitoring, SPIE Optical Engineering, GI Journal (EGU), QIRT Journal, Remote Sensing of environment, Building and Environment.

E. Denimal was reviewer for Mechanical Systems and Signal Processing, International Journal of Rail Transportation, Tribology in Industry, Shock and Vibration, Journal of the Brazilian Society of Mechanical Sciences and Engineering, Journal of Engineering for Gas Turbines and Power.

R. Noel was reviewer for Aerospace, Applied Sciences, GI journal (EGU), Chemical Engineering, Fluids, Sustainability, Symmetry.

C. Droz was reviewer for Applied Sciences.

X. Chapeleau was reviewer for Buildings.

Q. Zhang was reviewer for IEEE Transactions on Automatic Control and Automatica.

### 10.1.4 Invited talks

E. Denimal has been invited to give a talk at the UTP Technical Seminars (gather Imperial College London, Oxford University, Nottingham University), and at Journée Inria Environnement et Numérique à Rennes.

J. Dumoulin gave an invited talk at conference SPIE EOM21: 11785 (OM104) - Multimodal Sensing and Artificial Intelligence: Technologies and Applications, and at Journée Inria Environnement et Numérique à Rennes.

### 10.1.5 Scientific expertise

V. Le Cam was member of Jury HCERES du département RDT de l'IFREMER

### 10.1.6 Research administration

L. Mevel is member of CLHSCT committee in Rennes.

L. Mevel is member of Comité de centre committee in Rennes.

L. Mevel is deputy head of science of Inria Rennes.

V. Le Cam is head of SII lab at Université Gustave Eiffel in Nantes.

J. Dumoulin is deputy head of SII lab at Université Gustave Eiffel in Nantes.

V. Le Cam is member of the scientific council of WEN (West Electronic Network) since 2014, which is a cluster of about 200 companies, academics and research laboratories active in electronics.

## 10.2 Teaching - Supervision - Juries

### 10.2.1 Teaching

J. Dumoulin

- Master 2 ITII, BTP, module Maintenance et réhabilitation des ouvrages, Transferts thermiques dans les Structures : Des principes physiques à l'application sur site réel, 12 h, Ecole Centrale de Nantes(ECN), France.

#### V. Le Cam

- ESEO, 32h, practical lessons on embedded and smart systems under Linux, France
- Master 2 Electrical Engineering (GEII), 3h on electronic systems and Structural Monitoring, Université Bretagne Sud, France
- Polytech la Roche sur Yon, 3h embedded wireless algorithms
- UBS Lorient, formation 3 jours techniques avancées du Linux embarqué pour enseignants

#### M. Doehler

- Cycle préparatoire intégré, STPI, mathématiques, 48h TD, INSA Rennes, France

#### X. Chapeleau

- Licence Pro Mesures physiques, Mesures optiques, 15h, IUT de St Nazaire, Université de Nantes, France

#### R. Noël

- Master 2, conférence (2x4h), Advanced Fluid Mechanics, École des Mines de Saint-Étienne, France

#### E. Denimal

- Licence 3, Introduction to the use of numerical tools in research (10h), Ecole Normale Supérieure de Rennes, filière mécatronique
- Cycle préparatoire intégré INSA Rennes, STPI: TP découverte des mécanismes (8h), TD mécanique générale (24h), Projet hydraulique et résistance des matériaux (28h).

### 10.2.2 Supervision

- PhD: Bian Xiong, *Vibration analysis by video image processing for civil engineering structure monitoring*, Q. Zhang, V. Balthazar. Ecole doctorale MathsTIC, Université de Rennes 1, 10/2018 - 12/2021.
- PhD: Eva Viefhues, *Statistical damage detection for civil structures*, L. Mevel and M. Doehler. Ecole doctorale MathSTIC, Université de Rennes 1, 09/2016 - 12/2021.
- PhD: David Pallier, *Sensor Enhancement to Augmented Usage and Reliability*, S. Pillement, IETR, V. Le Cam, Ecole doctorale MathSTIC, until 03/2021.
- PhD: Ambroise Cadoret, *Couplage d'un modèle numérique d'éolienne avec un algorithme de type « Operational Modal Analysis » (OMA)*, L. Mevel, Ecole doctorale MathSTIC, since 10/2020.
- PhD: Quentin Sourisseau, *Evaluation de stratégies de dimensionnement de renforcements composites collés sur structures métalliques offshore*, Phd thesis director: S. Chataigner (UGE/MAST), Phd thesis co-supervisors X. Chapeleau and E. Leprêtre (UGE/MAST), Ecole doctorale SPI, since 09/2019.
- PhD: Cédric Nzouatchoua, *Apport des réseaux de capteurs à ultrasons sans-fil dans la surveillance de l'état de santé des structures composites*, M. Bentahar, V. Le Cam and N. Collin, Ecole doctorale SPI, since 11/2020.
- PhD: Zhilei Luo, *Vision-based vibration analysis*, Q. Zhang and M. Doehler, Ecole doctorale MathSTIC, since 11/2021
- PhD: Clément Rigal, *Modélisation multi-échelle d'écoulements convectifs avec des matériaux à changement de phase micro-encapsulés à travers un milieu poreux*, Y. Hoarau, R. Noël and J. Dumoulin, Ecole doctorale MSTII, since 12/2021

- Boualem Merainani, postdoc in H2020 Desdemona, then SNCF
- Swarup Mahato postdoc in RFI WISE Musiwind, until 03/2021
- Thibaud Toullier, postdoc funded by Siemens
- M1 intern: Raphael Chevalier, Intégration de contraintes mécanique pour l'optimisation d'amortisseurs de vibrations non-linéaires. E. Denimal, 05/2021 - 07/2021

### 10.2.3 Juries

Q. Zhang

- Université libre de Bruxelles – Vrije Universiteit Brussel (co-tullelle). Sandra Vásquez, “Design of model-based fault diagnosis systems from concatenated data application to wind turbines”. Private defense July 8, 2021, public defense September 08, 2021.
- Université de Lyon. Alexandre Kircher, “Design and Analysis of Resilient state estimators for Linear Discrete-time systems”. Defense June 15, 2021.
- Harbin Institute of Technology. Wentao Tang, “Set-membership estimation for discrete-time systems and its applications to fault diagnosis”. Defense April 29, 2021.

## 11 Scientific production

### 11.1 Major publications

- [1] J. Brouns, A. Crinière, J. Dumoulin, A. Nassiopoulos and F. Bourquin. ‘Diagnostic de structures de Génie Civil : Identification des propriétés spatiales et de la surface d’un défaut’. In: *SFT 2014*. Société Française de Thermique. Lyon, France, May 2014. URL: <https://hal.inria.fr/hal-01082184>.
- [2] A. Crinière, J. Dumoulin, C. Ibarra-Castanedo and X. Maldague. ‘Inverse model for defect characterisation of externally glued CFRP on reinforced concrete structures: comparative study of square pulsed and pulsed thermography’. In: *Quantitative InfraRed Thermography Journal* 11.1 (Mar. 2014), pp. 84–114. DOI: [10.1080/17686733.2014.897512](https://doi.org/10.1080/17686733.2014.897512). URL: <https://hal.archives-ouvertes.fr/hal-01081174>.
- [3] M. Döhler and L. Mevel. ‘Efficient Multi-Order Uncertainty Computation for Stochastic Subspace Identification’. In: *Mechanical Systems and Signal Processing* 38.2 (June 2013), pp. 346–366.
- [4] M. Döhler and L. Mevel. ‘Fast Multi-Order Computation of System Matrices in Subspace-Based System Identification’. In: *Control Engineering Practice* 20.9 (Sept. 2012), pp. 882–894.
- [5] M. Döhler and L. Mevel. ‘Modular Subspace-Based System Identification from Multi-Setup Measurements’. In: *IEEE Transactions on Automatic Control* 57.11 (Nov. 2012), pp. 2951–2956.
- [6] M. Döhler and L. Mevel. ‘Subspace-based fault detection robust to changes in the noise covariances’. In: *Automatica* 49.9 (Sept. 2013), pp. 2734–2743. DOI: [10.1016/j.automatica.2013.06.019](https://doi.org/10.1016/j.automatica.2013.06.019). URL: <https://hal.inria.fr/hal-00907662>.
- [7] J. Dumoulin and V. Boucher. ‘Infrared thermography system for transport infrastructures survey with inline local atmospheric parameter measurements and offline model for radiation attenuation evaluations’. In: *Journal of Applied Remote Sensing* 8.1 (2014), pp. 084978–084978.
- [8] J. Dumoulin, A. Crinière and R. Averty. ‘The detection and thermal characterization of the inner structure of the ‘Musmeci’ bridge deck by infrared thermography monitoring’. In: *Journal of Geophysics and Engineering* 10.6 (Dec. 2013), p. 17. DOI: [10.1088/1742-2132/10/6/064003](https://doi.org/10.1088/1742-2132/10/6/064003). URL: <https://hal.inria.fr/hal-01081320>.
- [9] A. Jhinaoui, L. Mevel and J. Morlier. ‘A new SSI algorithm for LPTV systems: application to a hinged-bladed helicopter’. In: *Mechanical Systems and Signal Processing* 42.1 (Jan. 2014), pp. 152–166.

- [10] P. Lair, J. Dumoulin and P. Millan. ‘Inverse method for flux characterization using infrared thermography in die forging’. In: *Numerical Heat Transfer, Part A Applications* 33.3 (1998), pp. 267–277.
- [11] F. Loete, Q. Zhang and M. Sorine. ‘Experimental validation of the inverse scattering method for distributed characteristic impedance estimation’. In: *IEEE Transactions on Antennas and Propagation* 63.6 (2015), p. 7. DOI: [10.1109/TAP.2015.2417215](https://doi.org/10.1109/TAP.2015.2417215). URL: <https://hal.inria.fr/hal-01231807>.
- [12] L. Marin, M. Döhler, D. Bernal and L. Mevel. ‘Robust statistical damage localization with stochastic load vectors’. In: *Structural Control and Health Monitoring* 22.3 (Mar. 2015).
- [13] M. Zghal, L. Mevel and P. Del Moral. ‘Modal parameter estimation using interacting Kalman filter’. In: *Mechanical Systems and Signal Processing* 47.1 (Aug. 2014), pp. 139–150.
- [14] Q. Zhang, M. Sorine and M. Admane. ‘Inverse Scattering for Soft Fault Diagnosis in Electric Transmission Lines’. In: *IEEE Transactions on Antennas and Propagation* 59.1 (2011), pp. 141–148. URL: <https://hal.inria.fr/inria-00365991>.

## 11.2 Publications of the year

### International journals

- [15] N. Aswal, S. Sen and L. Mevel. ‘Estimation of local failure in tensegrity using Interacting Particle-Ensemble Kalman Filter’. In: *Mechanical Systems and Signal Processing* 160 (Nov. 2021), p. 107824. DOI: [10.1016/j.ymsp.2021.107824](https://doi.org/10.1016/j.ymsp.2021.107824). URL: <https://hal.inria.fr/hal-03468255>.
- [16] M. C. Austin, T. Vogt Wu, A. Sempey, A. Sommier, J. Dumoulin, D. Bruneau, J.-C. Batsale and Y. Yang. ‘Investigation into the use of thermoelectric modules as an alternative to conventional fluxmeters: application to convective and radiative heat flux in buildings’. In: *International Journal of Thermal Sciences* 160 (2021), pp. 1–13. DOI: [10.1016/j.ijthermalsci.2020.106653](https://doi.org/10.1016/j.ijthermalsci.2020.106653). URL: <https://hal.inria.fr/hal-03145206>.
- [17] X. Chapeleau and A. Bassil. ‘A General Solution to Determine Strain Profile in the Core of Distributed Fiber Optic Sensors under Any Arbitrary Strain Fields’. In: *Sensors* 21.16 (1st Jan. 2021), pp. 1–33. DOI: [10.3390/s21165423](https://doi.org/10.3390/s21165423). URL: <https://hal.archives-ouvertes.fr/hal-03328823>.
- [18] B. Delyon and Q. Zhang. ‘On the Optimality of the Kitanidis Filter for State Estimation Rejecting Unknown Inputs’. In: *Automatica* 132 (13th July 2021), article n°109793. DOI: [10.1016/j.automatica.2021.109793](https://doi.org/10.1016/j.automatica.2021.109793). URL: <https://hal.inria.fr/hal-03041232>.
- [19] E. Denimal and J.-J. Sinou. ‘Advanced computational technique based on kriging and Polynomial Chaos Expansion for structural stability of mechanical systems with uncertainties’. In: *Journal of Engineering Mathematics* 130.1 (Oct. 2021), pp. 1–19. DOI: [10.1007/s10665-021-10157-9](https://doi.org/10.1007/s10665-021-10157-9). URL: <https://hal.inria.fr/hal-03341899>.
- [20] E. Denimal and J.-J. Sinou. ‘Advanced kriging-based surrogate modelling and sensitivity analysis for rotordynamics with uncertainties’. In: *European Journal of Mechanics - A/Solids* 90 (June 2021), pp. 1–20. DOI: [10.1016/j.euromechsol.2021.104331](https://doi.org/10.1016/j.euromechsol.2021.104331). URL: <https://hal.inria.fr/hal-03246852>.
- [21] S. Gres, M. Döhler, P. Andersen and L. Mevel. ‘Kalman filter-based subspace identification for operational modal analysis under unmeasured periodic excitation’. In: *Mechanical Systems and Signal Processing* 146 (2021), p. 106996. DOI: [10.1016/j.ymsp.2020.106996](https://doi.org/10.1016/j.ymsp.2020.106996). URL: <https://hal.inria.fr/hal-02613501>.
- [22] S. Gres, M. Döhler, P. Andersen and L. Mevel. ‘Subspace-based Mahalanobis damage detection robust to changes in excitation covariance’. In: *Structural Control and Health Monitoring* 28.8 (Aug. 2021), pp. 1–22. DOI: [10.1002/stc.2760](https://doi.org/10.1002/stc.2760). URL: <https://hal.inria.fr/hal-03336674>.
- [23] S. Gres, M. Döhler, P. Andersen and L. Mevel. ‘Uncertainty quantification for the Modal Phase Collinearity of complex mode shapes’. In: *Mechanical Systems and Signal Processing* 152 (1st May 2021), p. 107436. DOI: [10.1016/j.ymsp.2020.107436](https://doi.org/10.1016/j.ymsp.2020.107436). URL: <https://hal.inria.fr/hal-03276212>.

- [24] S. Gres, M. Döhler and L. Mevel. ‘Statistical model-based optimization for damage extent quantification’. In: *Mechanical Systems and Signal Processing* 160 (Nov. 2021), pp. 1–19. DOI: [10.1016/j.ymssp.2021.107894](https://doi.org/10.1016/j.ymssp.2021.107894). URL: <https://hal.inria.fr/hal-03468260>.
- [25] S. Gres, M. Döhler and L. Mevel. ‘Uncertainty quantification of the Modal Assurance Criterion in Operational Modal Analysis’. In: *Mechanical Systems and Signal Processing* 152 (May 2021), p. 107457. DOI: [10.1016/j.ymssp.2020.107457](https://doi.org/10.1016/j.ymssp.2020.107457). URL: <https://hal.inria.fr/hal-03276725>.
- [26] N. Le Touz, T. Toullier and J. Dumoulin. ‘Study of an optimal heating command law for structures with non-negligible thermal inertia in varying outdoor conditions’. In: *Smart Structures and Systems* 27.2 (2021), pp. 379–386. DOI: [10.12989/sss.2021.27.2.379](https://doi.org/10.12989/sss.2021.27.2.379). URL: <https://hal.inria.fr/hal-03145348>.
- [27] A. Mendler, M. Döhler and C. E. Ventura. ‘A reliability-based approach to determine the minimum detectable damage for statistical damage detection’. In: *Mechanical Systems and Signal Processing* 154 (June 2021), p. 107561. DOI: [10.1016/j.ymssp.2020.107561](https://doi.org/10.1016/j.ymssp.2020.107561). URL: <https://hal.inria.fr/hal-03276728>.
- [28] K. Mharsi, X. Chapeleau, J. FAJOUI, A. Sellami, P. Casari and M. Kchaou. ‘Characterization Shear Properties of PVC Foams Instrumented by Optical Fiber under Flexural Loading’. In: *Journal of Testing and Evaluation* 49.4 (1st July 2021), pp. 2507–2517. DOI: [10.1520/JTE20200123](https://doi.org/10.1520/JTE20200123). URL: <https://hal.inria.fr/hal-03284231>.
- [29] D. Pallier, V. Le Cam and S. Pillement. ‘Energy-efficient GPS synchronization for wireless nodes’. In: *IEEE Sensors Journal* 21.4 (2021), pp. 5221–5229. DOI: [10.1109/JSEN.2020.3031350](https://doi.org/10.1109/JSEN.2020.3031350). URL: <https://hal.archives-ouvertes.fr/hal-02968155>.
- [30] S. Sen, N. Aswal, Q. Zhang and L. Mevel. ‘Structural health monitoring with non-linear sensor measurements robust to unknown non-stationary input forcing’. In: *Mechanical Systems and Signal Processing* 152 (May 2021), p. 107472. DOI: [10.1016/j.ymssp.2020.107472](https://doi.org/10.1016/j.ymssp.2020.107472). URL: <https://hal.inria.fr/hal-03275936>.
- [31] Z. Wang, T. N. Dinh, Q. Zhang, T. Raissi and Y. Shen. ‘Fast interval estimation for discrete-time linear systems: An  $L_1$  optimization method’. In: *Automatica* (26th Aug. 2021). DOI: [10.1016/j.automatica.2021.110029](https://doi.org/10.1016/j.automatica.2021.110029). URL: <https://hal-cnam.archives-ouvertes.fr/hal-03346716>.
- [32] Q. Zhang. ‘Dynamic System Fault Diagnosis under Sparseness Assumption’. In: *IEEE Transactions on Signal Processing* (8th Apr. 2021), p. 10. DOI: [10.1109/TSP.2021.3072004](https://doi.org/10.1109/TSP.2021.3072004). URL: <https://hal.inria.fr/hal-03195954>.

### International peer-reviewed conferences

- [33] N. Aswal, E. Kuncham, S. Sen and L. Mevel. ‘Robust Interacting Particle-Kalman Filter based structural damage estimation using dynamic strain measurements under non-stationary excitation -an experimental study’. In: SHMII-10 2021 – 10th International Conference on Structural Health Monitoring of Intelligent Infrastructure. Porto, Portugal, 30th June 2021, pp. 1–8. URL: <https://hal.inria.fr/hal-03277241>.
- [34] I. Catapano, G. Ludeno, F. Soldovieri, T. Toullier and J. Dumoulin. ‘TeraHertz inspections of painted steel samples’. In: MetroAeroSpace 2021 - IEEE 8th International Workshop on Metrology for AeroSpace. Naples, Italy: IEEE, 23rd June 2021, pp. 647–652. DOI: [10.1109/MetroAeroSpace51421.2021.9511692](https://doi.org/10.1109/MetroAeroSpace51421.2021.9511692). URL: <https://hal.inria.fr/hal-03500762>.
- [35] M. Döhler, Q. Zhang and L. Mevel. ‘Damage Localization in Mechanical Systems by Lasso Regression’. In: SYSID 2021 - 19th IFAC Symposium on System Identification. Padua / Virtual, Italy, 13th July 2021, pp. 1–6. URL: <https://hal.inria.fr/hal-03292476>.
- [36] S. Gres, M. Döhler and L. Mevel. ‘Hankel matrix-based Mahalanobis distance for fault detection robust towards changes in process noise covariance’. In: SYSID 2021 - 19th IFAC Symposium on System Identification. Padua / Virtual, Italy, 13th July 2021, pp. 1–6. URL: <https://hal.inria.fr/hal-03292515>.

- [37] S. Gres, M. Döhler and L. Mevel. ‘Statistical optimization for subspace-based damage quantification’. In: SHMII-10 2021 - 10th International Conference on Structural Health Monitoring of Intelligent Infrastructure. Porto, Portugal, 30th June 2021, pp. 1–8. URL: <https://hal.inria.fr/hal-03276871>.
- [38] A. Mendler, A. Cadoret, C. Freyssinet, M. Döhler, Y. Lecieux, L. Mevel and C. Ventura. ‘Minimum Localizable Damage for Stochastic Subspace-based Damage Diagnosis’. In: SHMII-10 - 10th International Conference on Structural Health Monitoring of Intelligent Infrastructure. 1-8. Porto, Portugal, 30th June 2021. URL: <https://hal.inria.fr/hal-03276737>.
- [39] B. Merainani, B. Xiong, V. Baltazart, J. Dumoulin, M. Döhler and Q. Zhang. ‘Experimental investigation of structural modal identification using pixels intensity and motion signals from video-based imaging devices: performance, comparison and analysis’. In: SPIE Optical Metrology 2021. Virtual, United States: SPIE, 21st June 2021. DOI: [10.1117/12.2595019](https://doi.org/10.1117/12.2595019). URL: <https://hal.inria.fr/hal-03276900>.
- [40] R. Noël, L. Navarro and G. Courbebaisse. ‘Lattice Boltzmann Method for Mathematical Morphology: Application to Porous Media’. In: SPIE Optical Metrology 2021. Vol. 11785. Online Only, United States: SPIE, 21st June 2021, pp. 1–16. DOI: [10.1117/12.2593731](https://doi.org/10.1117/12.2593731). URL: <https://hal.inria.fr/hal-03346769>.
- [41] Q. SOURISSEAU, E. LEPRETRE, S. Chataigner, X. Chapeleau, L. Mouton and S. Paboef. ‘Use of Distributed Optical Fibre to Monitor the Crack Propagation of an Adhesively Bonded Joint During an ENF Test’. In: CICE 2021 - 10th International Conference on FRP Composites in Civil Engineering. Vol. 198. Lecture Notes in Civil Engineering. Istanbul, Turkey: Springer International Publishing, 30th June 2021, pp. 253–265. DOI: [10.1007/978-3-030-88166-5\\_21](https://doi.org/10.1007/978-3-030-88166-5_21). URL: <https://hal.inria.fr/hal-03507675>.
- [42] E. Viefhues, M. Döhler, P. Simon, R. Herrmann, F. Hille and L. Mevel. ‘Stochastic subspace-based damage detection of a temperature affected beam structure’. In: SHMII-10 2021 - 10th International Conference on Structural Health Monitoring of Intelligent Infrastructure. Porto, Portugal, 30th June 2021, pp. 1–6. URL: <https://hal.inria.fr/hal-03276865>.
- [43] B. Xiong, Q. Zhang and V. Baltazart. ‘Analysis of Quadratic Surface Fitting for Subpixel Motion Extraction from Video Images’. In: EUSIPCO 2020 - 28th European Signal Processing Conference. Amsterdam / Virtual, Netherlands: IEEE, 18th Jan. 2021, pp. 695–699. DOI: [10.23919/Eusipco47968.2020.9287872](https://doi.org/10.23919/Eusipco47968.2020.9287872). URL: <https://hal.inria.fr/hal-03129172>.
- [44] Q. Zhang and L. Zhang. ‘Boundedness of the Kalman Filter Revisited’. In: SYSID 2021 - 19th IFAC Symposium on System Identification. Padova, Italy, 13th July 2021, pp. 1–5. URL: <https://hal.inria.fr/hal-03485750>.

### 11.3 Cited publications

- [45] M. Basseville and I. V. Nikiforov. ‘Fault isolation for diagnosis : nuisance rejection and multiple hypotheses testing’. In: *Annual Reviews in Control* 26.2 (Dec. 2002), pp. 189–202. URL: [http://dx.doi.org/10.1016/S1367-5788\(02\)00029-9](http://dx.doi.org/10.1016/S1367-5788(02)00029-9).
- [46] B. Delyon, A. Juditsky and A. Benveniste. *On the relationship between identification and local tests*. Publication Interne 1104. IRISA, May 1997. URL: <ftp://ftp.irisa.fr/techreports/1997/PI-1104.ps.gz>.
- [47] M. Jaulent. ‘The inverse scattering problem for LCRG transmission lines’. In: *Journal of Mathematical Physics* 23.12 (Dec. 1982), pp. 2286–2290.
- [48] G. L. Lamb. *Elements of Soliton Theory*. New York: John Wiley & Sons, 1980.
- [49] M. Oumri. ‘Fault diagnosis of wired electric networks by reflectometry’. Theses. Université Paris Sud - Paris XI, May 2014. URL: <https://tel.archives-ouvertes.fr/tel-01165039>.
- [50] C. R. Paul. *Analysis of multiconductor transmission lines*. New York: Wiley, 2008.

- 
- [51] H. Tang and Q. Zhang. ‘An Inverse Scattering Approach to Soft Fault Diagnosis in Lossy Electric Transmission Lines’. In: *IEEE Trans. on Antennas and Propagation* 59.10 (2011), pp. 3730–3737. URL: <http://dx.doi.org/10.1109/TAP.2011.2163772>.
  - [52] P. Van Overschee and B. de Moor. *Subspace Identification for Linear Systems*. Boston: Kluwer Academic Publishers, 1996.
  - [53] E. Visco Comandini. ‘Some inverse scattering problems on star-shaped graphs: application to fault detection on electrical transmission line networks’. Theses. Université de Versailles-Saint Quentin en Yvelines, Dec. 2011. URL: <https://tel.archives-ouvertes.fr/tel-00748216>.