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Sensor Fusion on Structural Monitoring Data Analysis: Application to a Cable-Stayed Bridge

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Abstract. This paper illustrates an application of Bayesian logic to monitoring data analysis and structural condition state inference. The case study is a 260 m long cable-stayed bridge spanning the Adige River 10 km north of the town of Trento, Italy. This is a statically indeterminate structure, having a composite steel-concrete deck, supported by 12 stay cables. Structural redundancy, possible relaxation losses and an as-built condition differing from design, suggest that long-term load redistribution between cables can be expected. To monitor load redistribution, the owner decided to install a monitoring system which combines built-on-site elasto-magnetic and fiber-optic sensors. In this note, we discuss a rational way to improve the accuracy of the load estimate from the EM sensors taking advantage of the FOS information. More specifically, we use a multi-sensor Bayesian data fusion approach which combines the information from the two sensing systems with the prior knowledge, including design information and the outcomes of laboratory calibration. Using the data acquired to date, we demonstrate that combining the two measurements allows a more accurate estimate of the cable load, to better than 50 kN

Introduction

Adige Bridge is a new cable-stayed bridge spanning the Adige River 10 Km north of the town of Trento, Italy. It has a composite steel-concrete deck of length 260 m overall, supported by 12 stay cables, 6 per deck side with diameters of 116 mm and 128 mm, as shown in Figure 1, with design operation load varying from 5000 to 8000 kN. The deck cross section consists of four “I” section weathering steel beams 2 m high with flange dimensions variable along the span and a 25 cm thick concrete slab. The bridge antenna consists of 4 pylons of height 45 m at the centre of the span. Bridge construction was completed in 2008 when the owner, the Italian Autonomous Province of Trento, decided to install a monitoring system, to continuously record the tension and elongation of the stay cables.

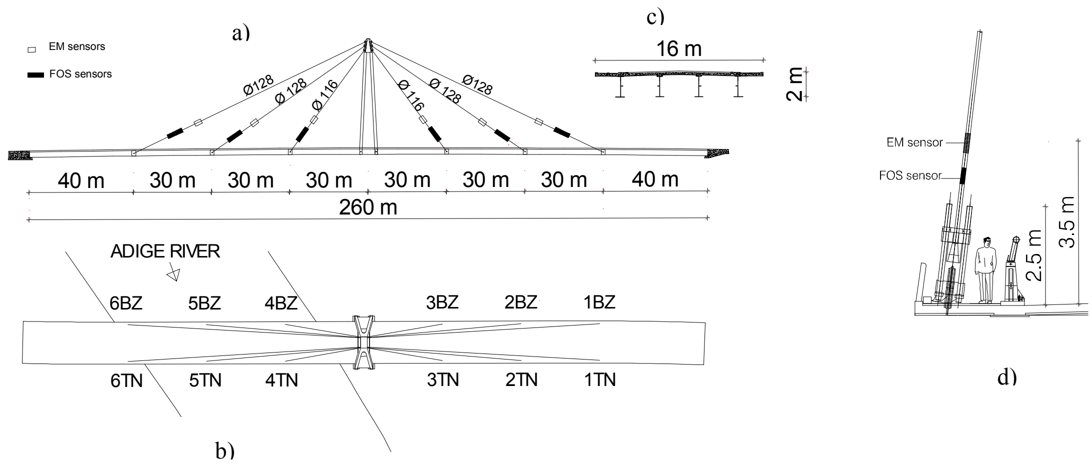

Figure 1. Elevation(a) plan view (b) and deck cross-section (c) of Adige Bridge; detail of sensors location on a cable (d).

Structural redundancy, possible relaxation losses and an as-built condition differing from design, are among the reasons that suggested the monitoring effort, as discussed in [1]. Because changes in strain and load are not directly correlated, the system installed records the two quantities through two separate instrument networks. Elongation is recorded by 1m-long gauge sensors, placed on each of the 12 cables; these are optical sensors, based on Fiber Bragg Grating (FBG) technology and supplied by Smartec SA [2]. Similarly, load is directly acquired at each cable by site fabricated Elasto-Magnetic (EM) sensors [3], developed and supplied by Intelligent Instrument System Inc. [4]. In addition, both types of sensor record local temperature for thermal compensation.

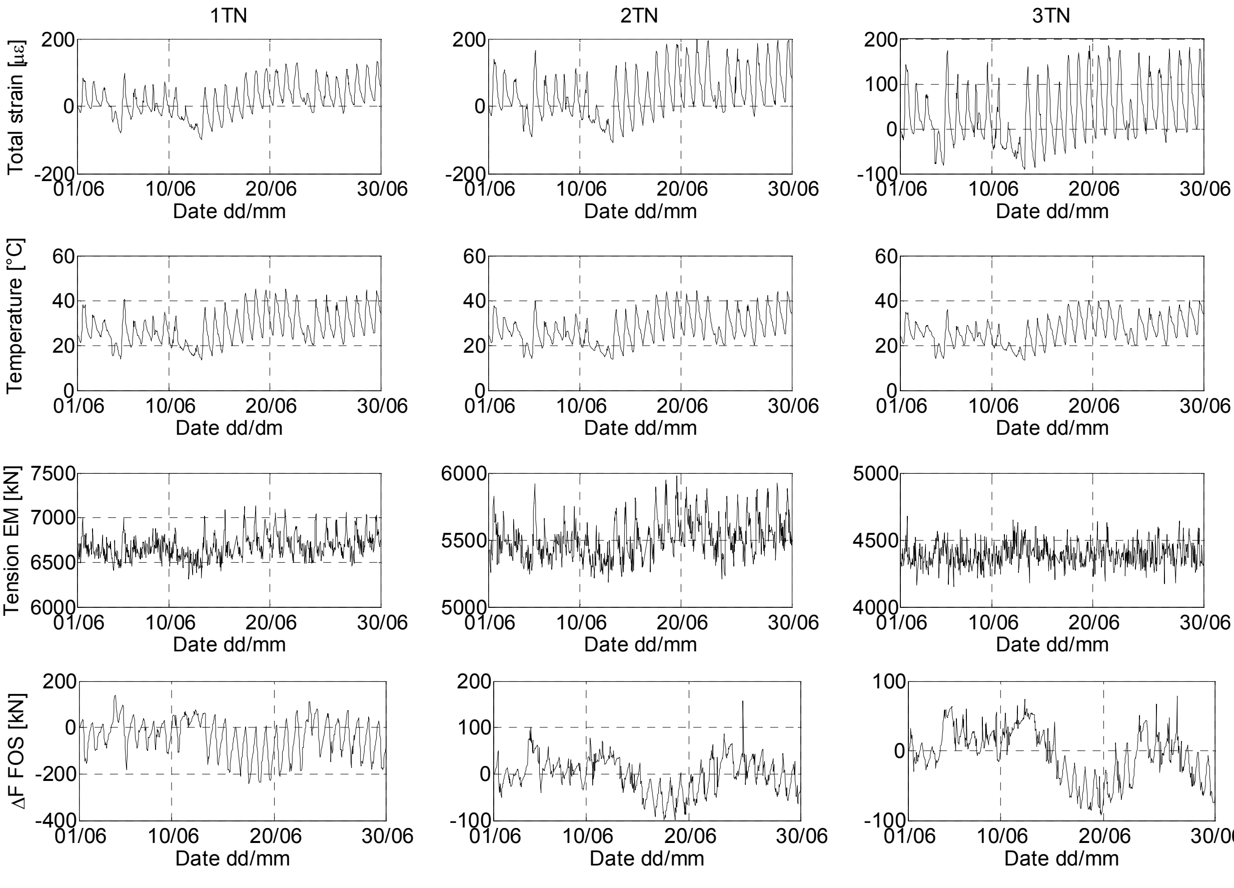

Figure 2. Data acquired by FOS (strain) and by elasto-magnetic sensors (force and temperature).

The system has been operating since March 2011, continuously recording elongation, tension and temperature of the 12 cables. As an example, Figure 2 shows data acquired in June 2012, for the three of the cables, namely 1TN, 2TN and 3TN. We can clearly see how the strain recorded by FOS follows the daily temperature changes. Note that the temperature variation is very similar for all the cables (about 30 °C on a sunny day in June), while its effect changes with the strand as a result of load redistribution, and for example is greater in strand 3TN, the shortest of the three, than in strand 1TN, the longest. This behavior is perfectly in line with expectations, based on the prediction from Finite Element analysis [5]. Similarly, load redistribution produces changes in stress, recorded by the EM sensors, which in turn follow the temperature variation, as seen in Figure 2.

In principle EM sensors are the most logical way to measure cable tension, but their inherent sensitivity to temperature and the site fabrication process limit their accuracy to 200-300 kN, depending on the cable length: as discussed in [1] and briefly summarized in the next section. While there is no alternative to the EM sensors to detect the absolute tension F, relative changes in tension ΔF could be estimated by using the FOS strain measurements. In principle, we could estimate the change in tension via an equation of the type:

$$\Delta F(t) = EA\,\Delta\varepsilon_e(t) \tag{1}$$

where E is Young's modulus for the cable steel, A is the cross-section area of the cable and $\Delta\varepsilon_e$ is the change in elastic strain of the cable. The issue with Eq. 1 is that most of the change in strain observed at the sensor $\Delta\varepsilon$ is due to thermal expansion/contraction and, to a minor extent, creep and relaxation, thus the elastic strain must be inferred from an equation of the type

$$\Delta\varepsilon_e(t) = \Delta\varepsilon(t) - \alpha\Delta T(t) - \Delta\varepsilon_c(t) \tag{2}$$

where α is the thermal expansion coefficient, ΔT is the observed change of temperature with respect to the baseline condition and $\Delta\varepsilon_c(t)$ is the elongation due to creep and relaxation. In the last row of graphs of Figure 2, for example, we can see the tension variation on the three cables estimated using the model of Equation (1). Comparison of the tension history estimated with data from the EM sensors and from the FOS shows that the two are not fully consistent.

In this note, we discuss a rational way to improve the accuracy of the load estimate from the EM sensors, taking advantage of the FOS information. More specifically, we use a multi-sensor Bayesian data fusion approach [6] which combines information from the two sensing systems with prior knowledge, including design information and the outcomes of laboratory calibration. In the following section, we first discuss the expected accuracy of the two measurement systems. Next, we formulate the Bayesian data fusion algorithm and we state the relationship between parameters and observations of the problem. Using the data acquired to date, we demonstrate that combining the two measurements allows a more accurate estimate of the cable load. The results are discussed at the end of the paper.

Accuracy of measurement systems

The FOS installed on Adige Bridge are based on Fiber Bragg Grating (FBG) technology and provide measurements of strain and temperature [7,8]. The system records one measurement every 15 minutes, where one measurement is the average of 4000 samples acquired with a sampling rate of 500 Hz. In references [1] and [5], the accuracy of the measurements is shown to be of the order of 5 με.

Table 1. Mean value and standard deviation of coefficients *a* and *b* after laboratory calibration [3].

Cable diameter[mm]	*a* [kN/V]		*b* [V/°C]	
	μ	σ	μ	σ
116	6.35	0.34	-7.48	2.08
128	6.2	0.66	-8.88	1.32

An EM sensor measures the magnetic permeability of the cable steel and uses this quantity to estimate its stress status. The working principle of the sensor, based on the observation that the magnetic permeability of a ferromagnetic material varies with the applied stress, was first suggested by Jarosevic [9] in 1998, and later developed by Sumitro et al. [10] into an industrial prototype. An EM sensor consists of two coils wound around the cable: the primary coil applies the magnetic field, and this induces an electric current in the secondary coil, proportional to the cable stress. The cable load *F* is therefore related to the voltage *V* produced in the secondary coil. Zonta et al [3] report the results of the laboratory calibration of sensor prototypes built on cables identical to those installed on Adige bridge. The calibration showed that for loads greater than 4000 KN, the *F-V* relationship is approximately linear, and that the sensor measurement is sensitive to temperature *T*. A good estimate of load *F* at temperature *T* is given by [3]:

$$F(V,T) = F_0 + a \cdot [(V - V_0) - b \cdot (T - T_0)] \tag{3}$$

where V_0 is the voltage recorded at a known reference load F_0 and temperature T_0, T is the temperature, a=dF/dV is the force to voltage slope at reference temperature T_0 and b=dF/dT is the force to temperature sensitivity. Repeatability tests showed that coefficients *a* and *b* change with the sensors, with statistical distribution reported in Table 1.

Data fusion problem formulation

Our goal is to refine the estimate of *F* based on the voltage *V*, temperature, *T* and elongation ε dataset acquired by the monitoring system: to do this we seek to find the optimal values of those parameters, *a*, *b*, *E* and α, which control the theoretical relationship between load and measurements. In general terms, our problem it to infer a set of parameters $\boldsymbol{\theta} = \{a, b, E, \alpha\}$ starting from a observation set $\mathbf{y}$, where $\mathbf{y}$ is the dataset including all measurements taken at any time t_i. Parameters $\boldsymbol{\theta}$ and observations $\mathbf{y}_i = \left\{\Delta\varepsilon_i, \Delta V_i, \Delta T_i\right\}$ acquired at time t_i are correlated through a probabilistic model, which can have a physical or heuristic background. In general terms, we can express this model in the form:

$$z_i\left(\boldsymbol{\theta}\right) = z\left(\boldsymbol{\theta}, \mathbf{y}_i\right) = 0 \tag{4}$$

Here we use Bayesian inference [6,11,12] to solve the parameter estimation problem. Parameters $\boldsymbol{\theta}$ are regarded as random variables with prior distribution $\mathrm{pdf}(\boldsymbol{\theta})$, which represents our state of knowledge of the parameters *before* we analyzed the current data. The posterior distribution $\mathrm{pdf}(\boldsymbol{\theta} \mid \mathbf{y})$ is state of knowledge about the parameters *after* observing the monitoring data $\mathbf{y}$; according to Bayes' Theorem [12], it can be seen as an update of the prior $\mathrm{pdf}(\boldsymbol{\theta})$ through:

$$\mathrm{pdf}(\boldsymbol{\theta} \mid \mathbf{y}) = \frac{\mathrm{pdf}(\mathbf{y} \mid \boldsymbol{\theta}) \cdot \mathrm{pdf}(\boldsymbol{\theta})}{\mathrm{pdf}(\mathbf{y})} \tag{5}$$

where the first term in the numerator, $\mathrm{pdf}(\mathbf{y} \mid \boldsymbol{\theta})$, is known as likelihood, assuming that observations $\mathbf{y}_\mathrm{i}$ are not correlated in time we can write:

$$\mathrm{pdf}\left(\mathbf{y} \mid \boldsymbol{\theta}\right) = \prod_{i=1}^{N_t} \mathrm{pdf}\left(\mathbf{y}_i \mid \boldsymbol{\theta}\right) \tag{6}$$

where N_t is the number of measurement times. The evidence is simply a normalization constant which transforms the unscaled posterior in a density function and is calculated by integrating over the parameter space D$\boldsymbol{\theta}$:

$$\mathrm{pdf}(\mathbf{y}) = \int_{\mathrm{D}\boldsymbol{\theta}} \mathrm{pdf}(\mathbf{y} \mid \boldsymbol{\theta})\, \mathrm{pdf}(\boldsymbol{\theta}) \mathrm{d}\boldsymbol{\theta} \tag{7}$$

A closed form for the integral in the denominator exists only for some particular cases; otherwise Eq. 5 must be solved numerically. When many parameters are involved, the exact integration of Eq. 7 might require an exceptional computational effort which can be reduced with numerical techniques such as Monte Carlo algorithms. MC methods include Classic MC and Markov Chain MC methods [13]: both rely on the possibility of drawing samples from a target distribution and of computing an integral, averaging along the sample. While classic MC methods draw samples independently from a fixed distribution, the latter produces a step by step random walk in the parameter domain; the Metropolis-Hastings algorithm [14] is possibly the most popular in this family.

Probabilistic relationship between parameters and observations

To solve our data fusion problem, we must first state the probabilistic model, that is to say the probabilistic relationship between the observations $\mathbf{y}$ and parameters $\boldsymbol{\theta}$. To start, consider an individual cable at time t_i and focus first on FOS measurements. Assuming creep to be negligible, we can combine and rewrite Eqs. 1 and 2 in the form:

$$\Delta\hat{F}(t_i) = EA\left(\Delta\hat{\varepsilon}(t_i) - \alpha \cdot \Delta\hat{T}(t_i)\right) \tag{8}$$

where the hat on $\Delta\hat{F}(t_i)$, $\Delta\hat{\varepsilon}(t_i)$ and $\Delta\hat{T}(t_i)$ is to remind us that these are theoretical physical quantities which in general differ from the sensor observations ε_i and T_i, due to sensor noise and/or model inaccuracy. The discrepancy between physical quantities and observations can be expressed in probabilistic terms as follows:

$$\Delta\varepsilon_i = \Delta\hat{\varepsilon}(t_i) + g(\sigma_\varepsilon); \quad \Delta T_i = \Delta\hat{T}(t_i) + g(\sigma_T) \tag{9a,b}$$

where the notation $g(\sigma)$ indicates a zero mean Gaussian noise with standard deviation σ. Substituting Eqs. 9 in Eq. 8 we obtain:

$$\Delta\hat{F}(t_i) = EA\left\{\Delta\varepsilon_i + g(\sigma_\varepsilon) - \alpha\left(\Delta T_i + g(\sigma_T)\right)\right\} = EA\left\{\Delta\varepsilon_i - \alpha\Delta T_i\right\} + g(\sigma_1) \tag{10}$$

where the standard deviation of noise is itself a function of parameters E and α, according to:

$$\sigma_1 = EA\sqrt{\sigma_\varepsilon^2 + (\alpha\sigma_T)^2} \tag{11}$$

Eq. 10 formulates a probabilistic estimate of the change in cable load based on parameters E and α and on FOS observations, thus σ_1 can be regarded as the standard deviation of this estimate. In a similar way, focusing on EM measurements, we can rewrite Eq. 3 in the form:

$$\Delta\hat{F}(t_i) = a\left\{\Delta\hat{V}(t_i) - b \cdot \Delta\hat{T}(t_i)\right\} \tag{12}$$

with obvious meaning of the symbols. Assuming, similarly to Eq. 9, a probabilistic relationship between observed and physical voltage:

$$\Delta V_i = \Delta\hat{V}(t_i) + g(\sigma_V) \tag{13}$$

we obtain another probabilistic estimate of the same cable load variation, this time based on EM measurements:

$$\Delta\hat{F}(t_i) = a\left\{\Delta V_i - b\cdot\Delta T_i\right\} + g\left(\sigma_2\right) \tag{14}$$

where σ_2, the standard deviation of the estimate, is:

$$\sigma_2 = a\sqrt{\sigma_V^2 + \left(b\sigma_T\right)^2} \tag{15}$$

Because physical quantity $\Delta\hat{F}(t_i)$ is the same in Eq. 10 and Eq. 15, we can combine the two into a single equation, in the canonic form of Eq. 4,

$$z_i\left(\boldsymbol{\theta}\right) = z_i\left(\alpha, E, a, b\right) = a\left\{\Delta V_i - b\cdot\Delta T_i\right\} - EA\left\{\Delta\varepsilon_i - \alpha\Delta T_i\right\} + g\left(\sigma_3\right) = 0 \tag{16}$$

where the standard deviation σ_3 is also function of the four parameters and reads:

$$\sigma_3 = \sqrt{\sigma_1^2 + \sigma_2^2} = \sqrt{\left(EA\sigma_\varepsilon\right)^2 + \left(a\sigma_V\right)^2 + \left\{\left(EA\alpha + ab\right)\sigma_T\right\}^2} \tag{17}$$

In summary our probabilistic model, (i.e., the relationships between observations **y** and parameters **θ**) is defined by a set of uncorrelated probabilistic equations of the type of Eq. 16, one for each of the N_t observation times t_i.

Bayesian parameter identification

Having defined the probabilistic model, we can now estimate the optimal values of parameters **θ** using the Bayesian updating scheme of Eq. 5. First, we must set the prior distribution of our parameters. From calibration of EM sensors, we know that the mean value and the standard deviation of parameters *a* and *b* are those reported in Table 1, and we will assume the two to be normally distributed. Based on technical literature, the thermal expansion coefficient α of the cable steel is taken as normally distributed with mean value of 12με°C^{-1} and standard deviation 1με°C^{-1}. The prior distribution of Young's modulus of steel *E* is also assumed normal, with mean value equal to the nominal value *E*=165000 MPa provided by the supplier and standard deviation of 5000 MPa.

To run the Metropolis-Hastings (M-H) algorithm, we define an initial guess for parameters $\boldsymbol{\theta}^{(0)} = \{a^{(0)}, b^{(0)}, E^{(0)}, \alpha^{(0)}\}$. Then, we generate a candidate $\boldsymbol{\theta}^{(1)}$ state that is conditional on the previous state of the sampler using a Gaussian proposal distribution $q(\boldsymbol{\theta}^{(1)} \mid \boldsymbol{\theta}^{(0)})$. This candidate can be either accepted or rejected: in an M-H algorithm, the probability of accepting the proposal is the ratio $\beta = \text{pdf}\left(\boldsymbol{\theta}^{(1)} \mid \mathbf{y}\right) / \text{pdf}\left(\boldsymbol{\theta}^{(0)} \mid \mathbf{y}\right)$ between the new posterior and the previous one. Thus, drawn a random number u from a uniform distribution in [0,1]: if $\beta > u$, we accept the proposal and the next state is set equal to the proposal; if $\beta < u$, we reject the proposal, and the next state is set equal to the old one. This procedure continues until the sampling converges.

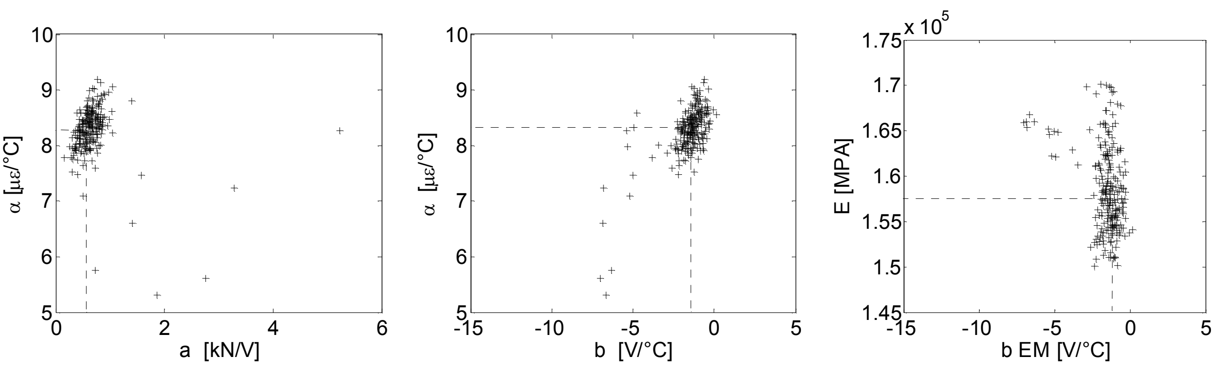

Figure 3. Drawn from a Metropolis-Hastings chain for cable 1TN, after 500 accepted values.

Table 2. Mean value and standard deviation (in parentheses) of the posterior parameters

Parameter			1TN	2TN	3TN	4TN	5TN	6TN
Force-Voltage sensitivities	a	[KN/V]	0.69 (0.49)	0.79 (0.30)	1.63 (0.32)	2.6 (0.34)	0.62 (0.30)	0.64 (0.33)
Voltage-Temp. sensitivities	b	[V/°C]	-1.47 (0.98)	-2.38 (0.70)	-2.83 (1.41)	-4.37 (1.02)	-1.98 (0.72)	-1.99 (0.73)
Thermal expansion coefficient	α	[με/°C]	8.31 (0.45)	11.53 (0.78)	13.5 (1.83)	13.5 (1.84)	9.63 (0.58)	9.69 (0.67)
Young's modulus	E	[MPa]	155920 (3806)	162080 (3242)	162080 (4379)	158780 (5063)	156600 (4253)	155330 (3328)

Figure 3 shows the resulting posterior sampling after accepting 500 samples; after a burn-in time, the parameters converge and the samples distribute according to the target posterior distribution. Table 2 reports the best estimate of the posterior parameters $\boldsymbol{\theta}$ calculated separately for each of six of the twelve cables (1TN to 6TN). We immediately note that the posterior values of parameters E and α are very close to the prior prediction, and do not change significantly with the cable. On the contrary the optimal values a posteriori of a and b depart significantly from the value expected from calibration. We also note that the longer strands have similar behavior, but this differs from that of the shorter cables. The same table reports within brackets the standard deviation of the posterior distribution of each parameter, which can be seen as an index of the accuracy of the posterior estimate. The resulting values show that the mechanical parameters E and α are identified, after acquisition of the monitoring data, with high accuracy, while the parameters a and b are still very uncertain. This suggests that in the estimation of the force variation in the cable, the data from the FOS dominate information from the EM sensors.

This outcome is even clearer from examination of Figure 4. The two graphs above report the history of force variation during the month of June 2012, estimated with EM sensor and FOS measurements, respectively, using the prior values of the parameters, while the third graph is the estimate of the two after data fusion. It is clear that the posterior distribution is driven by the FOS measurements.

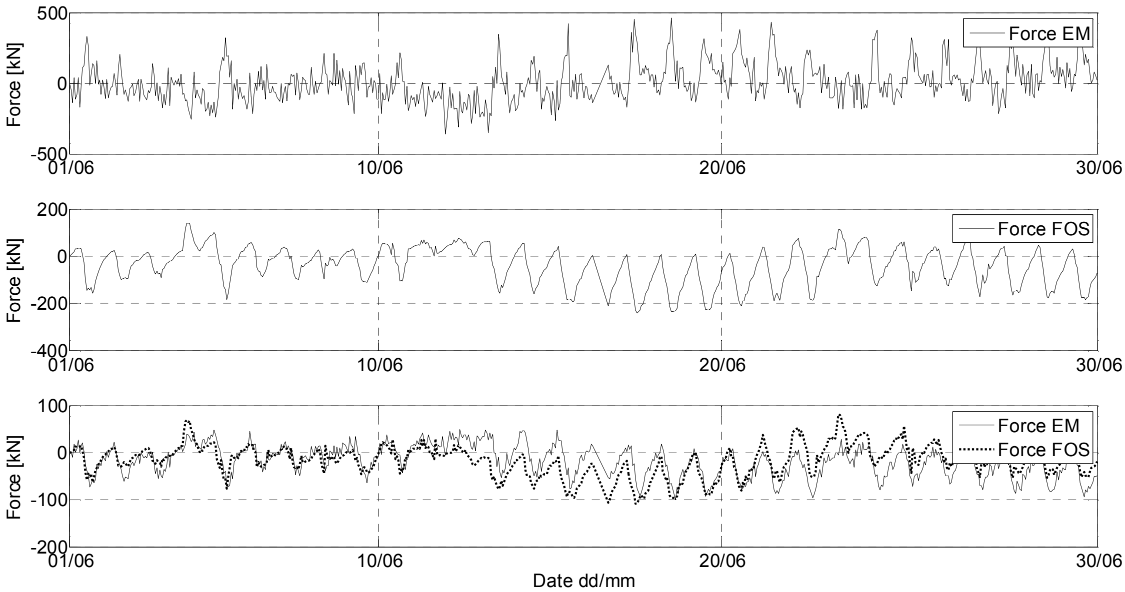

Figure 4 . Force variation estimated *a priori* from EM (a) and FOS (b) measurement, and *a posteriori* (c) after data fusion.

Conclusions

We have outlined a procedure to improve the accuracy of the estimate of a physical quantity, the load variation in a stay cable, using a data fusion technique. In particular, the method uses the observation from the FOS to enhance the load estimation from the EM sensors. Bayesian logic is employed to combine the information from the two sensing systems with prior knowledge, this including design information and the outcomes of laboratory calibration. With the data acquired to date, we demonstrate that combining the two measurements allows a more accurate estimate of the cable load, to better than 50 kN.

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