MODELLING THE MOTIONS OF A FAST FERRY WITH THE HELP OF GENETIC ALGORITHMS

B. de Andrés Toro, S. Esteban, J.M. Giron-Sierra, J.M. de la Cruz
Dept. ACYA. Fac. Fisicas. Universidad Complutense de Madrid
Ciudad Universitaria. 28040 Madrid. Spain. E-mail: deandres@eucmax.sim.ucm.es

Abstract. Models suitable for control analysis are found for a particular fast-ferry. A replica of the ship has been employed to get experimental data. Another set of data has been obtained with the program PRECAL. The models are transfer functions. Genetic algorithms have been employed to explore the best data adjustment, for a set of candidate models. Satisfactory results have been obtained for 20, 30 and 40 knots.

Introduction.

Fast ships are of increasing importance. But there are several problems that arise against speed: for instance, those related with the vertical motions of the ship (heaving and pitching motions) due to ocean waves. Passenger comfort is degraded by vertical motions. To counteract the effects of waves, our ship has two flaps below the transom, that we can move under control. Our problem is to move the flaps in an adequate way: this is a matter of control design. From the point of view of automatic control, is most convenient to have a good model of the plant to be controlled. And what is more, the model should be suitable for mathematical analysis. This is the objective of the present work.

If possible, the good way to obtain a model is by first principles: in this case, to reason with the physics of a moving ship. The scientific literature helps in this sense. The main phenomena are studied in the books [1,2,3]. Focusing on the dynamic response to waves, the article [4] analyse the case of regular waves, and [5] completes the view for more general situations. In addition, the article [6] presents several curves describing the behaviour of some fast ships.

Since linear transfer functions are very convenient for automatic control study, the modelling effort has been directed to such objective. This has been not easy. But, by means of a vast exploration, with the help of *genetic algorithms,* satisfactory results have been obtained.

The Problem.

The research deals with the ship "Silvia Ana", a fast-ferry working now in La Plata (south summer) and in the Baltic Sea (north summer). References [7,8] contain technical descriptions of the ship. To increase speed, the ship is aluminium-made. The main characteristics of the ship are the following: 110m. length, 14.696m. beam, 2.405m. draught, 475tons. deadweight , 1250 passengers. Our work contemplates the heaving and pitching motions, which take place in the vertical plane. The ship is moving, with a speed V_b, against head waves of pulsation w_{ola}. The pulsation of encounter is: $w_e = w_{ola} + w_{ola}^2 . V_b / g$

Both the measured inputs (the waves) and the outputs (heaving and pitching motions), can be processed to obtain an approximation of the frequency response of the ship (as required by the transfer function approach), related to the pulsation of encounter. Once the frequency responses are plotted, the problem to be solved is to get two transfer functions in agreement with the data: one for heaving motion, and the other for pitching motion.

The Data.

To obtain the pertinent data, a scaled down replica of the ship has been built, and employed for experiments in a towing tank institution (CEHIPAR, Madrid, Spain). By means of a wave generator, in a big pool, experimental data have been measured, with the replica, for speeds of 20, 30 and 40 knots, and for regular and irregular waves. The experiments with regular waves have been performed for 15 different wavelengths. The irregular waves have been generated according with STANAG 4194 (Standarized Wave and Wind Environments and Shipboard Reporting of Sea Conditions), for sea states 4, 5 and 6, with JONSWAP spectra. The data have been sampled, and saved as computer files. From this information, some identification studies have been done in terms of time-series [9], and a pre-conditioning of the data has been accomplished.

The mentioned institution (CEHIPAR) can also provide with simulated data, generated by the program PRECAL, which uses a geometrical model of the ship to predict her dynamic behaviour. With this program, a complete set of data tables have been generated, reproducing the same conditions of the experiments with regular waves. The data generated by PRECAL can be displayed as Bode diagrams, representing the frequency response of the ship. Figures 1 and 2 show the Bode diagrams for heaving and pitching motions, at 30 knots.

From the Bode diagrams, and reasoning about the physics of the ship motions, some clues and criteria can be extracted for modelling in the form of transfer functions. For instance, at low frequencies the transfer function of heaving must have unity gain, $\left|G(jw)\right|_{w\to 0} = 1$

and the transfer function of pitching must have zero gain and a phase of 90 º: $\left|G(jw)\right|_{w\to 0} = 0$ $\quad \left|G(jw()\right. = 90^{o}$

Modelling with the Help of Genetic Algorithms.

Starting from the acquired experience, and from the study of experimental data, the following general expression of the transfer functions of heaving and pitching can be written:

$$G(s) = \frac{Heave(s)}{Wave(s)} = \frac{k\cdot(s^2 + s\cdot p_o + p_1)(s^2 + s\cdot p_2 + p_3).......}{(s+p_4)\cdot(s^2 + s\cdot p_5 + p_6)\cdot(s^2 + s\cdot p_7 + p_8).......} = \frac{k_1.s^m + k_2.s^{m-1} + k_3.s^{m-3} + ... + k_{m+1}}{r_1.s^n + r_2.s^{n-1} + r_3.s^{n-3} + ...r_{n+1}}$$

$$G(s) = \frac{Pitch(s)}{Wave(s)} = \frac{k\cdot s.(s^2 + s\cdot p_o + p_1)(s^2 + s\cdot p_2 + p_3)......}{(s+p_4)\cdot(s^2 + s\cdot p_5 + p_6)\cdot(s^2 + s\cdot p_7 + p_8).......} = \frac{k_1.s^m + k_2.s^{m-1} + k_3.s^{m-2} + ... + k_{m+1}.s}{r_1.s^n + r_2.s^{n-1} + r_3.s^{n-2} + ... + r_{n+1}}$$

These transfer functions must agree, as much as possible, with the experimental data (the Bode diagrams). Our problem is to determine the best combination of m and n, and the values of the numerator and denominator coefficients, for such purpose. To measure how good is the agreement, the following adjustment criterion is defined:

$$J_{Real} = \sum_{i=2}^{n}\left(Real_{Data} - Real_{Model}\right)^2 \qquad J_{Imag} = \sum_{i=2}^{n}\left(Imag_{Data} - Imag_{Model}\right)^2 \qquad J_1 = J_{Real} + J_{Imag} \qquad J = \frac{100}{J_1}$$

The data of the Bode diagrams are complex numbers. After adding squared errors, the above equations get a final value J: the higher J, the better the adjustment.

At this point, our main idea is to define a set of combinations of m and n values, and apply genetic algorithms for each combination to determine the value of the numerator and denominator coefficients that gets the best J. This idea has been implemented in two stages: first an exploration of value ranges for the coefficients (here to have some clues from physics are important), and second a complete study getting the best J for each valid combination of m and n, with m and n taking values from 2 to 7 (always m <= n).

Specifications of the Genetic Algorithm.

There are many books and articles explaining genetic algorithms. For instance [10,11]. A very important application field where genetic algorithms prove to be useful, is optimisation. In particular, the adjustment problem (between model and experimental data) is an optimisation problem.

The key for the application of genetic algorithms to a problem, is to be able to represent the problem in terms of chromosomes and a fitting function. In our case, the fitting function will be the J of the adjustment. Regarding to chromosomes, one of the important features of genetic algorithms is that they allow to incorporate the knowledge of the problem to the code. We take advantage of that in our codification. Instead of looking directly for the values of the numerator and denominator coefficients, we will look for their roots, in order to reduce the searching space. The coefficients can have values belonging to [-∞,+∞], but, as we know the plant is stable, the value of the denominator roots must belong to [-∞, 0], so we have eliminated a half of the searching space. Moreover, since the module of the roots must be of the same order than the maximum pulsation of encounter, the range of values must be inside [-4,0]. With that, we have delimited a reasonable searching space. Similar reasoning can be applied to the numerator roots, with the only difference that they can be positive.

Suppose that the combination m=4, n=5, has been selected. In that case, we have to find the roots of the following functions:

$$(s^2 + p_0\,s + p_1)(s^2 + p_2\,s + p_3) \qquad \text{in } [-4,4]$$
$$(s + p_4),\ (s^2 + p_5\,s + p_6),\ \text{and}\ (s^2 + p_7 s + p_8) \qquad \text{in } [-4,0]$$

The roots of these polynomials are complex numbers. We will denote them as z_1+z_2j, z_3+z_4j,d_1+d_2j,d_3+d_4j, and d_5+d_6j respectively. An individual will be represented by a chromosome with 10 genes, as follows:

$$[z_1\ z_2\ z_3\ z_4\ d_1\ \ d_2\ \ d_3\ d_4\ \ d_5\ d_6\ ]$$

A direct codification by integer numbers has been chosen, to improve implementation performance. Thus, for a precision equal to 0.001, the alphabet is Ω = [-4000,4000], where 4000 represents 4.000, 3999 represents 3.999, and so on. For instance, if we have a solution represented by the following individual:

[243 –1325 1019 –2681 2386 0 –2912 –1283 –601] the roots of the numerator and denominator are: 2.43±1.325j, 1.019±2.681j, 2.386±0j,-2.419±2962j, and 1.283±601j, and the model represented by the chromosome is:

$$G(s)=\frac{(s^2-0.486\cdot s+1.8147)(s^2-2.038\cdot s+8.2261)}{(s+2.386)(s^2+4.838\cdot s+14.3313)(s^2+2.565\cdot s+2.0073)}$$

Taking advantage of our previous experience with genetic algorithms, the specification of the genetic operators has been the following: probability of mutation: 0.008; probability of crossover: 0.8; initial population: 10 individuals; parent selection by roulette-wheel, 4 substitutions/generation.

Each evolution encompass 10000 generations, along 40 epochs. A superindividual is created, by local optimisation, at the end of each epoch.

Results.

The following table shows part of the results obtained for heaving and pitching. For instance, the entry w3p1416 means 30 knots, pitching, 1 real zero, 4 complex zeroes, 1 real pole, 6 complex poles. Each case (entry) included in the table means a study with genetic algorithms, repeating five times a complete evolution of 10000 generations.

Model	Zeroes	Poles	J
w2h0406	(0.562 ± 1559j) (-1.086 ± 0.045j)	(-0.384 ± 0.556j) (-2.797 ± 0.706j) (-0.368 ± 1.085j)	7033.31
w3h0406	(0.732 ± 2.026j) (-0.636 ± 2.959j)	(-3.032 ± 3.977j) (-0.489 ± 0.855j) (-0.286 ± 1.514j)	6202.35
w2p1214	(2.048 ± 0j) (0.482 ± 1.824j)	(-4.784 ± 0j) (-0.256 ± 1.360j) (-0.347 ± 0.817j)	1008.93
w3p1416	(4.01 ± 0j) (-0.704 ± 3.023j) (1.029 ± 3.018j)	(-6.009 ± 0j) (-0.276 ± 1.708j) (-0.582 ± 1.202j) (-3.465 ± -0.145j)	2090.48

From the results obtained, the best transfer functions can be selected for 20, 30 and 40 knots. For instance, at 30 knots, the best models are the following:

$$G(s)=\frac{Heave(s)}{Wave(s)}=\frac{16.52s^5+7.518s^4+75.75s^3+95.37s^2+0.466s+301}{s^6+23.27s^5+163.1s^4+353.6s^3+605s^2+543s+301}$$

$$G(s)=\frac{Pitch(s)}{Wave(s)}=\frac{s^6-4.148s^5+11.89s^4-48.22s^3+60.17s^2-192s}{s^7+13.11s^6+60.09s^5+159.9s^4+282.1s^3+374.9s^2+284.2s+162.3}$$

Figures 1 and 2 show how good is the agreement between data and models .

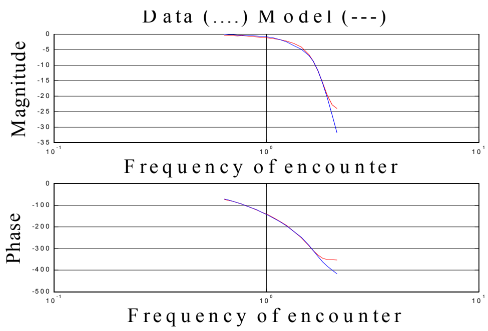

Figure 1: Adjust of heaving at 30 knots

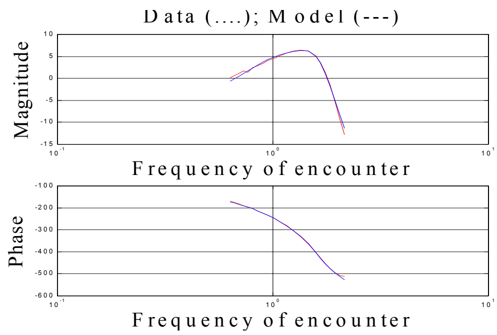

Figure 2: Adjust of Pitching at 30 knots

Once the best models have been found, we can validate them by a comparison between the motions measured by CEHIPAR with the replica, and the motions predicted by the model. Figures 3 and 4 show the results at 30 knots for regular waves. Figures 5 and 6 for irregular waves, also at 30 knots.

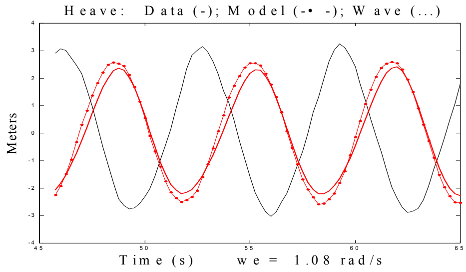

Figure 3: Validation of Heaving with Regular Waves

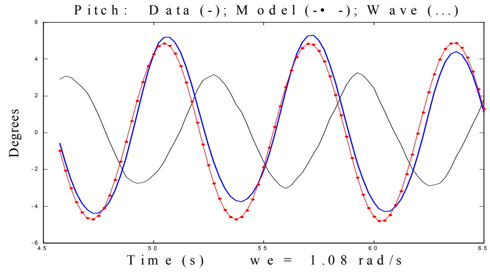

Figure 4: Validation of Pitching with Regular Waves

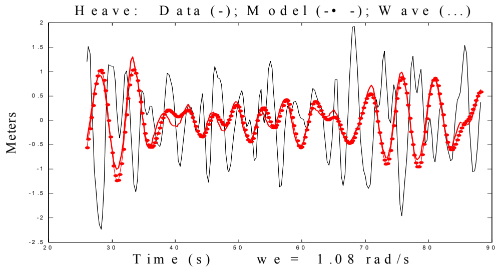

Figure 5: Validation of Heaving with Irregular Waves

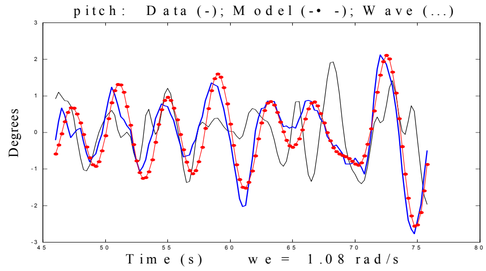

Figure 6: Validation of Pitching with Irregular Waves

Conclusions.

This paper dealt with the modelling, for control purposes, of the vertical motions of a fast ferry. The study started with an extensive experimental work, to obtain relevant data.

By means of genetic algorithms, a large set of candidate models have been explored. The results allow us to select good models for heaving and pitching motions at 20, 30 and 40 knots, with heading seas. The transfer functions obtained are more complicated than the simplifications published in the scientific literature (for conventional ships). Since the set of evolutions is large, the genetic algorithm has been parallelized [12] for calculation speed up. We think the method established is conceptually simple, and that can be easily applied to other modelling problems. In the future, we plan to model other sea conditions (not only heading waves) and other motions of the ship.

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