XVI IMEKO World Congress
Measurement - Supports Science - Improves Technology - Protects Environment ... and Provides Employment - Now and in the Future
Vienna, AUSTRIA, 2000, September 25-28

STUDENT-CENTRED COURSE ON DYNAMIC STATE ESTIMATION

F. van der Heijden, Z. Houkes and P.P.L. Regtien

Laboratory for Measurement and Instrumentation
Department of Electrical Engineering
University of Twente, NL-7500 AE, The Netherlands

Abstract: The design of a course on optimal dynamic state estimation is described. The accent of the course is on practical issues: How to design a well-functioning state estimator in a practical situation where we have to deal with uncertainties about the model that describes the physical process and the sensory system, and without having groundtruth data? The adjective "student-centred" refers to a number of characteristics of the course: students will have an active role, they are faced to real world problems that they have to solve, they are stimulated to work together, etc. The paper finalises with some experiences that have been gained with this type of education.

Keywords: problem based learning, ICT, dynamic state estimation, Kalman filtering, optimal estimation

1 INTRODUCTION

The 120h-course on "optimal dynamic state estimation" at the University of Twente is attended by 4th year-students from the departments of electrical engineering and mechanical engineering. The central subject of this (optional) course is estimation "how to measure the dynamic quantities in a physical process given the data from a sensory system?" [1]. Although the course contains a theoretical component, there is no accent on rigorous proofs of theorems and statements. Instead, the course emphasises on a number of practical issues: potential problems that an engineer is likely to meet during the implementation phase of his design. The goal setting is that students (after finalising the course) are able:

- to implement (sub)optimal estimators for dynamic systems with a given state space model. This includes the time-variant, nonlinear case.
- to perform "consistency checks" in order to find out whether the design really performs well, not only theoretically, but also in the real world.
- to adapt the design such that possible malfunctioning (due to modelling errors) are overcome.
- to formulate and discuss their ideas so as to be able to communicate with others about their design.

A traditional educational program consisting of lectures, a book and a written or oral exam is not adequate for the goals of this course. The main disadvantage is that students will have trouble in applying what they have learned in actual practice. In order to circumvent this kind of drawbacks, the course at the University of Twente is based on a so-called "student-centred" approach rather than the traditional "teacher-centred" approach.

2 STUDENT CENTRED APPROACH

In order to achieve the goals mentioned above it was decided that the course should have the following characteristics:

- The acquisition of knowledge must be such that it is better retained, and be more easily applied to practice.
- Students will have a more active role.
- Students will be faced up to realistic problems, i.e. to problems in a real physical process. Thereby, they are confronted with all kinds of complications that usually are not dealt with (and perhaps not even noticed) in pure theory lessons, or in courses working with simulations.
- The process of problem analysis, goal setting, theory application and problem solving is stimulated.
- The problems are selected such that the full subject matter of the course is covered.
- The purpose of the tutoring activities is twofold: instruction and (immediate) feedback. The purpose of the instructions is to prevent the students from wasting too much time (for instance, if they cling

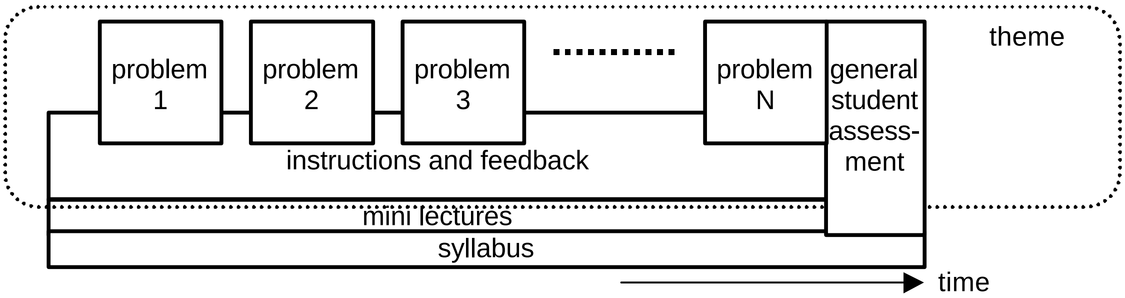

Figure 1. The structure of the course. (One problem takes about 10 student hours)

too much to a wrong idea). However, most of the feedback given to the students is on demand (i.e. for a great part individually and student driven).
- Students are encouraged to work together in small groups.
- Within a group, there may be individual differentiation, notwithstanding the fact that all members of the group have the full responsibility of any part of the work.

Most of these characteristics are also seen in so-called "problem based learning" (PBL) [2]. However, PBL is often interdisciplinary. Another distinction is that in PBL the amount of instructions by a tutor is minimised. The students themselves formulate the learning objectives. The role of the tutor is mainly to encourage the students to work systematically. Because of the time constraints of the course (120-hour) a pure PBL program is not feasible in our case.

Some of the characteristics are related to project oriented education (POE). However, POE is complementary to other program parts (e.g. traditional education). A group of students is confronted with one big task, which not necessarily covers the whole program. Within POE there will be a strong task division between students. At the end there will be a group assessment instead of an individual one.

Figure 1 shows the structure of the course. The lectures are meant to reveal the connecting lines, and to give access to the relevant literature. They are not essential for the course. The syllabus is a guide containing an overview of the full subject matter, and pointers to the literature. There are a number of problems that are all part of a central theme: the physical process and sensor system under consideration. A number of problems are obligatorily because they cover the essential parts of the course. The other problems are voluntarily, depending on the time left and the interests of the students. Each problem is introduced by some instructions. The students have to work out the problem: problem analysis, goal setting, theory application and problem solving. Their findings are laid down in a concise (group) report. Feedback to the students is offered in two ways: on demand and based on the reports. The final assessment takes place by means of an oral exam in which the whole group is involved, but where each individual member can be asked questions related to the work of the group.

a) b)

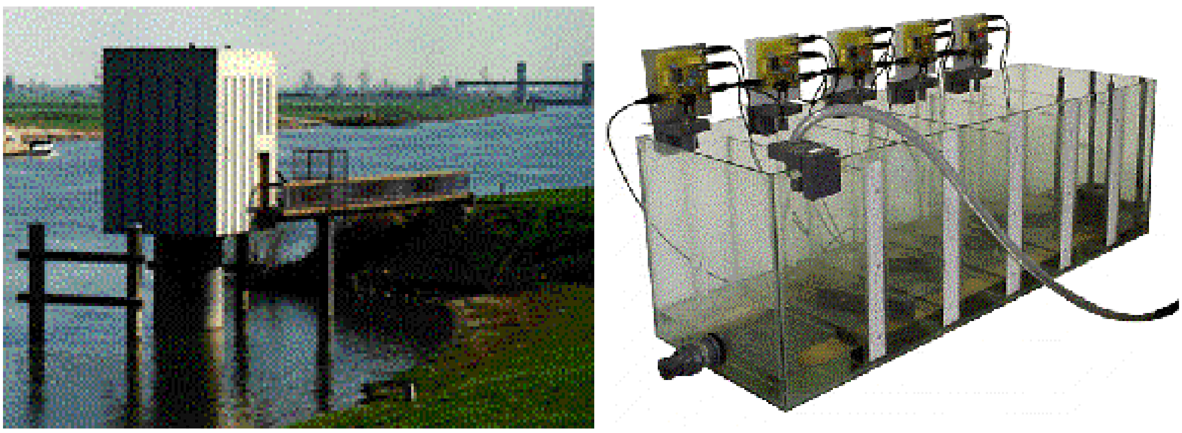

Figure 2. Water management in riverbeds.
a) a site of a water management system. b) a lumped model of a riverbed with level sensors

3 THE THEME: ESTIMATION OF WATER LEVELS IN A RIVER BED

The theme that is selected in the course is a water management system. The estimation of water levels in a riverbed is of great importance for shipping, for reasons of safety, and for level control. The question addressed here is as follows. Suppose that at a few sites in a river bed the water levels are monitored continuously with level sensors. See Figure 2a. How can we estimate the water levels elsewhere in the river? How can we predict them? What will be the accuracy?

The water management in a riverbed is too complex to be dealt with in a short course. Therefore, we consider the same physical process but in a simplified setting. Yet, it retains the most important features of the problem. The simplified process consists of a series of lumped elements: a hydraulic system consisting of compartments connected by small holes. See Figure 2b. There is a continuous, random flow of water generated in the leftmost compartment. Furthermore, there are some level sensors available. The whole physical process is modelled with a time-discrete, nonlinear state equation driven by process noise. The sensor system is linearly modelled with additive Gaussian white noise. However, the physical process shows some phenomena that are hard to model (e.g. turbulence and other fluid dynamical phenomena; hysteresis of the sensors, thermal offset and gain, etc.)

4 THE CHARACTERISTICS OF THE PROBLEMS

The problems are designed so as to match the real world situation that an engineer is likely to go through when he is faced to the task of designing a measurement system. This situation is characterised by a number of uncertainties the engineer has to deal with:

- There is no accurate mathematical model (state equation) that fully describes all the phenomena of the physical process. Only idealised models are available. These models ignore a number of phenomena. Since the system parameters of these models can only be estimated (as part of the design phase), they are only known with limited accuracy. The extension of models in order to incorporate more physical phenomena leads to more system parameters and more state variables. Consequently, the more complex a model becomes, the more likely it will be that the design is too sensitive to small uncertainties in system parameters.
- The sensors are non-ideal. Their specifications are given, but often only vaguely, and often not completely.
- Due to the uncertainties about the mathematical model and the sensors there will always be a need to check the proper working of a state estimator. Unfortunately, in a real world situation the evaluation of the design is often hampered by a lack of the groundtruth.

A successful design of a state estimator must be based on parsimonious and yet adequate models of the physical process and the sensors. These models should lead to a well-established trade-off between the usage of model-driven knowledge (the prediction stage in a Kalman filter) and the usage of sensor-driven knowledge (the update stage). The uncertainties about the model, the sensors, and the groundtruth raise the need of so-called “consistency checks”. One such a check is for instance the chi-square distribution test of the NIS (normalised innovation squared). This is a check that can be performed without the availability of the groundtruth.

The series of problems presented in the course starts with a simple, linearised model of the physical process and the sensory system. The application of the corresponding Kalman filter to a record of observed sensordata and the application of a consistency check will unmistakably show that such a design is not consistent, i.e. far from optimal. In consecutive problems various adaptations of the model are hypothesised, and it is checked to see whether such an adaptation leads to more consistent designs. The models that are considered are:

- a linearised Kalman filter assuming white system and measurement noise.
- a linearised Kalman filter assuming white system noise and coloured measurement noise.
- a first order, extended Kalman filtering with white system and measurement noise
- a first order, extended, adaptive Kalman filter.

As a preparation of this, students are first introduced to some related problems that provide them with the necessary background knowledge, i.e. estimation of expectations and covariances, chi-squared distribution test, linear mean square error estimation in the static case, etc.

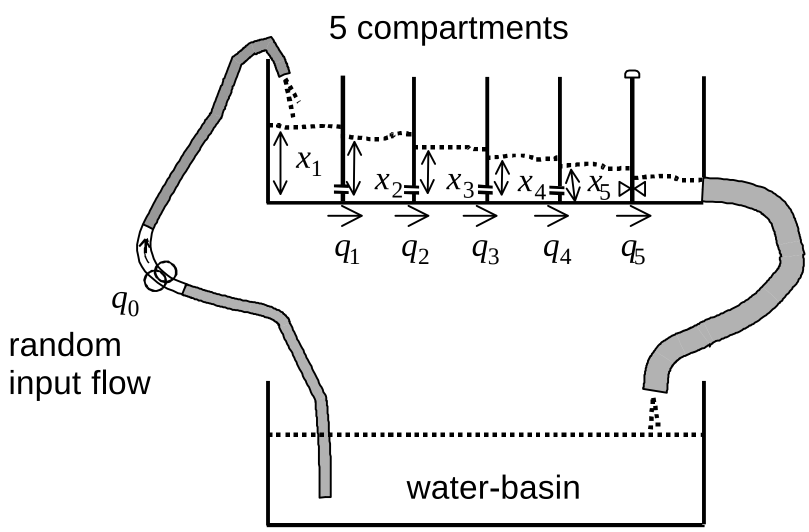

Figure 3: lumped model of the physical process

5 THE IMPLEMENTATION OF THE COURSE

A desirable feature of the course is that it is independent of time and place. This is obtained as follows:

- Students are not required to acquire the needed sensor data themselves. Instead, the data is logged in advance and available from file. Several runs are available. Since the emphasis is on the implementation of the design (and not on the realisation) students are allowed to use a simple software platform (such as MatLab or MathCad) that is available at many PCs and workstations.
- The application of ICT. A special website has been designed from where all relevant information can be read. The instructions and datafiles can be downloaded from here. In addition, possible errata and additional comments are published on this website. Students are encouraged to use their email facilities to contact the tutor. In the near future more sophisticated ICT tools for tele learning will be used, i.e. C@mpus+ and TeleTop [3].

6 AN EXAMPLE: ADAPTIVE KALMAN FILTERING

As an example, we discuss one of the problems the students have to solve. It is the last problem of the series. As such, it is not compulsory. Nevertheless, a considerable percentage of students voluntarily choose to solve this problem.

In one of the preceding problems the students have designed a first order, extended Kalman filter. The design is based on a nonlinear state equation of order 6, and on the usage of two level sensors measuring the levels in the first and second compartment. The nonlinear state equation consists of the following ingredients (see figure 3):

- The flow q of water through a hole depends on the difference Δx between levels in the neighbouring compartments. The law of Torricelli is the simplest model describing this phenomenon: $q^2 = a|\Delta x|$. The parameter a is a proportionality constant that depends on the area of the hole and the density of water.
- The buffering of water in a compartment is modelled by a linear capacitance. The equation is transformed to the time discrete domain: $x(k+1) = x(k) + \Delta T\, q_{netto}(k)/C$. Here, $x(k)$ is the water level at the discrete time point k. ΔT is the sampling period. C is the capacity, i.e. the area of the cross section of the compartment. $q_{net}(k)$ is the net flow inwards the compartment.
- The input flow of the first compartment is modelled by a first order autoregressive (AR) process: $q_0(k+1) = a + bq_0(k) + noise(k)$. b is the parameter of the AR process. a is a constant driving force of the process. $noise(k)$ is the random, zero-mean driving force.
- The system parameters of the equations above are available from an estimation procedure.
- The level sensors measure the pressure at the bottom of the compartments. The sensors are provided with the following specifications.
  - measurement range: from 0 to about $250\,\mathrm{mm}$
  - nonlinearity: max. $1\,\mathrm{mm}$ over the full range

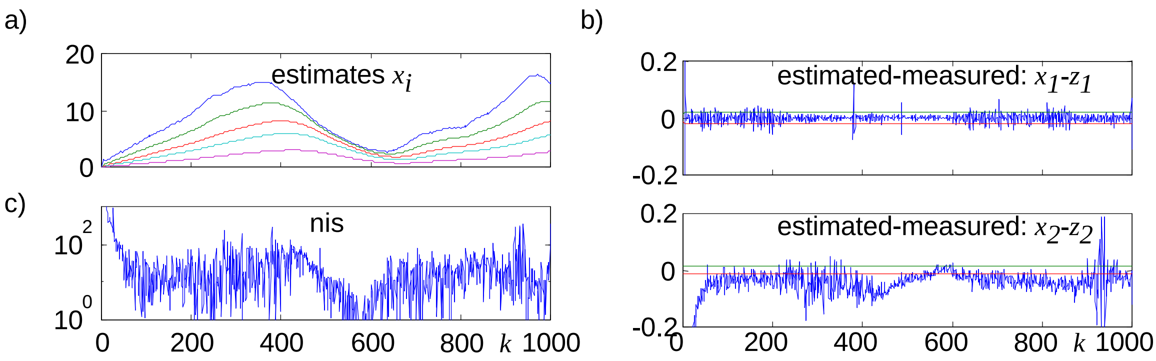

Figure 4. Results of the first order, extended Kalman filter:
- a) the estimated states for the five compartments
- b) the estimated states minus the measured states for the first two compartments
- c) the normalised innovations squared (NIS)

- temperature drift: max 1 mm/°C
- instability: max 1 mm
- The covariance matrix of the noise is estimated from a registration of measurement data obtained with zero input flow.

Figure 4 shows the result of the corresponding extended Kalman filter applied to a registration of measurement data of the process. The NIS is a statistic that is derived from the innovations of the Kalman filter. It can be derived that in any optimal design, the NIS has a chi-square distribution with (in this case) two degrees of freedom. Consequently, if the design is optimal about 95% of the time samples of the NIS should be less than 6. This is obviously not the case, and we conclude that the extended Kalman filter is far from optimal. The same conclusion can be drawn if we examine the difference between the estimated states and the directly measured states and compare these differences with their 1-sigma boundaries (figure 4b). Of course, this can only be done for the states that are sensed directly (i.e. the levels in the first and second compartments). Particularly, the level in the second compartment is not consistent with the indicated 1-sigma boundaries.

One of the reasons that the optimality of a state estimator fails might be that its design is based on inaccurate or even wrong system parameters. In our case, especially the a parameter of the hole in the fourth to fifth compartment is suspicious. In fact, there is valve mounted inside this hole. In normal operation, this valve is fully opened. (The valve has been placed for experiments that do not concern

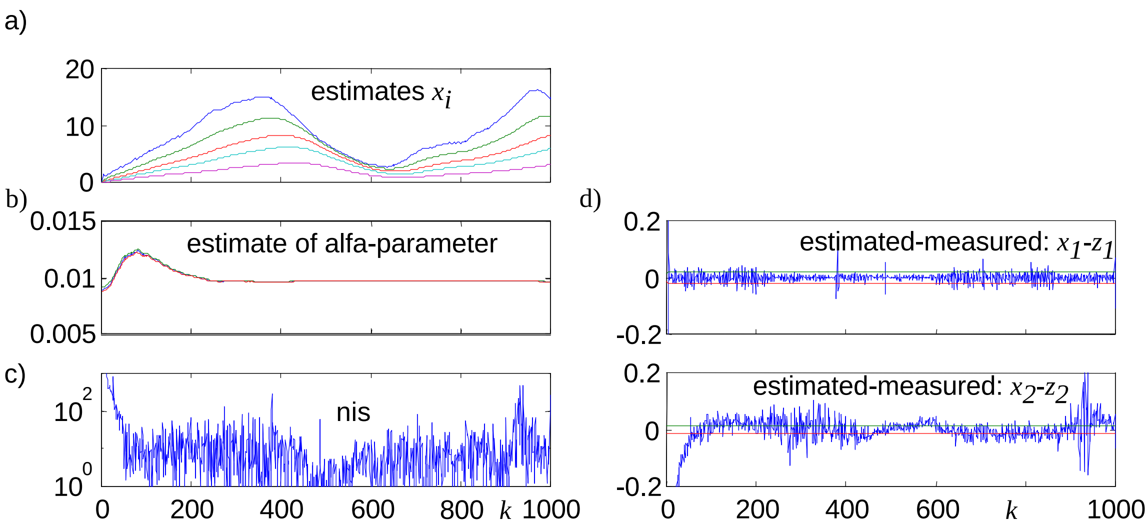

Figure 5. Results of the first order, extended, adaptive Kalman filter:
- a) the estimated states
- b) the estimated system parameter
- c) the normalised innovations squared (NIS)
- d) the estimated states minus the measured states for the first two compartments

the work here). However, in the "opened" state the valve is not fully stable. Consequently, from run to run the value of the corresponding a parameter does not reproduce.

Such a situation can be dealt with by augmenting the state vector with one extra state variable: the corresponding a parameter that now becomes time variant, i.e. $a(k)$. There are various models that might be appropriate to describe the uncertainty in $a(k)$:

- random constant: $a(k+1) = a(k)$
- slowly varying around a mean: $a(k+1) = m + ga(k) + noise(k)$ with $0 < g \leq 1$
- drifting constant: $a(k+1) = a(k) + noise(k)$

In the first model, the uncertainty is established in the initial condition of the equation, i.e. by means of the expectation and variance of $a(0)$. The uncertainty of $a(k)$ will continuously decrease as time proceeds. In the second and third model there is an additional source of uncertainty by means of the term $noise(k)$. This term will maintain the uncertainty to some degree as time goes by.

With the additional equation for $a(k)$ we have a (strong) nonlinear state equation the order of which is 7. Application of the first order, extended Kalman filter gives results as shown in figure 5. Here, $a(k)$ is modelled as a random constant. After a short transient, the estimate of $a(k)$ stabilises. The uncertainty (depicted by the 1-sigma boundaries in figure 5b) converges fast to zero. The differences between estimated states and directly sensed states are now in accordance with the 1-sigma boundaries (figure 5d). The NIS in figure 5c is about a factor 4 smaller than in figure 4c (note that the scale is logarithmic). Nevertheless, about 50% of the samples are above the 95% percentile of a chi-square distribution with two degrees of freedom.

This problem shows students that the adaptation of the parameter may significantly improve the performance of a state estimator, but this still does not guarantee optimality.

7 SOME RESULTS AND CONCLUSIONS

In the form as described above, the course is available now for one year. The experiences that have been gained so far are as follows:

- Most students that have attended the course are content. They have the feeling that they have learned something useful.
- The students tend to spend more time than the available 120 hours. At the same time, most students voluntarily choose to work on those problems that are not obligatory. A small part of the students (about 15%) stops attending the course untimely because they feel the load is too heavy.
- Because of the above, the remaining population (85%) tends to finalise the course with high marks.
- The design of the course, but also the maintenance of it is laborious.

The conclusion is that the goals of the course seem to be reached. However, there should be special attention in order to prevent students to spend too much time.

REFERENCES

[1] Y. Bar-Shalom, Xiao-Rong Li: Estimation and Tracking – Principles, Techniques, Artech House, Boston, 1993.
[2] H. G. Schmidt and 7.H. C. Moust: Probleemgestuurd Onderwijs - Praktijk en Theorie (in Dutch; translated to English: Problem Based Education – Practice and Theory), Wolters-Noordhoff, Hoger Onderwijs Reeks, Groningen, 1998.
[3] http://teletop.edte.utwente.nl/

AUTHORS: F. van der Heijden, Z. Houkes and P.P.L. Regtien, Laboratory for Measurement and Instrumentation, Dept. of Electrical Engineering, University of Twente, NL-7500 AE, The Netherlands