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SCUOLA DI INGEGNERIA INDUSTRIALE E DELL'INFORMAZIONE

Executive Summary of the Thesis

Combined grey- and black-box models with problem-tailored authority distribution

Laurea Magistrale in Automation and Control Engineering - Ingegneria dell'Automazione

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1. Introduction

In the process of setting up a control system and assessing its behaviour via analysis and simulation, several models of the controlled object may come into play. Some of these are based on the laws of physics, and we name these *first principle*; others come from prying correlations out of measured inputs and outputs, and – neglecting some *nuances* inessential at this point – we denote these as *data based*.
Besides the above partition, a parallel one is relevant. In any application of engineering interest, first principle models contain parameters for which only nominal or design values are known, and this is particularly true when those parameters in fact pertain to a somehow simplified version of the encountered physics — such as when, to obtain a compact model, a very coarse spatial discretization is applied to some distributed-parameter phenomenon. In such cases, identification techniques need applying in order to obtain values for the above parameters, either from physical I/O data or from data generated by simulating a complex model. Given the mixture of physics and data we name these *grey box* models, as opposite to *black box* ones, where no attempt is made to tie the model structure to any physics, and on the contrary the said structure itself is often selected on the basis of the identification data.
This thesis aims for initiating a wider research, targeted to combining grey and black-box models so that either of the two has the most appropriate amount of authority according to the purpose of the compound model and to the available (design and/or I/O) data. The ultimate purpose is to use the so obtained compound models for control design and assessment, and as such, the research is geared toward the technological aspect of the addressed matter.

2. Research question

The idea of joining grey and black box modelling, quite intuitively, is not new [9][11][14][1][6][5][13][8]. As such, we briefly outline the peculiarities of our research with respect to the vast literature already available on the subject, thereby also formulating the particular research question of this thesis.
First, as testified by many works such [12][10][4][3][2], a significant problem is how to distribute authority between the grey and the

black box part of the compound model. We attempt to circumvent this problem by a crisp separation between the parametrization of the former and the identification of the latter (note the two different terms used).
Second, and somehow consequent to the above, we aim for model combination techniques that are totally agnostic about the origin of the grey box part. This allows for example to employ both first principle models in the strict sense of the term, and models of structure dictated by the observed process dynamics but not constrained to abide by tightly to any conservation law. The reason for this is to permit the use of models conceived for controller (auto)tuning, which besides widening the applicability of our proposal, paves the way to using the black box part of the compound model as a "fake uncertainty" source and help exploit robust control techniques in the tuning domain — a long debated issue in the field of industrial controllers [7].
The above said, the purpose of this thesis is to

- outline the procedure we envisage for combining a grey and a black box model,
- provide and analyse examples with different kinds of grey box models,
- employing the above as proof of concept material, discuss the viability of our proposal and outline the sequel of the research.

3. Procedure outline

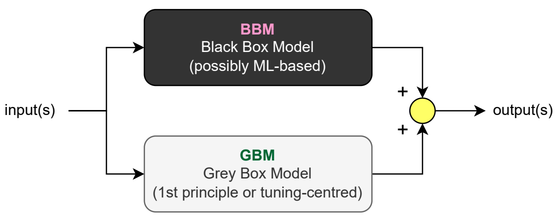

Figure 1: Compound of a grey box and a black box model.

The grey and black box model compound we consider is depicted in Figure 1, and the assumptions we make throughout the thesis can be summarised as follows.
First, GBM is either a "simplified physics" model, or a model geared to controller tuning. In the first case it will be in general nonlinear, and contain parameters with a clear physical meaning but not a direct relationship with the construction of the modelled object. For example, a parameter can be a heat capacity but not correspond to that of any particular component, being rather interpreted as contributing to the inertia of a certain temperature; such a parameter can of course be obtained by suitably combining/averaging strictly physical ones, and this exemplifies the role of grey box parametrization when applied to GBM. In the second case GBM will be generally linear, as this is preferred for controller tuning, and of structure chosen by taking an even more abstracted viewpoint on the observed dynamics. For example, it can be of a certain order because the corresponding number of major mass/energy storages are recognised; the parameters of such a model are typically obtained by simple experiments and fitting techniques, like the method of areas applied to a step response. In any case, to conclude, GBM is most frequently a continuous-time model, either because so is physics, or because so is required by the typical controller tuning rules.
Second, GBM is expected to not capture the entire behaviour of the modelled object for two basic reasons, namely structural mismatch with the real process (owing to simplified physics or *a priori* assumed structure) and imperfections in the parametrization procedure (owing to imperfections in data if these are real measurements, and in any case to numerical facts even if they come from simulations).
Third and most critical, the above mismatch in GBM produces a residual error that a BBM of sufficiently rich structure can effectively recover.
Given the above, our proposed procedure is articulated in the following steps.

1. Decide the structure of GBM with synthetic considerations as sketched above, that however are not the focus of this thesis as they stem primarily from knowledge of the object to control.
2. Perform experiments and get data to parametrise GBM. As these experiments can be simulated but also physical when possible/convenient, apply here only *stimuli* that could be actually used on the real object.
3. Parametrise GBM with the fitting/optimisation technique of choice, check the consistency of physical parameters wherever this applies, and obtain the

residual error by comparing the output of GBM to data.

4. Employ the said residual as the desired output to identify BBM, applying here structure and order selection techniques freely as this model is not bound to any physics-originated constraint.

Doing so, we expect that the authority left to BBM comes naturally from how much of the data GBM could not explain. We expect as a consequence that, with respect to the mainstream tendency to identify the two jointly, the authority of BBM decreases if the fidelity of GBM is increased. All in all, therefore, we argue that operating as we propose could lead to an effective use of modern techniques like machine learning, in that they come to target only what physical intuition could not explain.

4. Application and results

We applied the proposed procedure in some cases we deem representative of relevant *scenarii*, described below.

- A distributed-parameter thermal system where the simplified model is a first-order with delay one parametrised with the method of areas and a more detailed implementation involving the addition of a polynomial function to describe the static input-output characteristic.
- The same thermodynamic application where the simplified system is composed of differential equations describing the evolution of temperature as a function of time. The parameters of the GBM model were identified through the Trust-Region-Reflective optimisation algorithm.
- An RC electrical system consisting of nonlinear resistors and linear capacitors parameterized by polynomial curve fitting algorithm.

Therefore the methodology has been applied two case studies with different characteristics in the time and frequency domains in order to provide a complete picture, also analysing borderline cases in which the implementation of a black box model with high acquired authority can lead to disadvantages in the replication of a real process as it introduces spurious correlations (not physically explainable). More deeply, we will observe that in the first example (thermodynamic case study) the implementation of a more or less complex grey box model will be able to identify the main heat transfer dynamics and the addition of an ARX model will allow to mimic the residual dynamics always improving the fit of the overall model with respect to the real system. The variable that will most affect the accuracy of the overall model is the complexity assigned to the grey box model. In other words, the complexity of a grey box model used to tune a controller will give a worse contribution to the combined model than a more complex model used to accurately simulate the case study.

In the second example (electrical case study) the conclusions obtained in the first example are valid but the study of the above application will allow to validate the approach also on a process that shows a different behaviour in the frequency domain compared to the first case study. The applicability of the proposed procedure in two different areas with different characteristics enhances its possible generalisability. Detailed results can be found in the thesis but here we report just a sample for the convenience of the reader (Fig.2 and Fig.3).

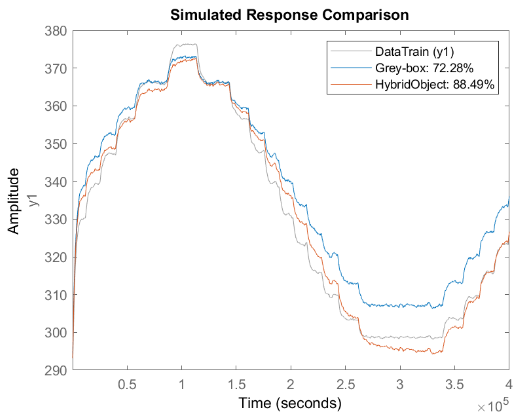

Figure 2: Time response comparison of the first case study

5. Conclusions

The advantage of our proposed procedure is its extreme versatility and its ability to combine the merits of a first-principle model with an data-based one. The flexibility translates into the possibility of implementing a combined structure of the two models which can fulfil the needs of both synthesising a controller and detailed simulation based on the authority im-

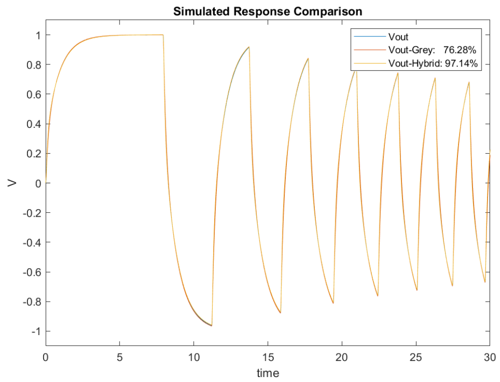

Figure 3: Time response comparison of the second case study

posed/acquired by the two structures respectively. On the one hand the implementation of a physics-based model guarantees interpretability and generalisability of the identified model; on the other hand the inclusion of a black box model ensures accuracy by identifying both dynamics that are too complex to depict in a deterministic manner and stochastic relationships among the data. Future work will behaved at identify possible classes of models that allows for a formal analysis to corroborate their conclusion here throw from case studies.

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