CH5230: System Identification

Motivation and Overview 1

A very good morning. Welcome to the course on system identification. This course is an elective and it's titled a system identification unfortunately not many really understand the meaning of the course straight away. Even when I enrolled this course way back about 20 years ago during my PhD. It was difficult for me to gauge really-- what this title means. But simple translation of this is nothing but Data Driven Modelling. That's it. So you're going to build-- it concerned with building models from input output data and the technical for that is system identification. There are people who believe that this course actually should be renamed as Data Driven Modelling. But we'll go with the technical term that's prevalent in the literature. What we'll do in this class is basically obtain an overview of what the subject is about and then briefly talk about the course. And if time permits, I'll talk about the course outline in the sense not only in terms of technical content, but also the mode of evaluation and so on.

If not really do it in the next class tomorrow. That's not an issue. But it's important to understand what the subject is about, especially for you because it's an elective and you can make a decision after this class, whether this course meets your expectations, or is this what you had imagined when you signed up for this course and so on. And that's therefore will begin our journey. So the subject or system identification as I had explained or just mentioned a few minutes ago is concerned with developing models from input output data. Now in the previous semester we had this course and apply time series analysis. The difference between for those of you who have taken time series analysis or those of you wanted to take and so I'm curious. The difference between time series analysis and system identification is pretty straight forward. In system identification, we are building models relating input and output. So the input can be thought of as a cause and output can be thought of as an effect. In time series as well we build models, but only based on the output. But what we mean by output here is a response of the system or the effect that you observe. And in time series analysis at least the univariate time series analysis. We assume that the causes are unknown. Even that's true partly Multivariate Time Series analysis. But the major difference between Time Series analysis and System Identification is that, in time series analysis, we do not-- either know the causes that drive the response or what we observed or we know and we cannot measure and there are many examples one can give. Whereas in System Identification, we do have the cause that means, we do have either in the form of a measurement or is a known signal, the cause of the input that is driving the response. So, it is closer therefore to engineering systems. Whereas Time Series analysis appeals to a wider community. It appeals to people in the field of economic trades, people in the field of neurosciences, finances, and so on where typically the causes are not known and when we say, not known it's not the knowledge itself, we do not have a measurement of the cause. That's what we mean by not known.

Whereas, the System Identification appeals to the engineering community because in the engineering field we do believe that whatever response we have is come-- is actually due to some calls, somebody is changing somethingand I can observe that physically and I can have a record of that, right. And there are numerous examples that one can give. We will go through three or four examples later on. And that is why if you see even in terms of enrolment in this course, it's much lower than what you see in Time Series analysis, at least probably an order of a difference. And generally people-- that the students who get into engineering decide on the first day that engineering is not for them. And gradually they're attracted towards finances because I think, working in a finance company gives them in good financial position. So and that's how they're attracted towards Time Series analysis and then the placement season comes in and so on. Where System Identification is more specific, so the subscriptions are low. Now historically, if you look at system identification that is this Data Driven modelling, it has come from Time Series analysis. The moment you say, that I know the cause as well, then you incorporate that into your modelling and that's how System Identification was born. But the theory that is required for System Identification, request some more-- even knowledge in additional fields, apart from Time Series analysis. There is significant overlap between the theory of-- or the principles of Time Series analysis and System Identification, but there are some additional concepts involved in system identification, particularly that of linear systems theory and so on, which, of course, we will spend considerable time on in this course. Okay, so that clarification I wanted to give to begin with. Now let's get back to what is System Identification. So if you look at the schematic that I show on the screen, you see there is a process, right? And then there is an input, which I've said, it can be thought of as a cause earlier, and then you have an output, which is a response of the process. So you have asked the process some question, you can think of the input as a question, I've asked some questions and the processes responding.

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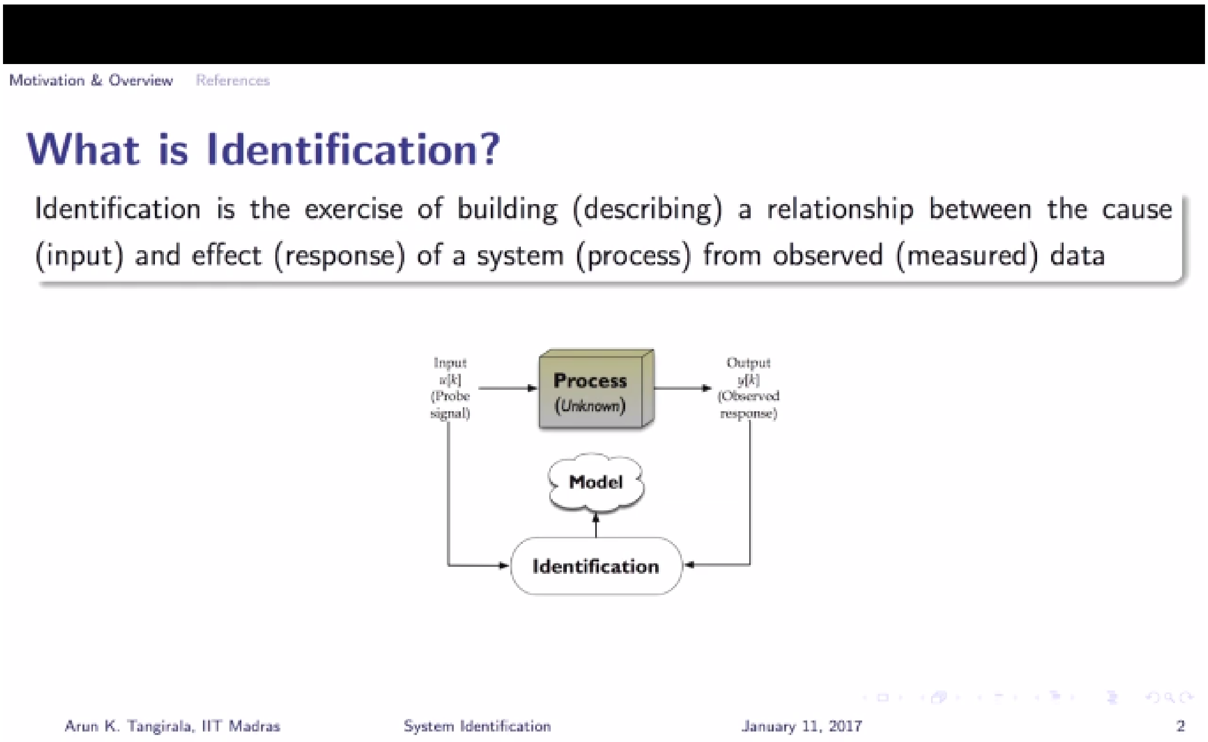

And now I want to build a mathematical model for this process using the input that I've given, which is in the form of numbers. So we'll assume throughout the course that we are dealing with numbers, we are not going to deal with categorical variables. Alright, so we're going to build quantitative models. So I have the record of the input that I've given, it could be in terms of, let us say, it could be a flow variable, I could be changing the flow or it could be pressure or it to be some other physical variable. And then I have the response again recorded through the data acquisition system. And I'm going to take both these data records and build a mathematical model. And how do I do that? So if you can see here the bottom, the input and output data records are fed to a block which is titled identification. And this course is all about what that block contains. Right? Mostly it's about that. So at the moment, you can think of this block titled identification, has some kind of algorithm, some kind of formula whatever pleases you, but some magic that eventually delivers a model for you. Okay. And as you can see, and as I always point out in my lectures on identification, that there is a reason why I have given a cloud like shape to this model, right? And let me see, if you're able to guess, why I have given a cloud like shape to this model. Why not rigid Kind of shape like, I have for a process? Sorry? Okay. So you believe that lack of uniqueness that they have many solutions and therefore, there is no-- there is some fluidity to this. Okay. Not bad.Uncertainty? Okay. That's also not bad. Any other? Good, so these are some good answers. The line of thinking is good. Any other thoughts on why cloud like shape? One more guess? Okay. So why should it be a cloud?

UNKNOWN: Because it does not give you exactly results the process will eventually because it means, it's going to think about--

That's a fact. That's correct. Sorry. It can change as you get more and so it's again there's some fluidity to this model. All your observations are correct, but need not be the reason for the cloud like shape. So if you're used to reading comics, right, like, you know, Tinkle, whatever favourite comic that you take.When a person is imagining, you know, there is a cloud like, shape this, as there are-- if you look at the shape that are drawn in this comics,for imaginations, you use this cloud like shapes. The model is also an imagination. It's a mathematical abstraction of how you think the processes evolving, what's underneath this block called process, right? It's just a mathematical imagination.At any-- no time in future or in past and present the process will come and speak to you and say, yes, you are,right, this is a differential equation which I'm obeying.It has never spoken to us and it will never speak to us. It's an inanimate thing. It's only our mathematical imagination that we want to go with it. And the technical term for that is abstraction. It is-- this model is, after all, only a mathematical abstraction of the processand as you have rightly pointed out in identification, and even in general, in modelling, you can-- there is some fluidity to the model. In particularly, in Data Driven Modelling,there's a lot of flexibility.The model can be this or that and so on. And that is what you're going to face and realized in this course, that there is not a unique answer. When I give you a data record, you may come up with a model, your friend may come up with some other model. Now, you have to figure out why if you've chosen a particular model? Why you are chosen this model-- that model.And you have to give a sound reasoning to it. It's not that okay, today's, Tuesday, therefore, I'll stick to this model or something like that. It cannot be done. There is flexibility,but then along with that flexibility comes with freedom and then responsibility as well. So the bottom line is-- that model is a mathematical abstraction. And it's only an imagination.And even more kind of an imagination in System Identification.As he's in first principles models also you develop mathematical models, they are also mathematical abstractions. But in System Identification, there is an additional layer of-- you can say abstraction, which gives rise to some obesity or a lot of obesity. In fact, these models that you develop are called Black Box models, okay. Why these are called Black Box models is because when I look at the final equation that I have fit to the data, the equation may not tell you anything about the physics of the process. By looking at the equation you can say, yeah, I know. You cannot say that I know, this is the thermodynamic phenomenon that's happening or this is the mechanical phenomenon that's taking place or you can't even infer physical properties and so on. So that's just a model. It's a working model, it does a good job of what it was designed for, which is prediction. Another for most purposes of a model is prediction.As long as it predicts well, you are happy. That is a typical model that you develop in System Identification that is a Black Box Model. Now, on the other hand, you also have this line of approach in System Identification,where you develop what are known as Grey Box Models.Where you want the model to tell you something about the physics or the process or to-- you want the model to look closer to what a first principles model would look like for example, or you want the model to tell you something about what's happening in the process, by looking at the coefficients you should be able to directly infer some properties of the process and so on. So you are going to impose a prior structure on the model, you know something a priori and you want to incorporate that into your model. And the model that is born out of such an exercise is called Grey Box Model.In the shade of greyness depends on the amount of prior information that you pump in. And that will talk about towards the end of the course. By enlarge, we will focus on Black Box Models. Okay.So, now that we have some idea of what is identification, a very simplistic viewpoint, that's enough to get started. We will zoom into that schematic very soon and then learn more details. The next question is, why should I get into this business of modelling or even system identification? Of course, there are two reasons. The first reason has got to do with the incentives and benefits that models bring with them. Why do I want a model, any idea? What will I use a model for? Why are we so keen on building models?

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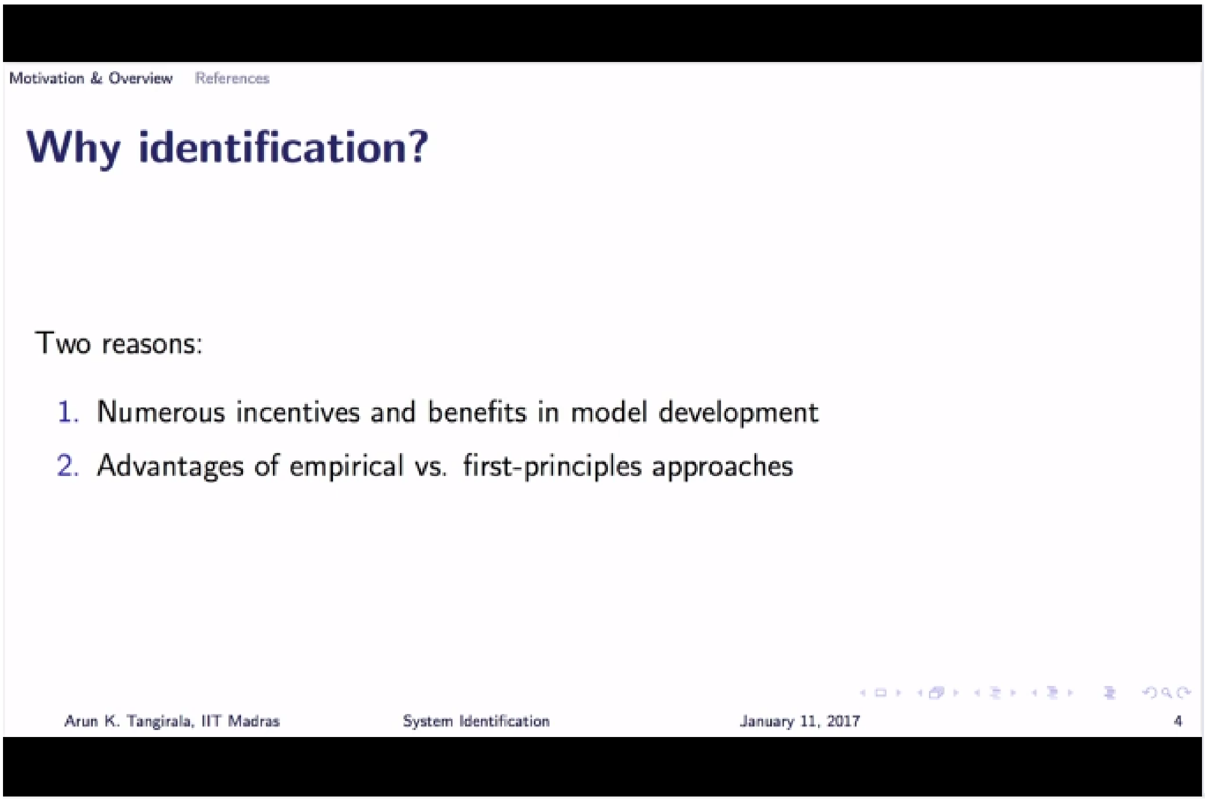

Prediction. Any anything else? Sorry. Reconstruct. Correct. So, all these reasons are connect. We need models for prediction, for understanding the process, maybe for recovering some missed missing value in the signal,many reasons. Essentially, I want to have some mathematical entity that will act as a substitute for the process. And I can play around with this model. In fact, today, if you look at one of the foremost users of models, apart from prediction is simulation.Prediction and simulation are almost identical in the sense in--at some technical level, but there is a distinction between prediction and simulation that will learn later on. So you see so many simulators around.You see aircraft simulator, flight simulators, you see chemical reactor simulator. There are so many simulators, when you go out to take lessons in car driving there is a simulator says, the simulator of how-- that guy so afraid to take you out on Indian traffic conditions, so he wants actually you to feel, what it feels like when you go out on the road. So he puts you through a simulator, so that you're all-- you're already and conditioned. So again, their models are used. So there are numerous incentives obviously in building a model and that's one of the first reasons why we are looking at System Identification. But in identification, we are building models using a particular approach which is using data.We are not relying on first principles approaches.That is what you're taught in most of the courses, how to write Navier–Stokes equations, if you're looking at a fluid system or order flow system or using conservation of energy, if you're looking at processes where energy transfers are taking place and so on. We are not using any of those fundamental laws.We are just going to rely on data.And that's the approach that we take an identification. So why are we taking that approach, any ideas? This approach to -- to model development is has gathered much more momentum than ever before in today's world, for reasons, you know, today, data analytics is a very hot field and people are increasingly turning towards this approach for model development. Engineering, process engineering has seen this for a long time, for decades now. But outside engineering you see this approach also quite prevalent. So any idea why I should turn to a data driven approach and not a first principles approach? Does it mean that whatever you've learned in other courses is kind of-- not useful anymore.Any idea? Why I should take a data driven approach. You should ask yourself because you have enrolled for this course. So why should you learn, an altogether new way of developing a model? When already you've been trained to develop models from first principles? Keep the job thing away, right? But if you look at it conceptually, why you should learn this concept at all of how to build models from data? Is there any incentive?Is there any reason? Sorry. Computation? And for what computation is? Quite complex to solve. Okay.

UNKNOWN: We do not know all the laws of nature.

We do not know all the laws of nature. Okay.So you're listening. Good. So you're listening some of the reasons, why one would be compelled to look at an empirical model. Any other reason?

Even if we know the laws we might [18:05] on somethings.

Such as? Practicality.

Like it's easier to [18:10 Inaudible] so it might use it but it may not be with the [18:20 Inaudible] So it take more time to generate theory, proper theoretical model for it than choosing an a data.

Data, right. Okay, good. Any other reason? All the reasons set have been listed are quite good.

[18:36 Inaudible]

All you can do is you can apply basic logic to whatever it is right now and create a platform so that it can improve with time.

Okay.

As we get data.

But the question is since I've already been trained to develop a first principles model.So as an example, suppose and this is example that will come across very soon.At the simplest of the examples is what we see,probably, we encounter reality.When I want to buy a vehicle, in that I want to buy a car or a two wheeler.And I would obviously there are some factors to take into account when I have to make this decision on what vehicle to buy, out what brand what model to buy, right? What make I should look at. And some of these factors is, of course, the top factor is how does it drive on the road that I'm going to use this vehicle on, right. So can I use the first principles models that I've been taught, let us say you're a mechanical engineer, you're a mechanical engineer, and you've been taught.You've taken a course on vehicle dynamics, right? And you've been kind of taught on how to write equations that will tell you how the vacant drives on the road. Can I use that? I've taken some maybe 10 courses on vehicle dynamics and I'm the gold medallist, what is this gold medallist do when he or she goes to buy a vehicle? Keeps a side all those equations or all the knowledge gained from those courses, theoretical courses.You-- have you ever seen anyone writing equations in showroom? Why? Why? Why don't we write equations of motion of that car? Let us say, I'm gonna buy a car. Why can't they write equation? Don't they know the equations of motion when it starts to roll on the road? What do you think? What prevents us from doing so?

[20:42 Inaudible]

Okay. So the inputs themselves are unpredictable. That's typical of our country's conditions, correct. Anything else?

[20:51 Inaudible]

So that may not hold.So, I'm not trying to tell you that all the courses that we have taken on first principle modellingis now a waste or something like that. I want you to understand that each modelling approach has its own set of limitations. And since this is a course on System Identification, obviously I'm highlighting.This is like a true researcher. I'm behaving like a true researcher,now, who is advertising a particular concept? If you read any research paper, the first paragraph or the second paragraph, you will see the researcher talking about existing methods and highlighting all the shortcomings and then presenting his or her method as a best one. So, first principles modelling approach is good, very good, because it uses the laws of nature but as someone said, I may not know exactly all the laws of nature.And these laws that I'm writing take into account certain phenomena and make certain assumptions that may not be valid for the process that I'm looking at. And unfortunately, there are too many processes that belong to that category, where I cannot sit and write a first principles--they just way too complex for me, complicated for me.To even first understand what are the phenomena? What I mean by phenomena is do enough energy transfer is taking place? Do I know which law to invoke? Should I write down a conservation of energy, conservation of mass or conservation of momentum? Or should I look at certain, you know, thermodynamical relationships? What are the things that are happening in a process itself is difficult to fathom. So, natural approach there for is to take an experimental approach, like we do for the vehicles, what do I do? I just take the vehicle out on a testride, and what am I doing in the test ride? I'm giving some inputs to the vehicle, right. I'm giving different inputs. I'm applying breaks and, you know, supplying more gas or I'm turning the steering wheel, doing many many things, and to every input that I gave to the vehicle I observed that response.At least before buying the car, after buying the car we don't bother,right. Before buying the car, we want to be really careful. So what we are doing in our mind is processing this input that we have given and the response that the vehicle is showing. And then I'm processing, we don't know what the algorithm is, I'm processing and I've come up with some understanding of the vehicle. That understanding is also model. Unfortunately, still I cannot write an equation out of it, right.That remains as some entity in my mind and I use that for making decisions.And as I always say, if you are-- if you are married and if you're a male then all this exercise is only a meth, it's only for your own satisfaction.The actual decision making happens elsewhere, Okay, so anyway, I mean, it still that-- I don't, I mean, I'm okay with that, no problem. So anyway. So that's a classic example of System Identification,where you are taking observations and inputs and building an empirical understanding because there is no other choice. And that's going to be the case in many many situations. And that is why system identification is one of the reasons, why system identification is a growing-- has been an evergreen field and continues to grow. And the other aspect that I want to highlight is, when you learn, when you have learned this first principles approaches, you've been trained to believe that things are deterministic. That means you know what's going on, but there are so many uncertainties as many of you have pointed out.There are so many uncertainties. How do you model those uncertainties? How do you factor and like when I take the vehicle on the road or let us say even I look at a heat exchanger or any other physical system.Most part of the process may be understood, maybe I would have comprehend it. But there are other aspects of the process that I would not have understood clearly. And these uncertainties unfortunately cannot be model using our mathematics. We need to turn to statistics, we need to turn to probability theory, the theory of random process. And you should expect, therefore, a mix of both in System Identificationbecause in System Identification we're going to build models from data and data comes with a lot of uncertainty whatever sources will discuss shortly. But in identification you have now the opportunity of modelling those uncertainties because the food for identification is data which contains uncertainty and we cannot ignore it. We have to take into account those uncertainties and the end result is a nice thing you would have a model that explains the deterministic part of the processand also models the stochastic part, which is kind of missing in the first principles approach. Right. So there are several advantages of looking at first principles approach.And we'll come back to that. I'll highlight a few others. And, of course, I will briefly talk about one or two limitations of system identification. It's not that-- I've been only singing the glory of system identification.