CH5230: System Identification

Motivation and Overview 3

What we will do today is continue with our discussion. The agenda for today is to give you a closer look into what System Identification actually consists of. In the schematic that we had yesterday, if you recall, it was a very simplistic view point that I had given of System Identification. It's a very innocuous looking schematic, but that's where, I mean, the gory details are hidden. And they will be slowly revealed. For example, if you look at the schematic, there are, obviously, there is an input that's been given to the process. And then you have the response coming out that being measure. And then, you have the identification algorithm, which produces a model. Every aspect of the schematic has a big story behind it. There is a lot of theory behind it. For example, what kind of inputs should I use to excite the process? How should I design them? What kind of question should I ask?

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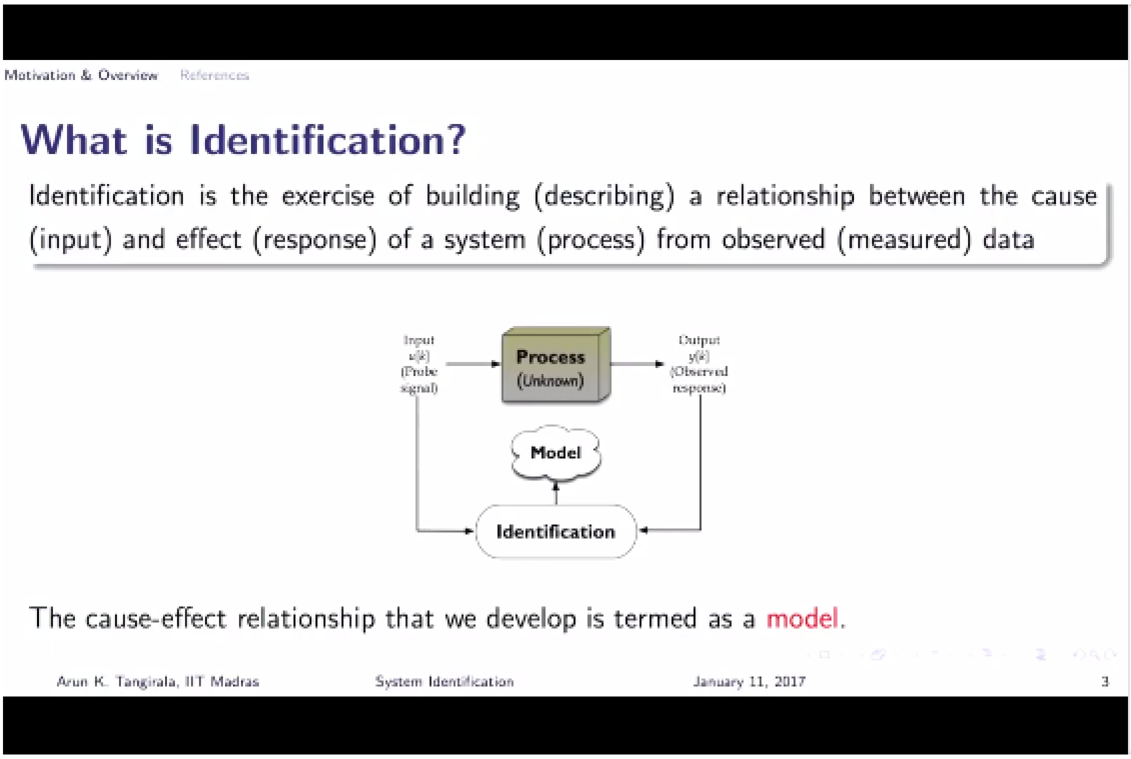

And that, even without going into the technicality, you can imagine with an analogy where I have to set question paper or you have to set a paper for some exam, right? Or for some interview. It's not easy. If you want to do a good job of it, it's not easy to set a question paper. Likewise, what models should I choose? Remember, we said in identification, we had, we said, we have great freedom, flexibility, and so on, which means there are many possible models that one can build. Which model should I choose? It's pretty much like, there are so many models of the cell phones that are available. Which model should I pick? Usually, that's a daunting task, unless someone comes and says, "Well, I recommend this for this purpose." You have to be clear, what's the end use of the cell phone. Likewise, here, one has to be clear on what kind of model we want to build. And of course, it's not always our choice. It heavily depends on the data that you have, and so on.

So at the output side, where I'm measuring the response, I have to decide on the sampling rate, I have to decide on where to place the sensors and so on. So, we'll talk about that. But what we will talk about is a more important aspect that is not visible in the schematic. And so, let's proceed. And hopefully, by now you're convinced as to why and when empirical models are useful. And be aware of the limitations time. And again, you should remind yourself that both these approaches have their merits and demerits, and one should not be possessive of one approach or the other. There are people who firmly stand by first principles models and reject empirical or statistical models straight away. And that's also not correct.

And likewise, there are people who really worship empirical models, and they don't really pay attention to the first principles part of it. So, both are not recommended. Often, once tries to strike a balance depending on what we want, and in the end, maybe you will be working with the gray box model. But, by and large in empirical approaches, you end up with a black box model. So be aware of the metrics and demerits, and be clear in your mind as to why you want to build a data driven model or a first principles model and so on.

So now, let's get into an aspect which was not visible in the first schematic that I showed you for identification. When I excite the process with an input, right, when I, for example, I'm driving a vehicle and I raise the acceleration of the vehicle. And I'm driving. I would definitely -- I'm observing the vehicle's response, not only the speed but also the sounds coming from the vehicle, if the engine is making noise and so on. But unfortunately, along with the noise of the engine, you hear the noise of the -- other kinds of noises coming from the road. So your ears, which are sensing this noise coming from the engine are also sensing other kinds of noises. But many a times we are fortunate enough to be able to distinguish between engine noise and the noise coming from the traffic, because our ears have fantastic filters built into them. So we are able to separate them. Whereas, in automation industry or when you're looking at measurements of any variables, be it level flow, pressure, and so on. When you're measuring the response of a process, an important point to keep in mind is, you are not just measuring the response to the input that you have given, but also the response of the process to other disturbances that may be simultaneously acting in the process as you're performing the experiment, right?

Another simple example is that of measuring the sounds of aquatic creatures. Let's say you're -- you want to -- you're interested in knowing what sounds these creatures or the animals in the sea are making, and you're standing on a ship, on the deck of a ship and recording. Along with the sounds of the aquatic creatures, you will -- your sensors will record the sounds made by the noise -- by the wind, right? In the end, what you have is not just a measurement of the whale or whatever sounds that you're recording, but also the sounds of the wind. Now, unfortunately, unlike ears, sensors do not have any built in filtering mechanism. They would just record all of it and present it to you. The data acquisition system will essentially record whatever has been perceived by the sensor and that's the measurement that you have. And that is what you would see here, you see here in the schematic.

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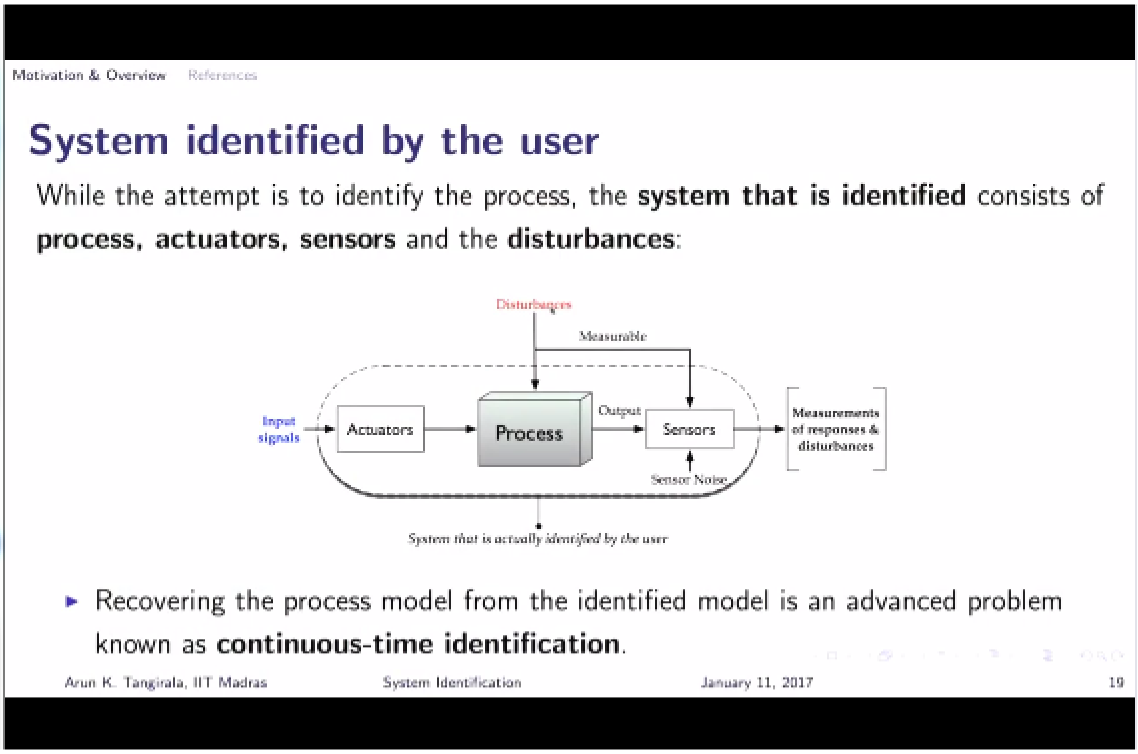

There is now a new channel called disturbances, which of course, was not seen in the previous schematic, because the purpose of that schematic was different. Now, we are getting slightly into the more gory unnecessary details. Within this disturbances, you have two classes. You have measured disturbances, some disturbances you can measure. But most of the times, a challenge comes from the effects of unmeasured disturbances, that which you cannot measure. And although I use the term disturbances here, slowly, you will get used to viewing these disturbances as some kind of uncertainties. Essentially, what you have here is the response of the process made up of the response of the input, and the response of the measure disturbances and unmeasured disturbances, and another variable, which is the sensor noise.

We know that, no sensor is perfect. It's going to give you some error, whenever you read, be it a thermometer that you use to measure your body temperature, or a level censor, or a position sensor. It doesn't matter. No sensor will give you an accurate reading. There is always going to be some error. Now unfortunately, this error is not going to be the same at all instance and time. So, it's going to change in from observation to observation, and the even more unfortunate part is, this change in the error, or the error characteristics of the function of time, cannot be modelled necessarily by a mathematical equation. In other words, you have to start treating them as random signals. And then you have to use the theory of probability and statistics to model that.

So, if I were to ask you, for example, in a very simple experiment, if you have access to any experimental setup, be it a liquid level system or the position, whatever it may be, do not excite the process at all. Just bring it to steady state, and now observe the readings. So, take a liquid level system for example, we have liquid systems in our lab, process control lab. You're most welcome to go and just take a look at the level readings. When the process is held at steady state, that means, you to the best of your knowledge are not going to make any changes to the flow into the liquid level system. The pump is going to be held at a constant voltage. You will still see fluctuations in the level. And why is that? Because of the sense of noise.

And if you observe it a bit carefully, you will find that it doesn't follow a particular mathematical, I mean, a pattern that can be explained by mathematical function. The error readings will be quite erratic. And therefore, one has to turn to the theory of random processes. And you may have to therefore invoke concepts of time series analysis to model that error. In other words, now, what we are presented with is a measurement that consists of composite effects. What we were hoping in the, when we looked at the first schematic, it's very easy. I excite the process with an input, I ask a few questions, it responds. And then I have to just put it through some mathematical algorithm, and I'm done. But of course, life is not that easy and for good reasons. If it was that easy, then many, many of us would be jobless. Seriously.

These are the challenges that feeds, that constitutes the basis of livelihood of many, many of us. So many a times, as we criticize uncertainty, we should also worship uncertainty, because it's divinity. I mean, it is actually feeding all of us. Nobody knows the truth. So, if you look at the measurement in an experiment, it consists of the response of the process, along with it come the other baggage, which is the effects of disturbances. You may say, “Well, there are no disturbances. I know for sure. I have designed the experiment in such a way or the process in such a way that there are no disturbances.” Good, no problem. But you cannot escape the wrath of sensor noise. You may buy the best sensor in the world, even that sensor would leave you with some uncertainty.

So the default uncertainty that you should expect to see in the measurements is from the sensor noise. Now, you should start getting a feel of the challenge in System Identification. Between you and the process, there is this noise. Like they say, I was saying, I was telling this to other person, “You remember this Bollywood dialogue, "You have to cross me before you reach,” something like, you know, “Mujhe paar karke jaana padega”, something like that. So the noise really stands as a big wall between you and the truth, which is the process that you want to model. And unfortunately, it is an inevitable passenger in the journey of Identification.

When we are travelling in, you know, in many buses that take you from one city to another city, even good buses like Volvo, and so on, do expect to hear some noise, right? You can't tell the driver, “Please get rid of that noise for me.” He would rather get rid of you, right, and have another passenger who is willing to tolerate that, because he's also unable to fix that. The sources of noise are beyond his control, right? So he would say, well, live with it, and you just learn to accept it as a fact of life. And this is also a fact of life. Sensor noise is a fact of data driven life.

One has to now be clever enough to accept, to accommodate that noise, and then still build a model. And that's a challenge. Okay. And then we'll -- and the entire System Identification is all about that. If there was no uncertainty, if there was no effects of unmeasured disturbances and so on, things are pretty straightforward. In the deterministic world, there are not too many challenges. It is the uncertainties that present enormous challenges and keep us excited forever. All right.

We'll talk about that again very soon. So, now you have to compare to what you learned in yesterday's class. Today, you have an additional piece of information which is extremely valuable, which is that identification is not just a simple cakewalk kind of exercise. One has to be able to get to the truth while accommodating the uncertainties. And I have to identify this model of the process. Now, there is another fact. Okay. So, one is uncertainty. There is another fact. The fact is that, you're going to deal with sampled data. The inputs are, you will not be able to move, adjust the inputs as a continuous function of time. You would tell the interface between you and the process that these are the input moves that have to be made at this instant in time, because there is a digital system sitting there, right, and it cannot accept continuous-time inputs.

The data acquisition system takes the digital inputs from the user, I mean, I should say discrete time inputs to be more precise. Discrete time input from the user, and constructs an approximate continuous-time signal, right? And then excites the process. And the process, in turn, responds. The process is continuous time, it has to receive continuous-time inputs. The process responds continuously in time. Unfortunately, I do not have the ability to observe continuously in time. In olden days, you would see a stencil drawing out, sketching out the response of the process. I think, some of the old experimental setups have that. And looking at the graph, and then you would do a fit, the paper would be like a graph paper, and the stencil would sketch out the response of the process. But now, those have been replaced by data acquisition systems, where you have sampled data. So, you have samples of the response. You do not have the response at continuous time.

Therefore, what you would identify is a model that relates the discrete time input to the discrete time output. In other words, you would, in the first stage, build a discrete time model, not a continuous-time model. Whereas, what I am interested in is a model for this continuous-time process. So now, one has to do this additional job of recovering the continuous-time model from the discrete time model. Now, fortunately, at least, there is some good news there. Fortunately, in many applications, I do not need the continuous-time model. I can just work with a discrete time model. If I'm designing a controller, a digital controller, I do not need the model of the continuous-time process. I can simply design the controller with a discrete time input. I can make forecasts with the discrete time input -- model that they have, and so on.

However, there are several applications in which continuous-time model is needed. And therefore, there is a branch of identification that deals with this recovery of continuous-time process from the discrete time model that you have identified. And that's kind of an advance subject as far as I see for a beginner in System Identification. Therefore, we shall not pursue, we shall not sit on the branch. The System Identification is a huge tree with many branches. What I'm trying to now slowly get to is which branch we will spend most of our time on. And definitely, it's not the branch of continuous System Identification that we'll spend our time on. Okay.

By the way, if you have any questions, please feel free to stop and ask. So that's the second thing. The first thing is that we learned uncertainties come in the way. Second that I identified discrete time model. And third, which is in fact the corollary of the second fact, is that, between the input and output, there is not just the process, there is not just the process. You see in the schematic, additional elements. What are they?

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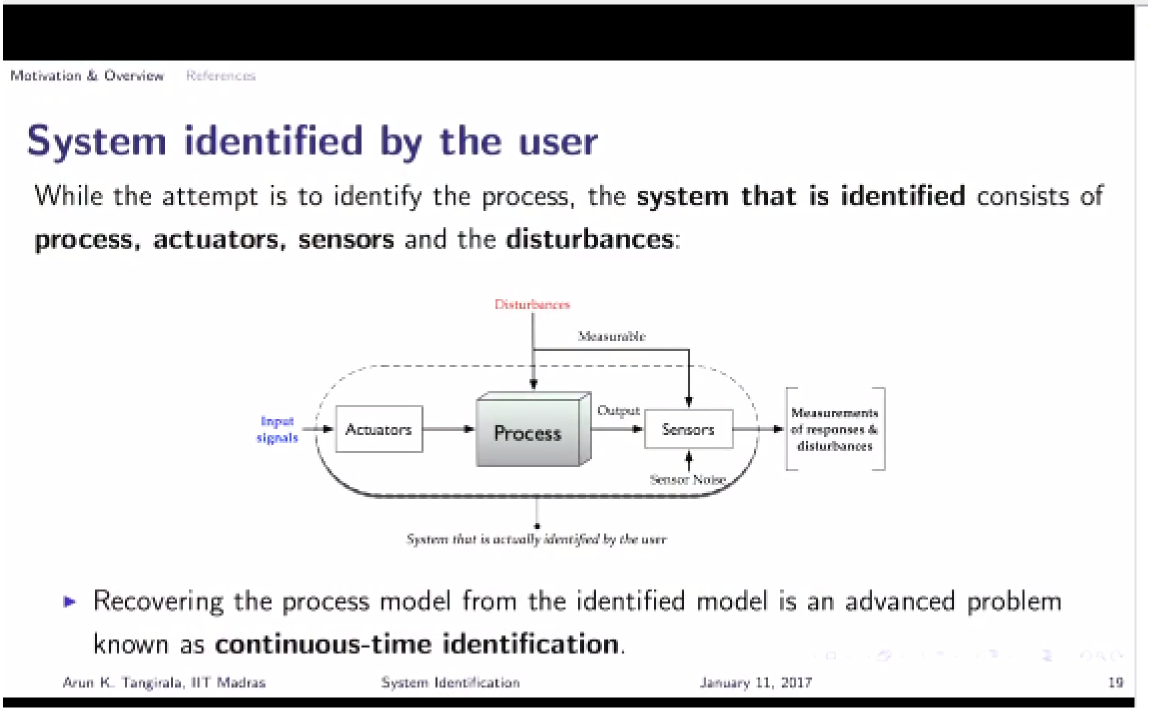

Actuators, right? On the input side, you see the actuator. What is the role of an actuator? Can anyone give me an example of what's an actuator? Control valve.

Control valve. Good. Any other example? Do you see actuators in your body? Right? We have that, right? The brain generates a command signal, but that's not enough. They have to be realized in actual, and that's why they're called, and of course, there are many reasons why these are called actuators. But yes, so, these are the physical elements. They are sometimes called the final control element. But that is more so in the control literature. Actuator is a much better word, generic word. They help connect the command signal and the reality that the process receives. So this actuators can have their own dynamics, agree? Do you think, if I tell my hand, move it this way, yeah, it will move. But it will have its own dynamics depending on the physiological condition of the body.

Likewise, if I take a control valve in a process, the computer may send out a signal to the valve, move by this much, open by this much or close by this much. It won't instantly do that. It will have its own dynamics, right? And if the valve is old, it's not a new one and it's not been nicely designed for, or nicely designed, then it will exhibit its own colours. And that can confound your model further, right? So, one has to now take into account actuated dynamics as well. Then you have on the output side, sensor. No sensor, in general, is going to give you an instantaneous reading. So if I place, for example, a thermometer on the body, does it instantly give you the reading? It takes a few seconds. So sensor also has its own inertia, has its own dynamics. Therefore, one has to take into account those sensor dynamics as well when you have to get the true model or that is a model of the process.

However, if all the time you're going to deal with so called sampled data system, what you see in the schematic is called a sample data system.

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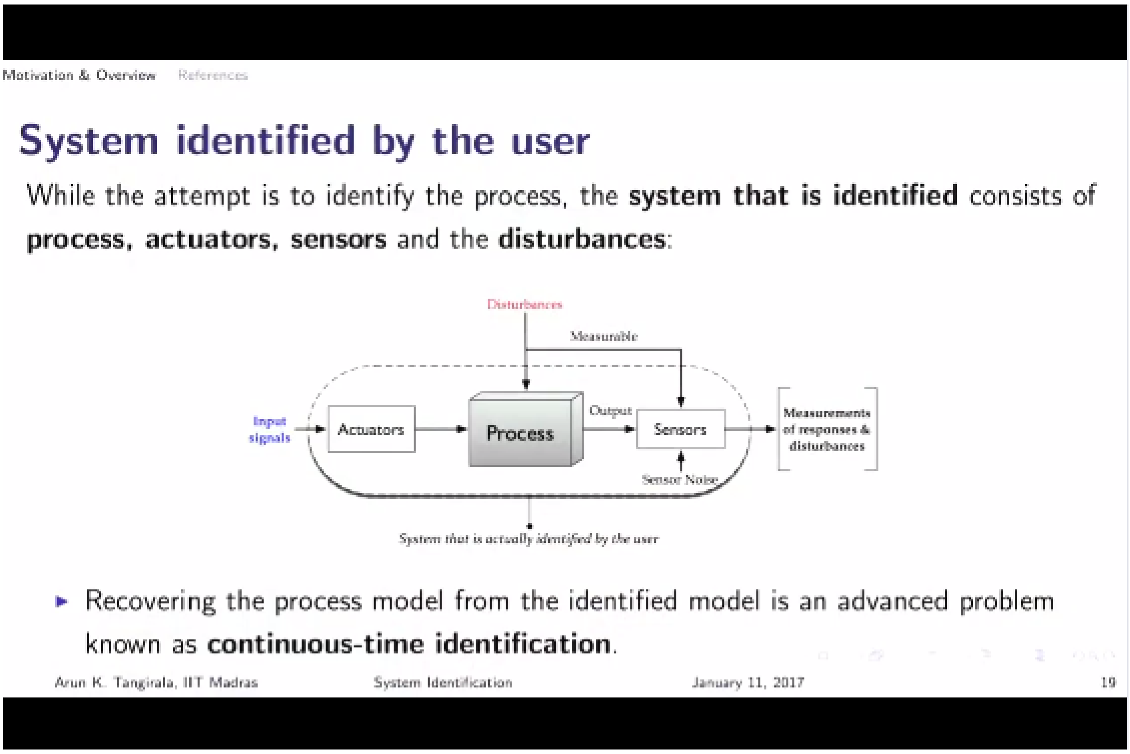

If throughout your operation, you're going to deal with the sample data system, you don't have to worry so much. However, in many applications such as fault diagnosis, suppose I have a model for fall detection, just predicted that there’s going to be a fault or a fault has occurred and I want to diagnose what's the source of the fault. At that point in time, I have to learn to distinguish between the actuated dynamics, the process dynamics, and the sensor dynamics, because all three could have faults or some could have faults. I cannot club them together because I have to take remedial action. And if it is -- for that, I have to first figure out what is the source of the fault, whether it's actuator and/or the sensor, or something wrong in the process, right? Accordingly, I'll take a remedial action. At that point in time, I'll have to zoom in further. So this is another aspect of identification that can come into play depending on the application that you're looking at.