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Using Feedback Control Principles as Guiding Metaphors for Business Processes

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Abstract— **This paper asks: how do we apply the fundamental principles of feedback in physical systems to business processes? This is a tempting idea because feedback is clearly present in business/decision processes, but as in the case of feedback of biological systems, getting beyond the qualitative and phenomenological descriptions to models with structure for which parameters can be determined from measurements is difficult.**

In this context, what can feedback principles, so often based on rigid mathematical analysis, provide to such systems for which any mathematical rigor is hard to find? Our approach in this section will be inspired by the words of Captain Barbosa in *Pirates of the Caribbean*[1], as to think of fundamental feedback principles as guidelines, rather than actual rules. That being said, we believe those guidelines provide a rich source of correction for business processes. In the end our feedback-fundamentals inspired guidelines may not guarantee us only correct decisions, but they can keep us away from practices we would never try in engineering systems.

I. Introduction

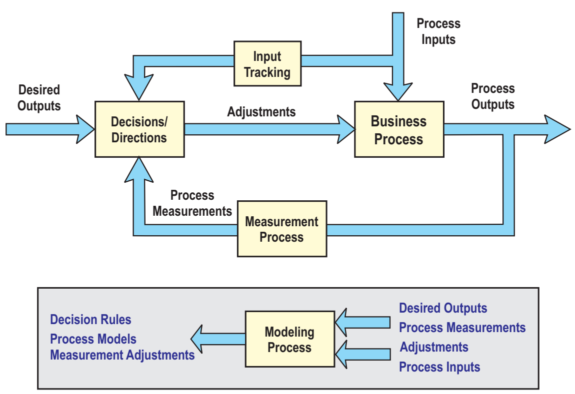

Fig. 1. A generalized control block diagram for business processes.

A variety of factors make analytical feedback difficult with business/management/decision processes. A non-exhaustive list of these includes:

- They are complex, nonlinear, and time varying.
- They are hierarchical with asymmetric information flow and actuation authority between layers.
- They are mediated by human interaction, including emotion, individual desires (and personal/local optimization), and imprecise language and information.
- More than hierarchical, many businesses have authoritarian elements: top down, emotion driven decision making, limited feedback authority from the lower layers interacting with the real world.
- Meanwhile, more democratically run businesses can suffer from "paralysis by analysis" – a metaphor that in this case refers to the inability of some well-meaning organizations to sift through data and make a decision (or choose a course of action) in a reasonable time.
- Information gathering (measurement) is uneven and often under sampled. While tracking of supplies, products, individual components, and money have gotten far more accurate, analysis of larger trends, marketing directions (or the effects of marketing trends), or matching a company's technology and cultural strengths to new product directions is still more of an art than a science.
- Models that go beyond empirical observations, best practices, heuristics, or black box models; anything with structure, are hard to derive and harder to verify against measurements, particularly if the measurements are undersampled. This makes having a causal understanding of any predictions from models difficult.

What can feedback principles, so often based on rigid mathematical analysis, provide to such systems for which any mathematical rigor is hard to find? Our approach in this section is inspired by the words of Captain Barbosa in *Pirates of the Caribbean*[1], as to think of fundamental feedback principles as guidelines, rather than actual rules. That said, we believe those guidelines provide a rich source of correction for business processes.

The dual of this approach is to look for business/management/decision phenomena that show a tight correspondence to known feedback and/or optimizations associated with control systems. For example, one can view the recently exposed fragility of the Just-in-Time (JIT)[2] optimized global supply chain – as evidenced by shortages and bottlenecks in the delivery of components and finished products during the Covid-19 pandemic – as a system that was optimized for maximum performance (bringing to mind H_2 optimization) with little concern for robustness to uncertainty in the supply model (as might be associated with H_∞ optimization)[3]. The practice of Management By Wandering Around (MBWA) employed by tech pioneers Bill Hewlett and Dave Packard [4] can be viewed as a business version of compressive sensing: generating a more accurate image from limited measurements by making randomized direct measurements of primary data. This is discussed in the session main tutorial paper [5].

A generalized control framework for business processes is shown in Figure 1. Here, input tracking takes the place of extra disturbance sensors in a physical system feedback/feedforward loop. The feedforward control generation

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is within the Decisions/Directions block, analogous to the physical system control block. The Measurement Process contains all the ways that businesses try to measure their outputs in order to improve their Decisions/Directions (and thereby Adjustments). Technically, Input Tracking could fall into the Measurement Process, but its current location preserves the analogy to the extra sensors used to track input disturbances in physical systems.

The Process Outputs include those that we measure and those that we do not. In a physical system feedback loop, measurements are typically made on a regular sampling interval and whatever data conversion we need is available. We cannot rely on such assumptions in business models. However, awareness of the need for such self-consistent measurement, conversion, and data handling – which occur by necessity in physical control systems – can be of great utility in improving the use of measurements in business. It is also worth becoming aware that not all outputs may be measured, so that this can be factored into any confidence in the Decisions/Directions process. These unmeasured outputs themselves are a form of Dark Data, which can sometimes surprise is in bad ways [6]. In business, there may also be "occasionally measured" outputs; ones that only get looked at when there is a problem. On can consider the idea of measured more of these outputs far more consistently as the first step on early diagnostics or predictive maintenance.

Perhaps worth of its own paper is the modeling block (discussed in Section VII), where all the various system signals are pushed into the Modeling Process to extract improved Process Models, which lead to better Decision Rules and Measurement Adjustments. In feedback control of physical systems, we know that the level of our improvement due to feedback (and feedforward) is directly tied to the quality and accuracy of our modeling.

In many instances, we might explicitly include a model block as part of the feedback mechanism e.g., internal model control (IMC) or in a state observer. We know, though, that these depend completely on a precisely defined and highly accurate model. As we are lacking in such precision for our application to business processes, we skip this in Figure 1.

II. The Role of Honest Feedback in Optimizing Business, Managerial, and Decision Processes

One of the hallmark methods of modern business school-based decision process optimization is to follow some case study of success or failure to try to learn "the lessons", while rarely examining the surrounding circumstances. In the controls world we would call this coupling and feedback from related processes that might have been far more impactful on the results than the "cause" that is being credited. Why would this more complete root cause analysis not be examined? The simplest answer is to "Follow the money" i.e., someone is selling something.

This issue is far more prevalent in organizational dynamics and business than in peer-reviewed research. While both idioms have individuals seeking personal reward based on their own success and "innovation", it seems that the intentional and far more immediate feedback of peer review is more consistent at finding false thinking metaphors than the less objective and personalized correction that may (or may not) happen in organizations. For peer reviewed research, the presence of anonymous feedback works to remove any biases based on personal or power relationships. It can be reasonably argued that the differences in behavior can be tied to the vastly weaker and delayed feedback in a large organization, coupled with the dramatically better (we might call it nonlinear) opportunities for personal success if we can be given credit for something. As HP co-founder, Bill Hewlett, said: "Tell me how I am going to be measured and I will tell you what I'm going to do." When one can have more effect on how they are measured by their skills of persuasion than their skills of problem solving, there is a recipe for future issues. The idea of the market correcting bad behavior is premised on notions of linearity, invertibility, and perfect information. When unchecked bad practices lead to outcomes that cannot be easily (or ever) reversed, no amount of market correction does as much good as early feedback that prevented the issue from the outset. (It is the old idea of putting in more effort to stay out of an accident rather than completely relying on a good mechanic and orthopedic surgeon.)

III. The Filtering Framework versus the Feedback Framework

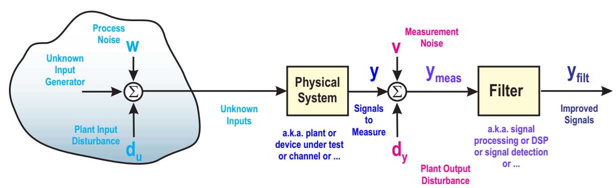

Fig. 2. A filtering structure for looking at processes.

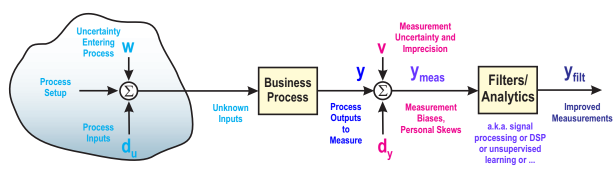

Fig. 3. Filtering framework applied to business processes.

Filtering and feedback are akin to cousins that both fight and get along. Despite many similar features, there are core differences in the way the two frameworks approach similar looking problems. Understanding those differences helps us apply them towards business decisions.

A filtering framework/perspective is depicted in Figure 2. Somewhere beyond our direct access is a physical process generating an input. Perhaps this unknown input is passing through some physical process or channel that shapes it (and for which we may have some form of a model). That unknown input can be corrupted by noise and disturbances (what we would call process noise and plant input disturbances). While both noise and disturbances are forms of uncertainty, we define noise as driven by a random process which we cannot predict (but we can characterize). We consider disturbances a form of uncertainty that has some predictable, repetitive, or structural component in it, so that with the right algorithm and/or extra sensors it would be measurable. The key point of the filtering framework is that we do not have access to any of these signals as they flow into a physical system, process, or communication channel only the measured outputs. Those outputs are corrupted by uncertainty (what we in the controls community would call measurement noise and plant output disturbance). It is on this latter type of signal that the filtering framework applies.

The lack of access to the original physical signal (the reason why we need to do filtering in the first place) places fundamental limits on the modeling that can be done to generate a filter. Learning systems, such as an adaptive filter or supervised machine learning (ML), would require "ground truth" (known as the desired signal in adaptive signal processing [7]) to train the model or digital filter. Without this ML is limited to unsupervised methods, which are far more limited. Figure 3 shows a filtering framework, applied to business processes. The term "analytics" is used now to make filtering seem more thoughtful. Certainly, the list of offline processes that can be applied to the measured data if we do not need to feed it back into a decision process is huge. However, without access to any system inputs, our ability to affect the process does not exist and our modeling will be limited.

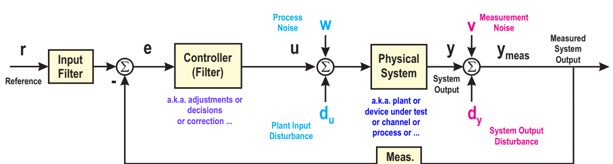

Fig. 4. A feedback structure for physical processes.

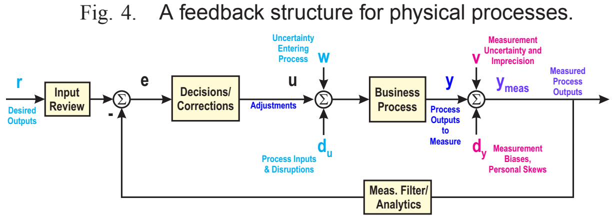

Fig. 5. Feedback framework applied to business processes.

The feedback framework, of Figure 4, considers access to the physical system input (at least some of them) as fundamental – else we cannot do feedback. The feedback framework allows us to affect the inputs to the physical process and so is in some ways far more relevant for decision making in business processes. After all, in business we would want to improve the process behavior by our adjustments. We still do filtering, but this can be in one or more locations including the feedback path (to filter measurement data), the input path (to filter the input commands or references) and in the controller itself (which is often implemented as yet another filter).

The filtering framework beckons as a simpler metaphor because it appears to have fewer perils. As we cannot affect the physical process, we do not take into account time delay or input disturbances. In fact, we must assume that the process is stable and relatively well behaved on its own, or there would be nothing to filter. We cannot get input-output behavior models from input-output measurements since we cannot generate inputs.

The filtering framework blinds us to the danger posed by latency, how a good correction done too late is a bad correction. It lacks the notion that measurement noise travels straight through to any corrected system output – a fundamental takeaway from that first controls class. Thus, without the feedback framework, decision makers would lack some fundamental intuition of how strongly measurement uncertainty limits their decision making.

The feedback framework tells us that we can use what we have measured to correct the process but a broader understanding would tell us that there are inputs to the process that we do not or cannot affect and outputs of the process that we do not or cannot measure. In this framework we would then be able to ask if more sensing and/or actuation is helpful in improving the behavior of the original process. On the other side, we could ask ourselves if there are outputs that – if ignored – can cause "Dark Data" problems [6]. Similarly, are there parts of the process that are far more easily adjusted and improved by adding another input to the system?

Even these intuitive arguments tell us that feedback is a far more complete framework than the filtering one. To be certain, as with physical systems, there are many processes that are so well behaved that only cleaned up observation and analysis a.k.a. filtered measurements are needed. To keep this interesting, we are focusing on those that could benefit from feedback. A feedback framework, as applied to business processes, is diagrammed in Figure 5.

IV. MIMO Systems and Coupling

Most physical systems have multiple inputs and multiple outputs (MIMO). Perhaps this allows us to determine if we can minimize the effect of the individual controllers on the cross-term outputs. A more complete design would likely attempt to add control structures to decouple the axes. Thus, the feedback control perspective brings in:

- Awareness of unintentional, parasitic coupling.
- Awareness that optimizing one sub-loop at a time may result in negative effects due to this cross-coupling.
- A sense that if we characterize the coupling, we can design our actions so as to minimize its effect.

In business processes there is always cross-coupling, often referenced as "The Law of Unintended Consequences". We optimize one measured variable only to inadvertently negatively affect the performance of others.

The big difference here is that for dynamic systems we generally have a model of the system and if that model is representative of the real-world behavior, we can minimize the negative effects of our adjustments by being clever with our algorithms (i.e., decisions and actions). The controls metaphor teaches us to look for unintended coupling, teaches us to be careful about over-optimizing on any one axis/decision/process without paying close attention to possible effects on others. We also know from dynamic systems that it might be possible to shape our actions so as to minimize the effects of cross-coupling.

In engineered dynamic systems, we can often make isolated measurements where only one input is stimulated and all measured outputs are observed. This is rarely feasible in an existing fully operational business environment. One engineering method that might be available is to prototype the new method/environment/organization as we do with an engineering prototype. Prototyping would allow us to observe the hidden coupling we might not have been aware of in or initial deigns.

V. Simplifying Hierarchical Systems: Using an Inner Loop to Simplify Handling of a Complicated Component in a Large System

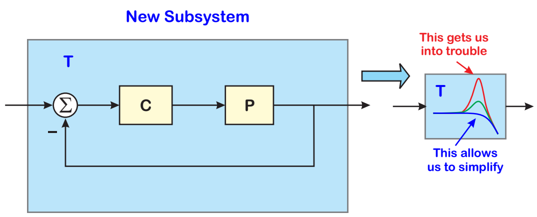

Fig. 6. Creating a simpler subsystem with feedback.

Model simplification of subsystems is often accomplished with a tight inner feedback loop, as diagrammed in Figure 6. In principle, such an arrangement would allow us to turn even the most badly behaved original component, P, to a new subsystem, T, whose behavior can be assumed good enough to be simplified to a constant. As we know that all physical systems and connections have finite bandwidth, our subsystem is really an ideal low pass filter: constant in the frequencies we are operating, and rolling off safely and smoothly outside our needed bandwidth.

The insight that feedback thinking for physical systems can give to business processes comes from the inherent underlying assumptions that are needed in order to take our subsystem from P to our ideal low-pass-filter, T. Those assumptions are not just on C, but on components left out of the diagram of Figure 6. Those assumptions provide our guidelines for mapping this into business processes.

- We want to have the behavior of the original component improved so much that it simplifies the subsystem – ideally to a constant – but more realistically to a low-pass-filter (LPF), constant in our needed frequencies and rolling off safely and smoothly above that.
- T as an ideal LPF implies that the inner loop has great gain and phase margin so as to minimize closed-loop peaking. At higher bandwidths, we know that these come from neutralizing any resonant peaks while minimizing the phase effects of that neutralization. The grim reaper of phase margin is time delay and so we must also look for places where either our sample period or the transport delay are unnecessarily large.

In a business decision context, we need to look for behaviors in the "business P" that result in large oscillations/deviations and avoid stimulating them. We also need to be acutely aware of the effects of time delay on our decisions and corrections. This type of sensitivity only comes from a feedback-thinking framework.

- What is the business equivalent of sampling data 20–100 times the closed-loop bandwidth? The first lesson is the very non-intuitive guidance that we need to look at data at significantly higher rates that would be expected in from a pure decision/business perspective. (We can expect to get a lot of pushback from folks not schooled in a feedback framework, including those with a filtering background. The systematic understanding of the effects of time delay on measurement-based decisions is unique to the controls framework.) As such, we will push for higher and more regular sampling than would be normal in "business intuition". What the controls framework would help us do is avoid having good adjustments turned into bad adjustments because they were made too late.
- We know from our control framework that sensor noise goes right through the controller to the system output. In our subsystem, we want to avoid driving sensor noise through the system. The natural "filtering framework" intuition would lead us to average the data to reduce the noise, but as control engineers we know that averaging is equivalent to a Finite Impulse Response (FIR) filter, and that this imparts significant time delay to our feedback loop. Instead, the feedback framework tells us that instead of haphazardly filtering without consideration for delay, we will explore a combination of improving the signal path, improving the sampling mechanism, sampling faster to allow more bandwidth for filtering, and a very judicious use of filtering to clean up the loop signals. In the business, this means taking a good look at how measurements on which these decisions are done, and what are the obvious sources of delay and uncertainty. It means making measurements more carefully and more often than what would be intuitive to non-controls folks.
- Feedback control also has a fundamental concept of limits: saturation of actuators and sensors, saturation of internal signals, slew rate limits, etc. For an inner loop to achieve its goal of simplification, those limits must either be gracefully handled or rarely approached. What do such limits look like in business processes? Perhaps the limit is on cash in an organization or what it can throw at any one project. Furthermore, certain business processes have slew rate limitations and they cannot be sped up simply by throwing more resources at them. Looking for these limits, and understanding how to avoid them or get graceful degradation is a real contribution we can get from control.
- In a physical system, we would test and verify the behavior of the inner loop before using the simplification. The rigorous testing of subsystems is the part of

any real design. For our business subsystem we know that we would want to test the input-output behavior, to prototype the policy as it were, fairly rigorously to assure ourselves that it behaved as expected in a robust way.

These are fundamental principles that show up in every system that incorporates feedback. Thus, we can look for the local loop opportunities in business processes and apply the above principles to guide those business loops.

VI. Measurements, Sample Rates, and Time Delay

Section V brought up the issue of time delay and sample rates for allowing an inner loop to simplify the system. The issues of time delays and concepts of gain and phase margin become less well defined as we move up the hierarchy of a physical system or a business process. Still, we know that time delay affects all feedback systems in a negative way, limiting bandwidth.

- It cannot be negated or inverted, only minimize through better design and slightly mitigated via model-based prediction.
- Rigid analysis is only really feasible on the simplest of problems but good rules of thumb exist.
- Minimizing time delay does not guarantee the success of any feedback loop, but it does help keep good corrections from becoming bad ones.
- In business processes, we can use the rules of thumb about the negative consequences of time delay in any measurement-based feedback process.
- Finding and minimizing useless sources of time delays in business process can also keep good decisions from becoming bad decisions, just because they are too late.

Similarly, the rigors of feedback systems teach us a bit about the need for getting measurements right in a minimal amount of time (of course, relative to the dynamics of the process). Measurements can be affected by bias, nonlinearities, time delay (again), and noise. Considerable effort is made to identify and calibrate out bias and nonlinearities (assuming they are repeatable). Once these have been calibrated out, we are looking at noise and time delay. Moore's Law allows not only faster sampling, but sampling of far more signals, allowing us to digitize far more processes. Understanding that those samples are still tied to physical processes and that the noise, biases, and timing of those measurements matter as much as our computation is something that is fundamental to the feedback perspective.

Section V mentioned the idea that to minimize negative phase effects of anti-alias filters, systems with feedback likely need to sample much faster than 20x the desired closed-loop bandwidth. This seeming oversampling comes almost entirely from a feedback framework: Averaging without extreme phase lag requires oversampling.

In business processes, the concepts of measurements, their timing, their biases, and the concept of uncertainty can be informed by our experience with physical feedback systems. This includes:

- Timing of measurements: Control and signal processing have well established that repeating measurements on a fixed schedule ($T_s = 1/f_s$ fixed), is a good idea. A fixed sample period provides an understanding of the "bandwidth" of the knowledge i.e., how fast we can make inferences and predictions. The faster the measure, the more tightly we can assess time windows for actions.
- In a business environment we would use this knowledge to adjust their measurement process by:
  - Measuring at regular intervals/sample rate, rather than some sort of ad-hoc scheduling.
  - Making the measurement rate 10-20 times faster than the behaviors/processes they are trying to adjust. (Understanding the time constants of business processes is a major modeling issue.)
  - Adding more automation to regularize and simplify the measurement collection.
  - Improving ways to aggregate small, easier to make measurements into a larger data set.
  - In business practices, measurements are noisy and biased (perhaps more so than in physical systems). Questionnaires/surveys based on what management chooses can bias or even blind measurements to things that should be measured.

One more truism from feedback control perspective is that – given enough signal-to-noise-ratio (SNR) – the faster the sampling, the simpler the model has to be. Thus, we know that looking at the data in a regularly spaced way and making those intervals significantly shorter, generally boosts the accuracy of anything we try without having to match complex models which may be difficult to derive.

VII. Actionable Models from Measurements

In any environment, the fundamental need of a model – as Stephen Hawking so clearly stated [8] – is to describe behaviors we observe and predict behaviors we may see. In dynamic systems, models might be derived using anything from deep learning neural network models to first principles "physics" models. While the former may give a more accurate empirical representation of the input-output behavior of the system, it may well be brittle (not able to handle new data that was slightly different from the old data). The latter would be easier to tie to physical properties and causes.

In both contexts we should ask how critical is the knowledge of physical properties and parameters to successfully understanding and using the model? We know that in many applications of DSP and feedback control that the physical meaning of any digital filter or model parameters not only are hard to extract, but also unnecessary for use of the model. On the other hand, modeling and control of highly flexible mechanical systems, as well as chemical and biological systems are far more successful with a close tie between physical properties and parameters [9], [10], [11], [12].

Our ability to make predictions and/or adjustments – whether in feedback or feedforward – depends upon modeling. The kind of analytical modeling is far more difficult in a business environment. This may be one of the reasons for the current stampede towards deep learning (neural network) methods, including large investments by corporations, universities, and governments: the lack of ability to extract analytical models from the tuned networks seems to give folks permission to not even try. Still, we know that modeling is critical to anything we want to do. A model that yields understanding and intuition can be a powerful tool in improving a process. To be certain, deep learning can provide advantages when physical insight is not easily accessible, but we would also like to find some structure in the latter models. We will at least touch on how to improve measurements and some possible considerations for modeling below.

So-called "intuitive, model-free" control is fully adequate to catch a ball on the run or to steer a car through a curve. In this human-in-the loop example "model-free" is a misnomer, as we know that the buildup of the intuition to catch a ball or drive a car can be either, the long training of a deep neural network or constructing an intuitive rule-based inferencing engine. The training is supervised (there is ground truth, be that not dropping the ball or driving off the road), and the training takes time. Through rule-based methods, we capture process experience; however, building such a rule base requires skill – another view of ground truth. In either case, there is a model being tuned. While tuning takes a lot of time (think years to learn tennis) the use of the model (called inference in AI speak) can be very fast (think of returning a serve in tennis).

We also realize that many model-based control strategies are very effective with substantially reduced-order models of the process. Experience indicates that if the sampling sampling and adjustment are fast relative to the process dynamics, feedback using a simple model can be more than adequate. This aligns with the inner-loop approach and correlates with the design of disturbance observers in the physical systems world.

For business processes, again it seems to depend on whether or not we need a physical explanation of our model. In some cases, we might cast a large deep learning network to draw out input/output considerations that might describe and predict behavior. On the other hand, for insight about what the trends mean, what causes them, or what specific actions should be taken, then we need more physical models.

It matters what types of measurements we can actually make to identify and model our systems. While engineers working on mechatronic, electrical, and/or mechanical systems are used to characterizing those systems with a lot of different types of external stimuli (step, pseudo-random, stepped sine, chirped sines, impulse tests), chemical and biological systems do not respond well to such inputs. Instead, the latter must characterize systems using mostly operational data. The presence of steps, ramps, and impulse like inputs to these systems enables some of the classical characterization. Identifying discrete parameters from operational data is possible, but these are hard to tie to physical meaning.

For business processes, we can think of very few processes involving people that would tolerate large sinusoidal stimuli (apart from roller coasters), chirps, or purposefully injecting noise. Instead, most modeling of business processes would likely be done using operational data. Even with this limitation, we can immediately glean some insights from measurements of chemical and bioprocesses. The most obvious is to look for the input steps in the operational data of the system. By locating the input steps and the output synced to those input steps as triggers, we can extract step responses from operational data. Now, the models that one can extract using step response data are only first or second order, and one usually needs to pick one to find all the parameters, but still these parameters are often easily relatable to physical properties.

VIII. Future Directions

There are many possibilities raised here and it is a bit early in the process to draw many conclusions. It seems that every section above yields a possible way of examining these connections. The key challenges are not the core principles but how to implement them in such an uncertain and non-analytical environment.

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