Digital Twin Reliability

ABSTRACT

Digital twins, reflecting physical assets, rely on rigorous data accuracy, clear purpose, and continuous validation. This column delves into potential pitfalls, including data security and model maintenance, emphasizing the balance between model and reality.

KEYWORDS:

Digital twin, data accuracy, algorithms, reliability, modeling, cyber security

What is a digital twin?

"So, what exactly is a digital twin?"

Well, start with what you want the twin to do – model the health of the transformer, identify the need for maintenance, plan for contingency loading, prevent conditionbased failures, or all of the above?

Once you've decided that, then work out what data is needed (and at what precision/accuracy and update rate), how to get it (and where from), what calculations to run (and how frequently), and what outputs to have (and how to display them). Most digital twins have some form of graphic or visualization, but they are still based on a simple process of input data – analysis – output data – visualization.

There is an old and oft-quoted line from a statistician: "All models are wrong, but some models are useful" [1], but it is seldom that the subsequent follow-up line is also quoted: "The practical question is how wrong do they have to be, not to be useful" [2]. And that usefulness is dependent on what you want the twin to do.

For example, a smartphone app that displays maps could help me get from some real address at point A, to another real address at point B. I'm not too worried about, say, how well the roads and buildings are colored in, how wide they have



the map roads compared to each other and so on: I know they are wrong, but not in a way which affects me. I just want to know how to get from A to B in an efficient manner. I will only be disappointed if it doesn't actually give me a sensible route. There are cases of people following such apps in the dark, turning onto railway tracks, or ending up in a canal. I think they would be entitled to be very disappointed.

Is an AHI a digital twin?

So, is a transformer asset health index (AHI) a digital twin? I did have a free and frank exchange of views on this topic earlier this year with some folks at an indus-

try working group. My contention would be that an AHI is a digital twin, as it represents the health of an asset and can be used to support decision-making. Admittedly, it is a very coarse twin, consisting of just one value, the index, and if you don't have a sensible, auditable, calibrated AHI, it could even be an evil twin and provide misleading information. If you want the twin to have cute graphics and pretty colors, we can add those – provide a color on a red-yellow-green spectrum which indicates the urgency of whatever intervention is needed.

You could, as we do at Doble, provide a systematic AHI based on failure mode analyses of components such as bushings, windings, oil, cooling, etc., that generates individual health indices for each one.

The twin is there to provide data to support a decision – even if that decision is a default decision to "do nothing" over and above what is normally done This then gives more numbers to put on the graphic, and it becomes a less coarse and more useful/detailed twin. The algorithms used to transform the input data to the output data are crucial to how well the twin represents reality. Assuming the input data has been verified and validated [3] we can compare the output data with reality and quantify the difference. For example, if a transformer loading scenario predicts a hot spot temperature of 140°C when we have continuous 1.2 p.u. load for 2 hours on a day when the ambient for the two hours is a constant 20°C, and the cooling is fully operational, we can check that against reality. In fact, we should check how well hot spot temperatures are predicted when just normal loading is applied as well - are the algorithms in the twin accurate?

The twin is there to provide data to support a decision – even if that decision is a default decision to "do nothing" over and above what is normally done. We know the twin is a model of a real object and thus will not be perfect. But we will need to know when it is wrong in a way which is important – in a way which means we may be misled into inappropriate actions. If I use a digital twin to model a GSU at a power plant to identify and prevent failures, I may not worry about small deviations of predicted hot spot temperature



There are many challenges with twins, from cyber security and data poisoning to twin maintenance, but the biggest challenge is that the twin may misrepresent the reality it is modelled for

from reality, but if I know the hot spot is, in fact, 60°C and my twin says it was expecting 80°C, that implies there is a serious problem in the twin algorithms which need to be addressed. We know there will be some variations, but let us not worry too much about mice when there are tigers abroad.

Twin reliability metrics

How, then, do we measure the reliability of a twin? That can only be done by understanding several things:

- the aim of the twin, and what is an acceptable variation from reality
- the accuracy/precision of the input data
- the impact of the accuracy/precision on the algorithms used
- the consequent uncertainty in the outputs of the twin
- the actual variance between twin values and reality

We can consider how badly the twin varies from reality, and what that variance is doing over time, but these variations may be mice in comparison to the tigers out there, such as the one where we make a wrong decision based on twin output: leaving a unit in service to then see it fail, or taking an outage and swapping out a bushing when there is nothing wrong with it. There are many challenges with twins, from cyber security and data poisoning [4] to twin maintenance (which is required to make sure the twin models the actual physical asset as it is, not as it was some time ago) [5], but the biggest challenge is that the twin may misrepresent the reality it is modelled for.

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