Research Cycles

Nearly all research goes in cycles, and I have already experienced this many times in my career. For example, when I started on the faculty at Stanford in 1994, it was at the end of the period of intense interest in controls-structures interaction [1], which had lasted the entire time I was a graduate student and postdoctoral candidate (a period of approximately eight years). However, by the time the Shuttle experiment we designed on the use of active control for space structures flew on STS-67 in March 1995 [2], that interest had waned significantly and the funding agencies had largely moved on to different topics. I have also seen interest in many other research threads come and go, such as research in the 1980s–1990s into robust control ($H\infty$ and μ), neural networks, and fuzzy logic and research in the 1990s–2000s into formation-flying spacecraft.

Of course, similar cycles occur in other fields, with perhaps the most famous being the artificial intelligence (AI) "winter" in the late 1970s following the Lighthill report that, in a section titled "Past Disappointments" in [3], reported

> Most workers in AI research and in related fields confess to a pronounced feeling of disappointment in what has been achieved in the past twenty-five years. Workers entered the field around 1950, and even around 1960, with high hopes that are very far from having been realised in 1972. In no part of the field have the discoveries made so far produced the major impact that was then promised.

This was followed by another AI "chill" in the 1980s [4], but the field is now undergoing a resurgence given the excitement about 1) self-driving vehicles (SDVs), building upon the many years of research into robotics and the control of embedded systems, and 2) deep learning, which builds on the earlier work on neural networks and reinforcement learning (see [5]–[7] for technical details and a historical perspective on that approach).

There are also many new exciting areas in the control field, such as the control of cyberphysical systems using techniques including linear and signal temporal logic; the control of biological and medical systems using techniques such as model predictive control; and the planning and control of networked teams of unmanned systems (collectively called UxVs) for commercial, farming, and environmental applications using a variety of techniques, including swarming.

While I was aware of the typical cycle of research for technologies such as these, it was only recently that I saw it codified in the form of a "hype cycle" [8]. The typical curve, shown in Figure 1, plots expectations (sometimes labeled as visibility) versus time and has the characteristic shape of a transient response of a lightly damped system to a step input, but with the longer timescale response dominated by that of a system with a slow (stable) real pole. With illustrative names, such as *peak of inflated expectations*, *trough of disillusionment*, and *plateau of productivity*, the curve shows the tendency for early expectations to become "overblown," which, once realized, leads to negative press and a large overcorrection during which time many investors and researchers tend to switch their focus to other problems, leaving the remaining few to resurrect what is left. Reflecting on that cycle led to the recent comment about the AI field [4] "'There's definitely hype,' adds Ng, 'but I think there's such a strong underlying driver of real value that it won't crash like it did in previous years.'"

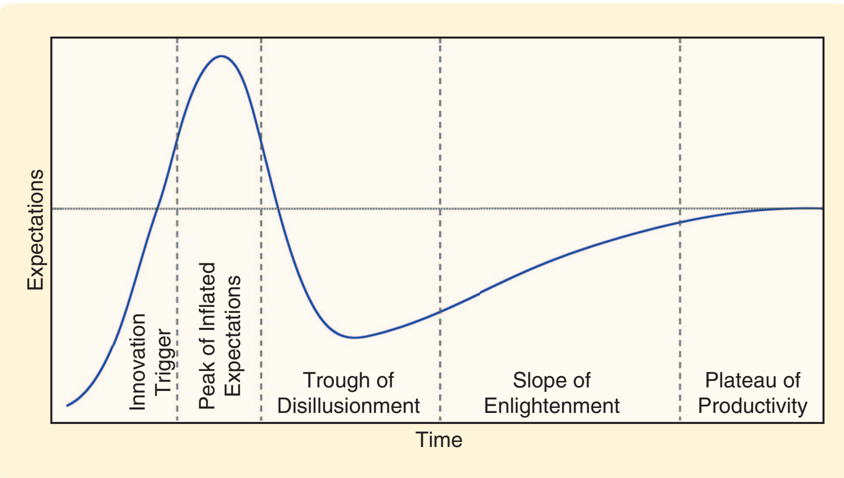

FIGURE 1 An example of a typical hype cycle plot [8]–[10].

Digital Object Identifier 10.1109/MCS.2017.2697199
Date of publication: 18 July 2017

Jonathan How below his favorite X-plane during a recent visit to the National Museum of the U.S. Air Force in Dayton, Ohio.


John Valasek (right) thanking Jonathan How after his seminar at Texas A&M University during the celebration of the 2017 Texas Systems Day.

The downturn after the peak in the expectations can occur for many reasons and could be driven by technical (too hard), legal (not allowed), policy (might be allowed but has undesirable side effects), and/or commercial (not cost-effective) factors. For scientific endeavors, we tend to focus on the technical issues, such as whether the algorithm is computationally tractable for a realistically sized problem, are the conditions on the stability theorem too tight to be practically useful, or do the performance improvements of the proposed approach meet prior expectations. However, the policy and legal factors often strongly depend on the technical issues, as is the case for the safety analysis of SDVs and UxVs, so it is important to be aware of, and help address, those issues as well.

Gartner publishes a yearly summary of its *Hype Cycle* [9], which is designed to provide a broad perspective on technologies and trends that have high potential impact. Perhaps not too surprisingly, items such as SDVs, the Internet of Things, unmanned aerial vehicles, and reinforcement/deep learning appear prominently near the peak of the 2016 curve. An analysis of the recent history (2013–2016) of these hype cycles [10] is insightful primarily in that it makes it clear that 1) many technologies relevant to the IEEE Control Systems Society community have hovered near the peak for some time and 2) very few of the ones analyzed have made it past the trough of disillusionment (with virtual reality being the primary exception).

It is important to recognize that the amount of hype about a technology can have a significant impact on the type of research being done by researchers in that community because hype has a tendency to dictate what is "valued," and not necessarily in a good way. Furthermore, while increased hype can simplify the process of obtaining funding, those funds will also attract many other researchers, thereby typically making it more difficult to differentiate your work from others and/or make a unique contribution to the field.

While it is sometimes necessary to "enhance expectations" to stoke interest in the ideas and work, it is also important to perform the research that addresses the issues that might lead to a down turn. If successful, work in that direction would be ahead of the pack, and even if not, then the results might provide the necessary damping on the hype peak overshoot.

While there are some criticisms about the hype cycle, including that there may be too much hype about it, I think this is a useful visualization of the typical ebb and flow of interest and research funding. As such, there is a fundamental question that I think should be carefully considered before investing time/effort into a new area (such as when making career decisions)—where on the hype curve is this field of interest?

As always, I look forward to your feedback on this topic.

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