Hype Cycle Dynamics: Microscopic Modeling and Detection

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Abstract

Hype cycle models are commonly used to quantify the state of development of an innovation, and to guide
decision-making in terms of associated strategic investments. The relevance of these models has long been
exemplified, in particular by the Gartner hype cycle. While the related literature contains numerous works
focusing on the macroscopic description of the emerging hype patterns, very little attention has been paid so
far to understanding the individual mechanisms that are creating these global patterns. In this contribution,
we introduce a microscopic model that explains the collective emergence of hype cycles, as well as the essential
human interactions that lie behind them.

Key words: Hype cycle, innovation diffusion, stigmergic interactions, collective dynamics.

1. Introduction

When a new technology emerges, how does one separate hype from commercial viability? This is one of the
fundamental decisions organizations face. Identifying and adopting the right technologies at the right time
is a critical task for decision-makers in corporate strategy, as embracing and then potentially abandoning, a
new technology can cause serious financial burden. Moreover, the ability to assess the maturity, benefit and
future direction of emerging technologies is crucial in evaluating various R&D proposals, both for corporations
and for government research funding agencies responsible for guiding the direction of R&D policies. Likewise,
people seeking to invest in innovation find a solid understanding of the dynamics governing the early stages
in the diffusion of new and emerging technologies to be a decisive tool for efficiently and optimally orienting
investments\textsuperscript{1}.

The Hype Cycle Model

The Hype Cycle model has been proposed by Gartner Inc. as a framework to facilitate the understanding
and forecasting of the trajectories, maturity level, and market potential of early-stage technologies \[4\]. The
framework provides a cross-industry perspective on technologies and trends, mapping the journey of new and
emerging technologies through their evolution via distinct phases, as illustrated in Figure\textsuperscript{1}. Each year, Gartner
publishes around 100 hype cycles with insight on about 1,900 different technologies. The framework has gained

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\textsuperscript{1}Forecasting the trajectory and diffusion of technological innovations is not a trivial process. As a historical example, consider
the stethoscope, a medical technology invention of the 1800’s was met with serious skepticism, as quoted in The Times of London
newspaper in 1834: \textit{That it will ever come into general use, notwithstanding its value, is extremely doubtful; because its beneficial
application requires much time and gives a good bit of trouble both to the patient and the practitioner; because its hue and character
are foreign and opposed to all our habits and associations.} Yet, this device has become known as one of the most valuable diagnostic
tools in medicine.
substantial attention from practitioners to facilitate strategic investment decisions, and recently from academic scholars.

**How Does the Hype Cycle Work?**

According to Gartner’s hype cycle framework [4], emerging technologies traverse a sequence of five distinct phases (see Figure 1) that begins with over-enthusiasm for a new technology.

- In the first phase, referred as the *Technology Trigger*, breakthrough research and technology innovation is made. It attracts significant interest, even before proof of commercial viability.

- In the second phase, known as the *Peak of Inflated Expectations*, the feedback produced by early adopters and the first successful basic implementations produce a wave of unrealistic expectations about the new technology as scientists, entrepreneurs, and investors let their imaginations run loose. At this stage, the maturity level and real capabilities of the technology innovation lie far below the raised expectations.

- In the third phase, the *Trough of Disillusionment*, interest in the proposed innovation decreases as technical challenges manifest themselves, and the technology fails to live up to the expectations raised by the early adopters. Some of these early adopters turn the corner into a period of disillusionment, due to their negative experiences. As companies bail out, investments fail to generate returns.

- In the fourth phase, referred to as the *Slope of Enlightenment*, the true potential and benefit of the new technology start to be better understood by a select group of true believers. These hardy individuals and organizations begin experimenting with second- or third-generation products, as they fund more pilot projects, and ultimately the global knowledge grows about how to efficiently use the new technology.

- Finally, in the fifth phase, the *Plateau of Productivity*, the benefits of the technology innovation are demonstrated and accepted, and mainstream adoption takes off. Correspondingly, the associated investments start paying off. The height of the plateau depends on the quality of the technology on the one hand, and on the market size on the other hand.

Although the Gartner hype cycle framework has gained substantial attention from practitioners for its explanatory power and predictive value, and likewise from academic scholars, the framework’s theoretical underpinnings have been barely studied in the existing literature. In that regard, the present paper attempts to fill this gap.
We propose a model to quantify the behavior of interacting agents on a collective scale, as a tool to help understand the early diffusion of technological innovation. Following [4], the hype cycle model aims at modeling the successive phases a new technology goes through, and it can be decomposed into two distinct and merged components, namely the Hype-Driven Expectations and the Technology Maturity (see Figure 1). While the first component is the result of social interactions, the second one represents the pure technical performance and maturity level of the newly introduced technology. In this paper, we focus on the human component of the hype cycle. We pay attention to the microscopic interactions that lead to the initial overenthusiasm for the new technology, which is then followed by disillusionment after the first implementations do not meet these overly promising expectations. At first glance, it might seem curious that investors overestimate then underestimate the prospects of a new technology time after time, as this would seem to reveal a certain form of naivety. Indeed, that would be contrary to the prevailing efficient market hypothesis, which holds that humans are always rational and not subject to bouts of unfounded exuberance or extreme pessimism. In that respect, we propose in this contribution a model that highlights how hype cycles can arise under rational human decision-making.

Multi-Agent Modeling

In this paper, we interpret the hype cycle phenomenon as a macroscopic temporal pattern resulting from the microscopic interactions of a large collection of autonomous human decision-making agents. Since hype oscillations are intimately related to opinion dynamics, adopting a multi-agent approach is natural and can in fact be traced back as early as 1936, when John Maynard Keynes described the equity markets as driven by speculators’ expectations of what average opinion expects the average opinion to be.

In the present approach, we view the collective opinion underlying the progressive hype generation as the result of mutual information exchanges between technology experts. These experts share either their enthusiasm or conversely their skepticism according to a gradually refining set of inquiries regarding a given innovation emerging on the market. Initially, enthusiasm dominates since potential drawbacks and/or flaws have not yet been unveiled. Later, thanks to the refinement of the information-gathering process, skepticism grows and ultimately dominates, producing the Trough of Disillusionment. The more refined information-gathering together with the mutual information sharing processes are stylized via a stochastic nonlinear dynamic which offers the attractive property of explicit analytic computability. Subsequently, we explicitly consider in the present modeling framework the ubiquity of the random environment characterizing the multi-agent dynamics under study. According to [3], the uncertainties affecting the diffusion of innovation originate from the type of customers, the technical feasibility, or the potential of the new technology. In essence, our model helps in tracing the origin of the hype oscillation as being due to a delay mechanism induced by the time required to process and build the economic agents’ opinions. On another note, our dynamic modeling finds also an elementary enlightening analogy with a simple feedback queuing network roamed by customers who, based on past experience (information), are allowed to autonomously decide their routing.

Structure of the Paper

The rest of the paper is organized as follows. In Section 2, we provide a concise overview of the related literature. In Section 3, we introduce the multi-agent dynamics and the queuing theory framework that model the collective emergence of the hype cycle. In Section 4, we draw an analogy between the proposed microscopic hype cycle behavior and a queuing system with feedback loop. Based on this analogy, we analytically compute the characteristics of the considered hype cycle dynamics in Section 5. In Section 6, we propose a methodology to detect the onset of the move towards the Trough of Disillusionment. Finally, concluding remarks and perspectives are given in Section 7.

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[12]: "It is not a case of choosing those which, to the best of one’s judgment, are really the prettiest, nor even those which average opinion genuinely thinks the prettiest. We have reached the third degree where we devote our intelligences to anticipating what average opinion expects the average opinion to be. And there are some, I believe, who practice the fourth, fifth and higher degrees."
2. State of the Art

In both the academic and the business worlds, the concept of hype has long been used to determine the evolution and maturity level of a newly introduced technology [3]. A general framework was presented in [20] to model social “bubbles” and their aftermath as the consequence of collective over-enthusiasm. According to the author, this phenomenon is based on positive feedback loops of reinforcing behaviors that are linked to imitation, herding, and self-organized cooperation, which ultimately lead to the development of endogenous instabilities. The **Social Bubble Hypothesis** is proposed as *levers of innovation*, describing how social interactions between enthusiastic agents result in the diffusion of technological advances.

As stated in [1], the emergence of the hype cycle phenomena is mainly due to the combination of two factors. On the one hand, the actual maturity of the technology directly affects the shape of the hype formation. On the other hand, early high-rising expectations about the technology are due to complex social interactions, and they are often spread through spoken and written words. These initial expectations can be defined as "*real time representations of future technological situations and capabilities*" [1]. Consultancy firms, in particular Gartner Inc. [4], have long been using this framework to provide advice in strategic decision-making. In [3], it is highlighted that the Gartner hype cycle has long been established as an empirical framework to describe the different phases of development and maturity of a new technology. Accordingly, it is widely used by practitioners in determining the current stage of a technology innovation and helping them in their investment decisions. While the hype cycle tool has been proven to be effective in practice, it has not been fully discussed on a scientific ground yet. However, the hype cycle model has attracted substantial attention from scholars and has been considered in numerous research fields dealing with the introduction and adoption of new technology. These studies range from the medical domain [10], the energy sector [13], information systems [17], consumer electronics [11], and even education [15].

Several recent contributions focus on qualitatively describing the characteristics of various hype cycles arising in different business contexts. In [21], three case studies are presented: specifically hype patterns for voice over internet protocol, gene therapy, and high-temperature superconductivity are analyzed. Sustained attention is focused on studying the possible business-specific causes that explain the emergence of these particular hype cycles. These include in particular environmental factors, such as the complexity of the underlying regulations [6] or the market structure [14]. Note that in the present contribution, we adopt a more generic point of view, the goal of which is to understand the nature of the multi-agent mechanisms responsible for the formation of the hype cycle. While based only on a restricted number of control parameters, our modeling nevertheless allows a fitting to generic hype patterns.

An attempt to describe the hype cycle quantitatively has been recently proposed in [19]. To that aim, a mathematical approach based on a probabilistic master equation is introduced, where all the required rate parameters are estimated from data by a fitting procedure. The basic difference between the present contribution and [19] is that here the hype phenomenon is viewed as emerging from microscopic human interactions. In [19], a unified framework is proposed to fit to any existing macroscopic hype pattern, but the very origin of the hype phenomenon is not addressed. Similar bubble-like dynamic behaviors are also thoroughly discussed in closely related areas. In particular, in the context of the stock market, a multi-agent model is proposed in [8] to describe the spontaneous development of bubbles and subsequent crashes. The interacting agents base their behavior on various type of information sources: public information, peers, and private information. It is shown that bubbles originate from an initial random streak of positive news, which is then relayed and magnified by a nonlinear feedback mechanism.

3. Collective Opinion Dynamics and Emergence of the Hype Cycle

As highlighted in [19], innovation hype cycles are macroscopic patterns depicting the time-dependent collective opinion of a society of autonomous, mutually interacting, decision-making agents. In order to understand the emergence of the hype cycle, we construct a multi-agent microscopic model describing how the hype cycle dynamics spontaneously emerges. The details of this multi-agent dynamics are described below.

The hype cycle is modeled as the dynamics of an abstract *collective mind* synthesizing the *business attitude* of potential investors (PIs) towards an innovation. The opinion of the PIs is built by gathering publicly available information, and it is stored in an abstract *information pool* $\mathcal{P}$. The facility $\mathcal{P}$ contains abstract *information queries* (AIQs) $Q(q, \tau; t)$, where $q$ and $\tau$ are internal variables that are described below and $t$ stands for the time
variable. The PIs’ collective opinion at time \( t \) is summarized by the number \( N(t) \) of AIQs that are present in \( P \); i.e. the larger is \( N(t) \), the stronger is the investment incentive for the new technology. Accordingly, a hype corresponds to a peak of \( N \), and therefore a hype cycle is described by a large oscillation of \( N \). We assume that the internal states \( q \) and \( \tau \) of the AIQs \( Q(q, \tau; t) \) are updated by technology experts (EXs), who act as opinion leaders when sharing their judgment about the new innovation and hence ultimately influencing the PIs’ strategic investment decisions. At any time \( t \), we assume that a single EX updates at most a single AIQ.\(^3\)

We assume that an external incoming flow of EXs drop their (single) AIQ into the information pool \( P \). After delivering her AIQ to \( P \), the bare EX (i.e. no AIQ is attached to it anymore) spontaneously becomes an information gathering expert (GEX), illustrating the fact that the experts steadily update their judgment regarding the technology innovation. GEXs are immediately lining up in an information gathering service area \( B \) with limited capacity \( B \) (namely, when the area \( B \) is filled with GEXs at level \( B \), any extra entering GEX is discarded from the system). The GEXs present in \( B \) have the task to extract one AIQ stored in \( P \). Provided \( P \) is not empty, the extractions are performed one by one at a rate \( \mu \). The AIQ extraction is achieved by systematically selecting the AIQ posting the largest \( \tau \) value. In \( Q(q, \tau; t) \), the internal variable \( \tau \) monitors the time spent by the AIQ in \( P \), i.e. it is actually a storage waiting time.\(^4\) After extracting an AIQ stored in \( P \), GEXs read the state of the binary variable \( q \in \{E, S\} \) where \( E \) stands for \\underline{e}nthusiastic and \( S \) for \\underline{s}keptical. Then, depending on the \( q \)-value of the just extracted AIQ, one of the two following alternatives occurs:

1. \( q = E \) (enthusiastic). A new AIQ \( Q(E, 0; t) \) is fed back to \( P \) and the reading GEX remains active and hence extracts available AIQs stored in \( B \).

2. \( q = S \) (skeptical). Both the AIQ and the reading GEX are permanently discarded from the system.

**Update of the Internal Variable \( q \).**

Upon entrance into \( P \), the \( q \) variable of any AIQ is systematically re-initialized to the state \( E \). Furthermore, the transition \( E \rightarrow S \) occurs at a rate which is monotonously increasing with \( \tau \). The flow dynamics of the AIQs stored in \( P \) is regulated by:

(a) an external incoming flow of AIQs (the external AIQ inflow rate is denoted by \( \lambda(t) \)).

(b) an incoming feedback flow of enthusiastic AIQs. Whenever a GEX reads an AIQ posting \( q = E \), she immediately feeds back one AIQ with \( \tau = 0 \) into \( P \), and the GEX remains active.

(c) an outgoing flow of skeptical AIQs. Whenever a GEX reads \( q = S \) in the extracted AIQ, both the GEX and the AIQ are permanently discarded from the system.

**Discussion of some Relevant Modeling Features.**

- By requiring the \( E \rightarrow S \) transition rate to be monotonously increasing with the sojourn time \( \tau \) of the AIQs in \( P \), we implicitly assume that during their storage in \( P \) the AIQs undergo an information maturation process. This models the fact that, while stored in \( P \), AIQs steadily scavenge information from their surrounding and hence are potentially better able to unveil potential shortcomings of the innovation under evaluation. This is stylized by a \( \tau \)-dependent enhancement rate of the transitions \( E \rightarrow S \).

- By requiring the GEXs to systematically extract those AIQs posting the highest \( \tau \), the AIQ feedback flow in \( P \) is reduced to the minimum, and hence the \( N \) level is minimized. Accordingly, when monitoring \( N \), the PIs are guaranteed to optimize the available information maturity.

- Restricting the storage area \( B \) of the GEXs to capacity \( B \) implies an information saturation mechanism which limits the average inflow of the new AIQs. The agent dynamics is effectively similar to a multi-server queuing system (i.e. with \( B \) parallel servers, see Figure 2 below), and hence limiting the number

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\(^3\)Assuming that the EXs hold a single AIQ effectively implies that they contribute with equal weight to the opinion formation dynamics.

\(^4\)For simplicity, we assume the pace to be common to all GEXs. Accordingly, let us observe that \( \mu^{-1} \) stands for the average time that a GEX requires for extracting one AIQ from \( P \).

\(^5\)In other words, \( \tau \) simply measures the waiting time spent by the AIQ since its last entrance into \( P \) before its extraction.
of servers to $B$ ensures that, on average, waiting time $\tau$ in the queue is greater than the average service time $\mu^{-1}$. Note in turn that the capacity restriction to $B$ implies a limitation of the feedback flow to a maximum of $B\mu$.

- The agent behavior under study shares some similarities with the "follow the crowd or avoid it" principle exposed in [9], in the context of queueing theory. However, the presence of a delay in the decision-making precludes here from the emergence of a stationary state.

4. Feedback Queuing System Representation of the Dynamics

As sketched in Figure 2, the agent mechanisms introduced in Section 3 can be naturally summarized by considering a multiple server queuing system (QS) with a feedback loop. An external random flow of incoming customers (corresponding to the AIQs) feeds a QS composed of $B$ parallel servers. The incoming AIQs are stored inside a waiting room (here denoted by $P$), and they are subsequently served in parallel by a set of multiple servers (representing the GEXs). In this abstract QS, the AIQs in circulation behave effectively as impatient customers who, after being served, autonomously decide either to use the feedback loop or to definitely leave the system. Their individual routing decisions are taken on the basis of their last experienced waiting time in the QS (denoted here by the internal variable $\tau$). If $\tau$ exceeds a critical threshold (i.e. the customer’s patience), the customer chooses to leave the system. The service discipline is First-In-First-Out (FIFO), which corresponds to the GEXs always serving the AIQ posting the highest $\tau$.

The QS analogy continues by assuming that the random times between two successive exogenously incoming AIQs is drawn from a stationary probability density $f(t)dt$ with average $1/\lambda := \int_0^{\infty} tf(t)dt$. Similarly, the random time interval required to read the internal state of an AIQ is drawn from a stationary probability law $g(t)$ with average $1/\mu := \int_0^{\infty} tg(t)dt$. For simplicity, we assume in the sequel that $\lambda << \mu$, and hence the average service time is much shorter than the average inter-arrival time. Finally, $h(\tau)$ denotes the hazard rate function characterizing the $E \rightarrow S$ transitions. In particular, when $h(\tau) = \delta(\tau - T)$, the transitions depend deterministically on the time $\tau$ the AIQ spent in the information pool $P$. In this latter case, as long as $\tau < T$, the internal state remains $E$, and conversely, when $\tau \geq T$, a switch to $S$ is triggered. In Section 5, we analytically show that the resulting queue dynamics $N(t)$ render quite faithfully the oscillatory behavior characterizing hype cycles. In particular, the observed oscillations are due to the routing selection, which is based on the waiting time and hence implicitly introduces delayed responses into the QS dynamics.

\[\text{h}(\tau)\text{ is assumed to be identical for all AIQs.}\]
5. Hype Cycle - Analytical Derivation of the Dynamics

In this section, we calculate the dynamical queue content \( N(t) \), which is meant to stylize the hype cycle oscillation. To allow for an explicit and analytical discussion, we first make the following simplifying assumptions (n.b. though it will become clear in the sequel how these assumptions can easily be relaxed):

\[
(i) \quad h(\tau) = \delta(\tau - T) \\
(ii) \quad T > \max \{1/\mu, 1/\lambda\}
\]

Assumption \((i)\) reflects a deterministic routing threshold and assumption \((ii)\) allows us, thanks to the strong law of large numbers, to ultimately enable purely deterministic considerations. At time \( t = 0 \), we assume \( N(0) = 0 \) (i.e. the information pool \( P \) is initially empty, as no available judgments nor expectations are available before the Technology Trigger). Accordingly, it is intuitively clear that, initially, all incoming AIQs are fed back to \( P \) since, in this short transient phase, we have \( \tau < T \) and hence all AIQs post the internal state \( E \) (n.b. according to assumption \((i)\), when \( \tau < T \), no \( E \rightarrow S \) transition is provoked). Hence, the information pool \( P \) is progressively fed with AIQs at the average rate \( \lambda \) (i.e. the exogenous rate of the incoming AIQs, since none are ejected from \( P \)). The resulting systematic increase of the queue content \( N(t) \) reflects the building of the hype pattern. As time proceeds further, an increase of \( \tau \) (i.e. the waiting time of the stored AIQs in \( P \)) follows an increase of \( N(t) \). Once \( N(t) \) reaches a critical threshold content, the corresponding \( \tau \) will exceed the critical waiting time \( T \) (i.e. \( \tau > T \)), implying that the corresponding AIQs undergo a \( E \rightarrow S \) transition which, after service, will ultimately imply definitive ejection from the QS. Since the QS service discipline is FIFO (n.b. remember that the GEXs systematically extract the AIQ posting the larger \( \tau \)), waiting AIQs which undergo \( E \rightarrow S \) transitions are lined up in a row before service. When such a cluster of \( S \) successive AIQs sequentially reaches service, it results in a collective ejection of AIQs from the QS. This sudden \( N(t) \) depletion of \( P \) directly reflects the negative hype between the Peak of Inflated Expectations and the Trough of Disillusionment, which is the signature of actual hype cycles. As waiting AIQs posting an \( S \) state remain stored in \( P \) until their definitive ejection, the elapsed time between the \( E \rightarrow S \) transitions and the arrival to service generates a delayed response in the dynamics which is at the origin of the sudden \( N(t) \) decrease. This delay between the updating of an AIQ and its reading by GEXs corresponds to the time required to amend their judgment about the new technology and to find out whether current expectations are met or not.

A useful intuition about the dynamics of \( N(t) \) can be gained by invoking the hydrodynamic picture offered by the Tantalus glass device (n.b. sometimes also referred to as the Pythagorean glass), as sketched in Figure 3.

![Figure 3: The Tantalus or Pythagorean glass device. In the three leftmost panels, liquid is accumulating (at rate \( \lambda \)) into the glass, which corresponds to expectations inflating until they reach the Peak of Inflated Expectations. In the two rightmost panels, liquid is escaping from the glass (i.e. siphoning of the glass content, at rate \( \lambda - \mu \)), representing the phase where disillusionment prevails until the Trough of Disillusionment is reached. The siphoning rate directly depends on the diameter of the internal tube. The distance between the bottom of the glass and the top of the internal tube is directly proportional to \( T \). Observe that for large values of \( T \), any fluctuations in the filling rate will be averaged during the filling cycle (n.b. this is an analogical manifestation of the strong law of large numbers), thus enabling a deterministic approach.](image-url)
Calibration of the Hype Cycle

Only three independent calibration parameters are required for the model calibration, namely:

(a) $1/\lambda$: the mean inter-arrival time of exogenous AIQs

(b) $B/\mu$: the mean service time needed to extract one AIQ from $P$ when $B$ servers are occupied

(c) $T$: the critical waiting time which triggers the $E \rightarrow S$ switches

These three control parameters enable replication of the three variables listed in [21] for characterizing the shape and size of a hype pattern, namely (i) the degree of enthusiasm during the positive hype leading to the Peak of Inflated Expectations, (ii) the degree to which enthusiasm breaks down in the negative hype leading to the Trough of Disillusionment, and (iii) the overall length of the hype pattern.

To simplify the analytical discussion, let us assume that $B = 1$, meaning that the full service capacity is used as long as the storage is not empty. For large enough values of $T$, the dynamics of $N(t)$ becomes quasi-deterministic and the resulting hype oscillation exhibits a saw-tooth shape with the three above control parameters. With respect to this set of three parameters, explicit expressions for the time duration $H$ and amplitude $\Delta$ of the hype cycle read as [5,8]:

$$
\begin{align*}
H &= P \left[ 2 + \frac{\lambda}{\mu} + \frac{\mu - \lambda}{\mu} \right] \\
\Delta &= T \mu
\end{align*}
$$

(1)

The limited set of control parameters which drive the considered dynamics opens the door for the possibility to classify hype cycles accordingly for various innovation domains. As a result, the present modeling framework would offer predictive estimation power for the onset of observed hype cycles.

6. Detection of the Peak of Inflated Expectations

Having proposed a dynamical model for the hype cycle formation, the next natural and relevant question is how to quickly detect the onset of the negative hype leading to the Trough of Disillusionment, in order to prevent bad investments. Based on the dynamics proposed in the earlier sections, our detection method can be decomposed into two steps:

(1) Construct a diffusive approximation for the stochastic filling of the information pool $P$.

(2) Apply an efficient detection method for the change of drift of the diffusion process (as described in [18]) to detect the onset towards the Trough of Disillusionment.

(1) Diffusive Approximation for the Filling Process of $P$

We need to construct a stochastic differential equation (SDE) of the form:

$$
dY(t) = \mu Y(t)dt + \sigma dW_t,
$$

where $dW_t$ is a standard White Gaussian Noise process, and $\mu$ and $\sigma$ are respectively the drift and the variance, which depend on the arrival and service of the underlying QS. The process given by Eq. (2) must approximate the filling of the information pool $P$, and it is therefore the net inflow balance resulting from the superposition of three (generally not independent) processes, namely: the incoming and the feedback flows which fill $P$, from

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7 Note that provided $T$ is large enough, full service capacity will always be realized and, in this case, we have to simply substitute $\mu \rightarrow B\mu$ in the $B = 1$ results given in Eq. (1).

8 In [4], focus is put on describing a perpetual periodic queue content. In the present application, a single cycle of such periodic dynamics is considered.
which one needs to subtract the flow due to service. In the early filling phase however, since all AIQs are fed back into \( P \), the average filling rate is simply given by:

\[
(\lambda - \mu) \quad \text{incoming - service} + \mu \quad \text{feedback} = \mu.
\]

While the drift in Eq.(2) is easy to calculate, a refined characterization of \( \sigma \) resulting from the superposition of several (generally dependent) renewal processes would obviously be more cumbersome. Indeed, \( \sigma \) depends on both the variance of the incoming flow and the service time. Note that the feedback loop alone does not add an extra noise source, and hence fluctuations are only due to inter-arrival and service times, implying that we can simply use the diffusion approximation models available for \( G/G/1 \) QS, as exposed in [16] or [2] (Section II):

\[
\sigma^2 = [\lambda C_A^2 + \mu C_S^2],
\]

where \( C_A^2 \) and \( C_S^2 \) respectively stand for the coefficients of variations of the inter-arrival and service times.

(2) Detection of the Onset Towards the Trough of Disillusionment

We use a diffusive dynamic similar to the one given by Eq.(2), and consider:

\[
\begin{cases}
    dY(t) = \mu Y(t) dt + \sigma dW_t, & \text{for } 0 < t < \theta, \\
    dY(t) = \rho \mu Y(t) dt + \sigma dW_t, & \text{for } t \geq \theta,
\end{cases}
\]

\[ Y_0 = 0 \]

where \( \rho \in [0,1] \). In other words, Eq (3) states that until time \( t = \theta \), the AIQs’ average filling rate in \( P \) is equal to \( \mu \), while for \( t \geq \theta \) it is weakened by an external factor \( \rho \), thus signaling the Peak of Inflated Expectations and the onset of the move towards the Trough of Disillusionment. The factor \( \rho \in [0,1] \) has to be chosen by the potential investor according to her risk aversion.

Following the method explored in [18], we define the stochastic process \( Z_t \) as:

\[
Z_t = \log \left( \frac{dP_0(t)}{dP_\infty(t)} \right),
\]

where \( dP_0(t) \) and \( dP_\infty(t) \) are respectively the probability densities for the laws of \( (Y_t \mid \theta = 0) \) and \( (Y_t \mid \theta = \infty) \). According to Eqs. (3) and (4), we obtain:

\[
Z_t = \mu(1-\rho)Y_t - \frac{\mu^2(1-\rho)^2}{2\sigma^2}t = \begin{cases} 
+\frac{\mu^2(1-\rho)^2}{2\sigma^2}t + \frac{\mu(1-\rho)}{\sigma}W_t, & \text{for } \theta = 0, \\
-\frac{\mu^2(1-\rho)^2}{2\sigma^2}t + \frac{\mu(1-\rho)}{\sigma}W_t, & \text{for } \theta = \infty.
\end{cases}
\]

Let \( A \) and \( B \) respectively be a lower bound and an upper bound for \( Z_t \), that will be used in the detection method (see Figure 4). In order to directly refer to the results derived in [18], we rescale the time as:

\[
t \mapsto \tau = \frac{\mu^2(1-\rho)^2}{\sigma^2}t.
\]

Applying the time rescaling of Eq.(6), Eq.(5) reduces to:

\[
Z_\tau = \begin{cases} 
+\tau + \sqrt{2}\tau, \\
-\tau + \sqrt{2}\tau.
\end{cases}
\]

which directly matches the framework explored in [18] (n.b. observe that the signs here are reversed compared to [18], and therefore the roles played by the boundaries \( A \) and \( B \) as given in [18] likewise have to be reversed). Denoting \( R_W(A,B) \) and \( T(A,B) \) as the average time delay before detection and the average time interval
between two false alarms respectively, we have according to [18]:

\[
\begin{align*}
R_W(A, B) &= \frac{A-B-2\frac{B(e^A-1)}{1-e^B} - B(e^A-e^B)(A-1+e^{-A})}{2[B(1-e^B)+A(e^A-1)]}, \\
T(A, B) &= \frac{B(1-e^A)+A(e^B-1))}{1-e^B}.
\end{align*}
\]  

(8)

Consider now all possible detection intervals \((A, B)\) leading to a given average time \(T(A, B)\) between two false alarms. Among all the pairs \((A, B)\), it is natural to select the optimal pair \((A^*, B^*)\) which leads to the minimal \(R_W(A^*, B^*)\). According to [18], one finds \(B^* = 0\) and, for large \(A^*\), we have:

\[
\begin{align*}
T^* &= T(A^*, 0) = e^{A^*} - A^* - 1, \\
R_W(T^*)(A^*, 0) &= \frac{1}{2} \left\{ 2A^* \left[ \sinh(A^*) - \frac{1}{2} A^* \right] - 6 \left( \sinh^2(A^*) \right) \right\}.
\end{align*}
\]  

(9)

In limiting cases, one approximately obtains, according to [18]:

\[
R_W(T^*)(A^*, 0) = \begin{cases} 
\log(T^*) - \frac{3}{2} + O \left( \frac{1}{T^*} \log^2(T^*) \right), & \text{for } T^* \to \infty, \\
\frac{5}{6} T^* + O((T^*)^2), & \text{for } T^* \to 0.
\end{cases}
\]  

(10)

Finally, coming back to the original scales by using Eqs. (9) and (6), we obtain:

\[
\begin{align*}
\tilde{T}^* &= \frac{\sigma^2}{\mu^2(1-\rho^2)} T^* = \frac{[MC^2 + \mu C^2]}{\mu^2(1-\rho^2)} T^*, \\
R_W(\tilde{T}^*) &= \begin{cases} 
\log(\tilde{T}^*) - \frac{3}{2} + O \left( \frac{1}{\tilde{T}^*} \log^2(\tilde{T}^*) \right), & \text{for } \tilde{T}^* \to \infty, \\
\frac{5}{6} \tilde{T}^* + O((\tilde{T}^*)^2), & \text{for } \tilde{T}^* \to 0.
\end{cases}
\end{align*}
\]  

(11)

Figure 4: Multistage Wald’s detection method [18]. When level \(B\) is reached, at time \(t_1\), the process \(Z_t\) returns to 0. Just after time \(t_1\), the observed process \(Z_t\) becomes \(Z_t - B\). At time \(t_2\), when \(Z_t - B\) in turn reaches level \(B\), the process returns again to 0 and the observed process becomes \(Z_t = Z_t - 2B\), and so on. When the lower bound \(A\) is reached (here at \(t_3\)), it will be interpreted as the Peak of Inflated Expectations and the onset of the move towards the Trough of Disillusionment.

In view of Eqs. (9), (10), and (11), the following observation can be drawn. Eq. (11) quantifies the intuitive fact that imposing a very large average time between two successive false alarms \(T(A, B)\) leads in parallel
to accepting a large delay before detection. This illustrates that requirements of simultaneously having large average times between false alarms and short average times for drift change detection are conflicting issues. The optimal trade-off should be adjusted according to predefined utility functions which are intimately connected with the risk aversion of the PIs. Strongly risk-averse PIs will insist on early detection of the Peak of Inflated Expectations and onset of the move towards the Trough of Disillusionment, implying that they will accept false alarms, thus potentially losing opportunities to explore high levels of the hype (i.e. those risky stages with high potential rewards). Conversely, risk-inclined PIs will not tolerate false alarms, and they are conversely willing to accept late warning on the beginning of the negative hype towards the Trough of Disillusionment.

Remarks:

(i) The parameter $\rho$ is closely connected with the detection sensitivity issues and therefore with $\hat{T}^*$ itself. Indeed, choosing $\rho$ close to unity (i.e. request to detect very tiny changes in the filing drift) leads, according to Eq. (11), to large average detection delays.

(ii) As is discussed in [18], one may raise the question regarding the optimality of the present cyclic detection method. Using a (more involved) optimal detection procedure (see Theorem 5.1 in [18]), one succeeds in slightly improving Eq. (11) to finally arrive at:

$$\mathbb{R}_W(\hat{T}^*) = \begin{cases} 
\log(\hat{T}^*) - 1.577 + \mathcal{O}\left(\frac{1}{\hat{T}^* \log^2(\hat{T})}\right), & \text{for } \hat{T}^* \to \infty, \\
\frac{1}{2} \hat{T}^* + \mathcal{O}((\hat{T}^*)^2), & \text{for } \hat{T}^* \to 0.
\end{cases}$$

(12)

7. Conclusion and Perspectives

In this contribution, we propose a synthetic and stylized multi-agent model that enables us to capture the emergence of collective temporal patterns, driving hype cycles which are the result of a collective mind phenomenon. In that respect, the present work can be considered as a specialized component of a more general and vast ongoing line of research centered around the Social Bubble Hypothesis, e.g. [7]. Since hype cycle dynamics is a complex phenomenon lying at the interface between qualitative and quantitative sciences, any relevant modeling approach should, as in the present contribution, offer both simplicity (i.e. limited numbers of external control parameters to get a rapid although rough calibration) and robustness (i.e. generic character, for which specific details regarding the considered dynamics and the nature of the underlying stochastic processes can be modified without altering the overall dynamical picture). As can be explicitly observed in the framework proposed in the present contribution, the origin of the hype phenomenon can be interpreted as being due to the presence of a delayed response in an underlying nonlinear dynamic decision-making process. In addition, the ubiquity of fluctuations in multi-agent decision-making processes requires the mathematical modeling to be intrinsically stochastic. Despite the joint presence of nonlinearity and randomness in the dynamics, the present approach offers the possibility to analytically study the considered dynamics for a wide class of cases. Hence, our model contributes to developing intuition regarding the essence of the phenomenon and the role played by the few external parameters which control the hype pattern (i.e. in particular the amplitude and the purging rate characterizing the disillusionment phase). While understanding the essence of the hype phenomenon is a natural first step, the second important action will be to try to enhance investors’ skill in detecting, as soon as possible and without error, the Peak of Inflated Expectations and the onset of the move towards the Trough of Disillusionment. One may think that efficient detection strategies are often based merely on hollow noise, or one may alternatively formulate a mathematical framework adapted to this specific situation. In the realm of stochastic processes, the very long history of optimal detection problems offers a natural set of methods to detect the start of the disillusionment phase. While early detection and preventing false alarms are conflicting issues, the specific risk aversion of the decision-maker, and in particular her choice of the average time between two successive false alarms (i.e. wrongly detecting the Peak of Inflated Expectations), constitute an appropriate performance measure for the detection process.
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