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**A TOOL FOR DESIGNING AND EVALUATING
THE TEMPORAL WORK PATTERNS
OF HUMAN AND ARTIFICIAL AGENTS¹**

Abstract: The measure of availability that is often used to compare the dependability of computer-based systems is imperfect, insofar as two systems with the same availability can display quite different performance characteristics. Here we develop a new fractal temporal measure for work effort that offers insights into a system's performance not captured by the traditional availability measure. Moreover, we show that this fractal measure can be used to compare the temporal work patterns of both human and artificial agents and identify their unique strengths and weaknesses. Such new comparative tools will become increasingly important as the development of more sophisticated artificial agent technologies creates situations in which particular functions within an organization can be carried out either by human or artificial personnel.

Keywords: Performance analysis, fractal dimension, management of computing and information systems, working hours, artificial intelligence (incl. robotics).

DOI: 10.15611/ie.2014.3.05

1. Introduction

As the sophistication of artificial agent technology grows, businesses are employing artificial agents in an increasing number of roles. In the form of web- or telephone-based conversational agents, artificial agents are on the front lines of complex interactions with customers that directly shape an organization's public image and customer-service performance. Advances in social robotics are also creating opportunities to deploy artificial agents in situations where they interact with human customers, coworkers, and partners – as well as other complex computerized systems – on an ongoing basis. In order to carry out these tasks, artificial agents are now being created that are capable of mastering sophisticated interpersonal workplace

¹ Selected parts of this article were published under nonexclusive copyright in Position papers of the Federated Conference on Computer Science and Information Systems FedCSIS 2014 (see [Gladden 2014]).

behavior such as using social intelligence to successfully manage the abilities, limitations, and expectations of human employees [Williams 2012], identifying and displaying culture-specific behaviors in interactions with human colleagues [Rehm et al. 2009], and evaluating the performance of the human members of virtual teams [Nunes, O’Neill 2012].

The fact that artificial agents are becoming capable of filling a growing number of organizational roles that have traditionally been filled by human workers means that practitioners of disciplines such as organizational design, solution architecture, and performance engineering will need ways of assessing and comparing how human workers and artificial agents would perform differently (or similarly) if assigned to the same role within an organization. New and more robust metrics for quantifying *managerial* performance are especially desirable, as it is typically more difficult to precisely quantify the performance of a manager than it is to quantify the performance of, say, a human worker or robot filling an assembly-line role, where job performance can be quantified relatively easily in terms of units assembled per hour or nonconformities per million opportunities (NPMO).

In developing new measures to compare the performance of human beings and artificial agents executing management functions, we find that one of the most crucial aspects of their work performance is the extent to which they effectively and efficiently use *time*. We have previously proposed a new temporal measure based on the Hurst exponent and fractal dimension that is useful for calculating and comparing the work effort dedicated to a given task within a particular time by either human personnel or artificial agent systems that are carrying out the four key management functions of planning, organizing, leading, or controlling [Gladden 2014]. In this paper, we further develop that proposed fractal measure as a means for identifying specific kinds of performance strengths and weaknesses that particular human or artificial agents are likely to demonstrate in such roles.

2. Formulating a fractal measure to assess agents’ temporal work patterns

2.1. Identifying relevant time-scales for human and artificial agents

When assessing the work effort of artificial understood agents as computer-based systems, the relevant time intervals to be taken into consideration range from the macrotemporal level of several years (i.e., the lifespan of a typical commercial artificial agent system as utilized within a business) down to the microtemporal level of around 17 milliseconds (i.e., the time needed to generate a single screen refresh) or less [Gladden 2014]. As Gunther notes, there is no need to consider much smaller time intervals such as a single CPU cycle [Gunther 2005] that do not have an immediate relation to the larger-scale processes that we describe as an agent’s meaningful “work.”

When assessing the work effort of human managers, the relevant time-scales are similar; the time intervals to be taken into consideration range from the macrotemporal level of several years (i.e., the length of time that a human employee typically spends working for a particular organization) down to the microtemporal level of around 50 milliseconds (i.e., the length of time needed to hear or speak a single phoneme or to consciously perceive a single coherent experience or event [Gladden 2014]).

Within this range, there are time-scales and activity cycles of different lengths that demonstrate significant self-similarity: within a given year of work, a typical human manager will spend many consecutive weeks working, interrupted periodically by non-work weeks of vacation; within a given week of work, he will spend spans of several consecutive hours working, followed by non-work hours when he is asleep or out of the office; and within a given hour of work, his spans of minutes spent working will be followed by non-work intervals when he is checking personal emails or taking a coffee break. The roughly self-similar nature of this temporal dynamic opens the door to understanding a human manager's work activity as a fractal time series.

2.2. Fractal dimension as an indicator of persistence and antipersistence

One of the most important attributes of a fractal time series is that it possesses a *fractal dimension* that captures valuable information about the series' temporal dynamics. The fractal dimension of empirically observed natural phenomena can be described by the equation $D = 2 - H$, where H is the Hurst exponent of the time series as graphed in two-dimensional Cartesian space [Mandelbrot 1983]. The case $0 < H < \frac{1}{2}$ reflects a dynamic that is variously described as “antipersistent,” irregular, or trend-reversing: if the value in one moment is greater than the mean, the value in the next consecutive moment is likely to be less than the mean. The case $H = \frac{1}{2}$ represents a random-walk process such as Brownian motion, in which the value in the next consecutive moment is equally likely to move toward or away from the mean. The case $\frac{1}{2} < H < 1$ is described as “persistent” or quasi-regular: the value at the next consecutive moment in time is likely to be the same as the value in the previous moment [Mandelbrot 1983, pp. 353, 354; Valverde et al. 2005, pp. 817–822]. In such a case, we say that the dynamic has long memory.

2.3. Work effort as a time series of binary values

Graphing an agent's work effort in two-dimensional space would be useful if the work effort displayed by a human or artificial agent manager at a particular instant of time were able to range across a continuous spectrum of values. However, in this case we have only a binary set of possible values: at any given instant, an agent is either focusing its attention on its work, or it is not [Marchetti 2000; Gladden 2014]. B.B. Mandelbrot notes [Mandelbrot 1983, p. 354] that if the fractal dimension of a time series graphed in two-dimensional space is represented by the equation

$D = 2 - H$, then the zero set (or any other level set) of the graphed time series would have fractal dimension:

$$D = 1 - H.$$

We can use this equation to relate the fractal dimension and Hurst exponent for work effort as graphed on a one-dimensional line segment. The length of the entire segment represents the entire time available (such as a year, week, or hour) during which an agent can potentially be performing work. Those instants of actual work form the set graphed on the line segment, while instants of non-work do not belong to the set.

In these circumstances, the Hurst exponent takes on a different meaning. For a two-dimensional graph of a time series with $H \approx 0$, successive y -values alternate antipersistently around the mean, and the graphed line fills up a relatively large share of the two-dimensional space. For a one-dimensional graph of a binary time series, one might visualize the set as though it contains a single point that is able to slide back and forth along the x -axis to occupy many different x -values simultaneously, thus forming the set. For a set with high persistence ($H \approx 1$), the point may be locked to a single x -value, reflecting a process with long memory. For a set with low persistence ($H \approx 0$), the point “forgets” where it is and is free to move up and down the line segment, occupying many different x -values [Gladden 2014].

2.4. Applicability of the box-counting method to work patterns

We can employ the Minkowski-Bouligand or box-counting method to estimate the fractal dimension of managerial workers’ temporal dynamics. (While this method lacks some of the mathematical import found in other definitions of fractal dimension such as the Hausdorff dimension, the box-counting dimension has an advantage in that it can easily be applied to empirically observed phenomena [Longo, Montévil 2014].) The box-counting dimension D of set F can be calculated as:

$$D = \lim_{\delta \rightarrow 0} \frac{\log N_{\delta}(F)}{-\log \delta}.$$

Here $N_{\delta}(F)$ is the smallest number of sets of diameter δ that cover the set F [Falconer 2004, pp. 41–44]. When using the box-counting method to estimate the fractal dimension of natural phenomena, this can be done by calculating the average value of D that results when one empirically determines $N_{\delta}(F)$ for multiple values of δ [Wahl et al. 1994, pp. 75–108].

2.5. Calculating our fractal measure for agents’ temporal work patterns

To apply the box-counting method to the temporal dynamics of a human or artificial agent’s work, we consider an agent’s typical work effort as viewed across on three different time-scales or levels: 1) The set F_1 includes those weeks worked within a

span S_1 of five years (or 260 weeks), for which the covering sets used for the box-counting estimation were $\delta_a = 4$ weeks, $\delta_b = 2$ weeks, and $\delta_c = 1$ week. 2) The set F_2 includes those hours worked within a span S_2 of one week (or 168 hours), for which the covering sets used for the box-counting estimation were $\delta_a = 4$ hours, $\delta_b = 2$ hours, and $\delta_c = 1$ hour. 3) The set F_3 includes those minutes worked within a span S_3 of one hour, for which the covering sets used for the box-counting estimation are $\delta_a = 1$ minute, $\delta_b = 30$ seconds, and $\delta_c = 15$ seconds. Using the box-counting method, we calculate D_1 , D_2 , and D_3 for the time-scales F_1 , F_2 , and F_3 , respectively, and average those values to produce a mean value of $D = \langle D_1, D_2, D_3 \rangle$ for a particular agent. We then calculate the estimated value for the Hurst exponent for that agent's temporal dynamic with the equation $H = 1 - D$.

2.6. Contrasting our fractal measure with availability and reliability

We can compare our fractal measure with two common measures of work effort for computer-based systems: namely those of *availability* and *reliability*. The reliability of a computer is frequently quantified in the form of its “mean time to failure” (MTTF), the average length of time a system will remain continuously in operation before experiencing its next failure [Grottke et al. 2008]. The mean time to repair (MTTR) is the average length of time needed to detect and repair the failure and return the system to operation. By combining these two measures, we can calculate a computer's steady-state availability A , which is the likelihood that the computer is operating at a particular moment and is given by the equation [Grottke et al. 2008]:

$$A = \frac{\text{MTTF}}{\text{MTTF} + \text{MTTR}}.$$

Availability's simplicity as a performance measure is both a strength and a limitation. Two servers with the same value for availability might possess radically different performance characteristics that are not captured by the availability figure [Gunther 2005]; for example, 1) a server that runs without a single instant's interruption for nine months and then needs to be taken offline for a month for maintenance, upgrades, and testing, and 2) a server that freezes for one out of every ten seconds but never requires any downtime for maintenance or upgrades each has an availability of 90%, but the performance characteristics (and potential practical uses) of the two servers are quite different.

Another limitation to the measure of availability is that it has traditionally been understood in a purely binary manner: a system is either ‘up’ or ‘down’. Rossebeø et al. suggest the need to develop a more sophisticated measure that takes qualitative aspects into account and allows for a range of intermediate qualitative states between simply ‘up’ and ‘down’ [Rossebeø et al. 2006]. While we strongly support such efforts, the new measure that we propose takes a different tack: its unique diagnostic

value comes not from adding a more robust qualitative component but from instead introducing a more sophisticated approach to the fineness and resolution of the time-scales on which the binary up/down measurements are being made.

3. Applying our fractal temporal measure to human workers

We can now apply our fractal temporal measure to the case of particular human managers and compare and contrast the results with those received when the traditional measure of availability is applied to the same cases.

3.1. Temporal dynamics of Human Manager A

Consider a hypothetical Human Manager A whose work effort nears the maximum of what is possible for contemporary human beings. This manager takes no weeks of vacation during the five years worked in his position ($S_1 = 260$ weeks, $N_\delta(F_1) = 260$ weeks). He focuses entirely on his career, working an average of 90 hours per week ($S_2 = 168$ hours, $N_\delta(F_2) = 90$ hours). During the work day, he avoids all possible distractions and spends only 5 minutes of each ‘work hour’ not performing work-related functions ($S_3 = 60$ minutes, $N_\delta(F_3) = 55$ minutes). In Figure 1 we have graphed each of these situations on a line segment. Within the graph of the time series, a moment of work is indicated with a colored vertical slice, and a moment of non-work is indicated with an unshaded interval. For an agent with these characteristics, we have calculated $D = 0.962$, $H = 0.038$, and availability (understood as the likelihood that any randomly-selected instant of time will fall during a moment of work rather than non-work) as $A = 49.1\%$.

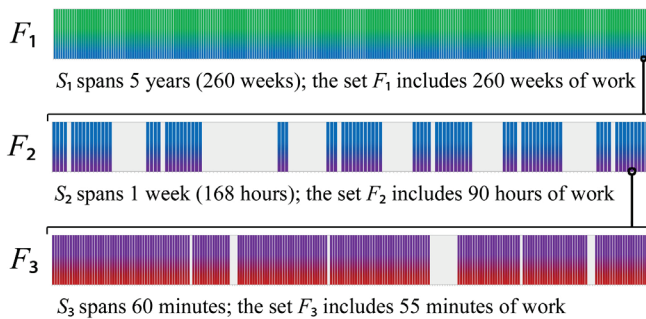


Figure 1. Human Manager A's periods of work and non-work

Source: author's own design.

3.2. Temporal dynamics of Human Manager B

Hypothetical Human Manager B represents the opposite end of the spectrum: his time commitment approaches the lowest amount possible for someone who is fulfilling a management role with an organization. We suppose that Human Manager B spends only half of the weeks in the year working ($S_1 = 260$ weeks, $N_\delta(F_1) = 130$ weeks), and even during those weeks when he is working, the manager dedicates only 10 hours of effort to this particular position ($S_2 = 168$ hours, $N_\delta(F_2) = 10$ hours). Moreover, during each hour of ‘work,’ the manager spends only a third of the time focused directly on work-related tasks, with the rest of the time representing distractions or non-work-related activities ($S_3 = 60$ minutes, $N_\delta(F_3) = 20$ minutes). A graph of the temporal work dynamics of Human Manager B is seen in Fig. 2 below. For an agent with these characteristics, we have calculated $D = 0.532$, $H = 0.468$, and $A = 1.0\%$.

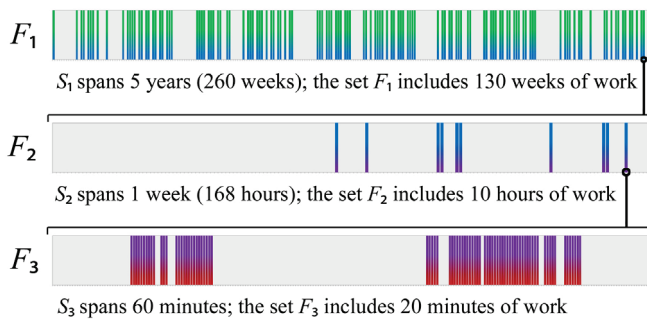


Figure 2. Human Manager B’s periods of work and non-work

Source: author’s own design.

3.3. Temporal dynamics of Human Manager C

Hypothetical Human Manager C takes off 16 weeks of vacation from work each year, scattered over the course of the year ($S_1 = 260$ weeks, $N_\delta(F_1) = 180$ weeks), however during weeks when he is working, he works an intense schedule of 50 hours per week ($S_2 = 168$ hours, $N_\delta(F_2) = 50$ hours). Such a schedule might reflect, for example, the routine of a part-time consultant who has frequent breaks between labor-intensive projects. During each hour of work, this manager spends 8 minutes on non-work-related activities – e.g., checking personal emails or taking an exercise break before launching into another focused session of work ($S_3 = 60$ minutes, $N_\delta(F_3) = 52$ minutes). A graph of the temporal work dynamics of Human Manager C is seen in Fig. 3 below. For an agent with these characteristics, we have calculated $D = 0.692$, $H = 0.308$, and $A = 17.9\%$.

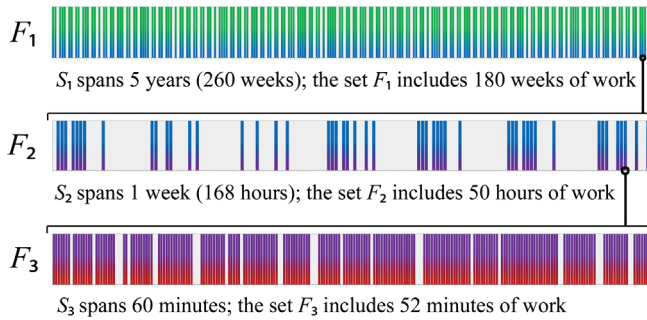


Figure 3. Human Manager C's periods of work and non-work

Source: author's own design.

3.4. Temporal dynamics of Human Manager D

Hypothetical Human Manager D works every week of the year ($S_1 = 260$ weeks, $N_\delta(F_1) = 260$ weeks), however during each of those weeks he works a comparatively relaxed schedule of 36 hours per week ($S_2 = 168$ hours, $N_\delta(F_2) = 36$ hours). Such a schedule might reflect, for example, the routine of a manager in a relatively quiet small business who is, however, never able to take a week of vacation because there are no other trained staff available to fill in for him during his absence. During each hour of work, the manager spends 10 minutes on non-work-related activities – e.g., checking personal emails and social media ($S_3 = 60$ minutes, $N_\delta(F_3) = 50$ minutes). A graph of the temporal work dynamics of Human Manager D is seen in Figure 4 below. For an agent with these characteristics, we have calculated $D = 0.908$, $H = 0.092$, and $A = 17.9\%$.

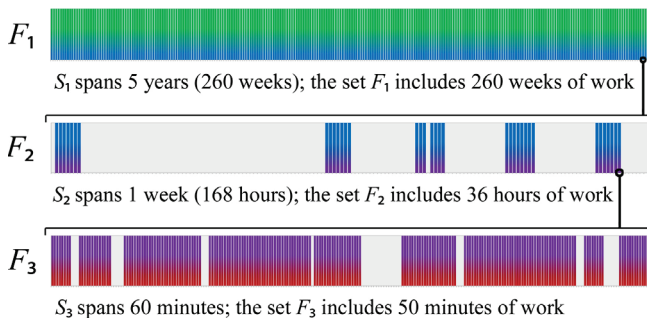


Figure 4. Human Manager D's periods of work and non-work

Source: author's own design.

3.5. Analysis of the cases of four hypothetical human managers

Through use of our fractal measure, we gain new insights into the unique strengths and weaknesses of managers' temporal work patterns. Table 1 below gives the values of fractal dimension (D), Hurst exponent (H), and availability (A) for all four hypothetical human managers described above, ranked from highest to lowest values of D .

Table 1. Human managers' work effort as characterized by fractal dimension (D), Hurst exponent (H), and availability (A).

Agent	D	H	A
Human Manager A	0.962	0.038	49.1%
Human Manager D	0.908	0.092	17.9%
Human Manager C	0.692	0.308	17.9%
Human Manager B	0.532	0.468	1.0%

Source: author's own calculations.

An examination of our calculations' results allows us to make the following observations:

1. Human Managers A and D display similar values of $H \approx 0$ (antipersistence), while Human Managers B and C display a value of $H \approx \frac{1}{2}$ (randomness). While more study is required to verify this supposition, it seems probable that managers with low persistence (as understood in the mathematical sense defined above) would as a practical matter experience fewer switch costs, as their work intervals last longer, and they spend a smaller share of their work time transitioning into or out of periods of work.

2. While the managers possessing values of $H \approx 0$ and $D \approx 1$ (i.e., Human Managers A and D) display "antipersistence" in the mathematical sense, in everyday terms this (perhaps counterintuitively) corresponds to a relatively continuous work routine composed of long intervals of uninterrupted work. From the perspective of solution architecture in the workplace, such managers possess a certain sort of "dependability," insofar as they are capable of working during almost all possible moments. However, they may simultaneously display a sort of "inflexibility," insofar as they are *used to working* in every possible moment, and thus unexpected interruptions may be more likely to derail the work of this sort of manager. On the other hand, managers with a value of $D \approx 0$ possess "flexibility," insofar as they are already used to working only sporadically and juggling intervals of work amidst many other activities, and thus unexpected interruptions to their work may not greatly faze them. At the same time, they may simultaneously display a sort of "undependability," insofar as their work intervals are generally short-lived and sporadic: the bulk of their time may already be filled with non-work-related activity,

leaving only brief, erratic slivers of time available for work. If an unexpected distraction prevents them from working during one of these windows, it may be some time before another window of availability for work appears. (Note that when making such assessments of an existing organization – rather than designing new organizational structures and processes – performance engineers must carefully distinguish whether the strengths and weaknesses identified result from a particular manager’s preferred “natural” work pattern or derive intrinsically from the structure and role of the manager’s position as currently designed.)

3. The scenarios and corresponding calculations described above demonstrate that the traditional measure of availability and our new fractal measure are not redundant or duplicative; each of the measures conveys unique information that cannot be derived from the other. For example, we can see that Human Managers C and D have identical values for A (17.9%) but different values for D (0.692 and 0.908, respectively). If a performance engineer were relying solely on the availability statistic, he could erroneously presume that Human Managers C and D have identical temporal work patterns, however our fractal measure reveals that this is not the case: Human Manager D displays a pattern of antipersistence (with its corresponding strengths and weaknesses, from a practical perspective) while Human Manager C reflects a pattern closer to randomness. This highlights the fact that if one only utilizes a simple measure such as availability in assessing (and ranking) the temporal work dynamics of human and artificial agents, one will miss out on additional information that our fractal measure can provide. While availability is an extremely useful measure, it is limited (and could potentially even be misleading) if not complemented by more sophisticated measures such as fractal dimension.

4. Using our fractal measure to design more effective artificial agent solutions for the workplace

4.1. The relationship of agent architectures to temporal work patterns

While current examples of artificial agent systems can generally be thought of as relatively conventional software applications (with the corresponding design elements and limitations), this will not always be the case. The kinds of autonomous artificial agents intended to interact with human beings will increasingly be expected to possess a more robust, human-like array of cognitive capacities. Artificial agents that utilize a neural net architecture will in particular display characteristics much different from those designed to run as a software application on a traditional serial-processor-based computer. Ongoing research indicates that as such artificial agents are designed with more advanced human-like cognitive capacities, they also begin to reflect a number of human-like cognitive needs and “limitations,” such as a regular need to temporarily shut off the stream of incoming sensory data in order to execute

a phase in which recently received data is fully processed and assimilated into long-term memory (i.e., an analogue to the daily human sleep cycle) and a need to “slow down” and reflect after some unfortunate event has occurred, in order to extract its meaning and identify ways of avoiding such disadvantageous events in the future (i.e., an analogue to human emotions such as sadness) [Friedenberg 2011, pp. 179–200].

Autonomous artificial agents possessing such cognitive and operational characteristics will find it increasingly difficult to maintain the high-availability work patterns (e.g., $A \approx 99.99\%$) demanded of most contemporary enterprise systems. Instead, their temporal work patterns will likely become more closely aligned with the range of patterns seen in human workers. In two examples below, we show how the use of our fractal temporal measure can – in conjunction with the measure of availability – highlight useful design considerations for organizational designers or solution architects who are incorporating advanced autonomous artificial agents into an organization’s business processes in roles in which they will interact over extended periods of time with human collaborators.

4.2. Temporal dynamics of Artificial Agent Manager A

We can first consider a hypothetical Artificial Agent Manager A in the form of a software program running on a computer with a typical serial processor architecture. (This represents the more conventional, relatively unsophisticated form of artificial agent.) We suppose that during a given five-year operating period, there may be brief service outages for scheduled maintenance or updates but that there are no extended outages ($S_1 = 260$ weeks, $N_\delta(F_1) = 260$ weeks). Each week, there is a scheduled maintenance window of one hour, when software updates are applied and the system is rebooted ($S_2 = 168$ hours, $N_\delta(F_2) = 167$ hours). We suppose that the software

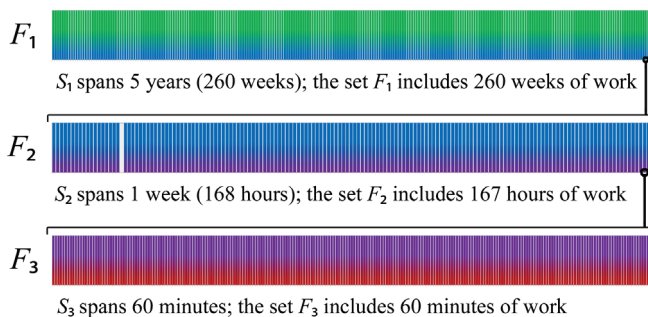


Figure 5. Artificial Agent Manager A’s periods of work and non-work

Source: author’s own design.

program and hardware substrate for Artificial Agent Manager A have no non-work-related functions and are not capable of being ‘distracted’ in the way that a human manager is; thus during a typical hour period of work, Artificial Agent Manager A does not dedicate any minutes to non-work-related functions ($S_3 = 60$ minutes, $N_\delta(F_3) = 60$ minutes). A graph of the temporal work dynamics of Artificial Agent Manager A is seen in Figure 5. For an agent with these characteristics, we have calculated $D = 0.999$, $H = 0.001$, and $A = 99.4\%$.

4.3. Temporal dynamics of Artificial Agent Manager B

Next we can consider the hypothesized future scenario of Artificial Agent Manager B, a more advanced form of artificial general intelligence with a distributed neural network architecture that is modeled on the human brain and – in comparison to contemporary artificial agents – displays more human-like motivations, emotions, and learning capacity [Friedenberg 2011, pp. 179–200]. While Artificial Agent Manager B enjoys its job, every two years it must spend a week away from work for a period of psychological assessment, maintenance, and relaxation, to reduce the likelihood of professional burnout ($S_1 = 260$ weeks, $N_\delta(F_1) = 258$ weeks). Moreover, during each week of work, its neural network architecture requires it to spend two hours daily in a “sleep” mode in which any new external stimuli are shut out, in order to facilitate the assimilation of the day’s experiences into long-term memory. In order to maintain its capacity for creativity, satisfy its intellectual curiosity, and avoid the development of cyberpsychoses, it must also spend two hours daily exploring spheres of experience unconnected to its work-related tasks ($S_2 = 168$ hours, $N_\delta(F_2) = 126$ hours). Because Artificial Agent Manager B reflects the full constellation of human-like cognitive and social behaviors, it spends five minutes of each hour on functions other than work, such as cyberloafing, following news stories, and communicating with friends ($S_3 = 60$ minutes, $N_\delta(F_3) = 55$ minutes). A graph of

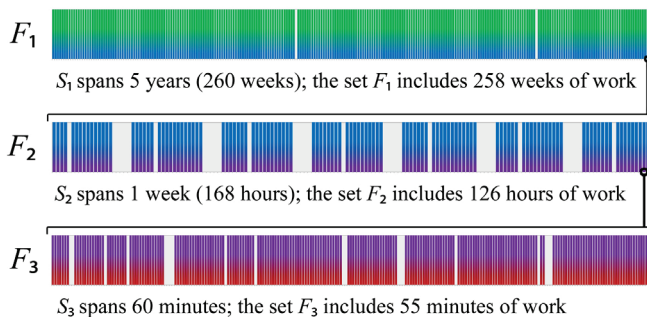


Figure 6. Artificial Agent Manager B’s periods of work and non-work

Source: author’s own design.

the temporal work dynamics of Artificial Agent Manager B is seen in Figure 6. For an agent with these characteristics, we have calculated $D = 0.945$, $H = 0.055$, and $A = 68.2\%$.

4.4. Analyzing the cases of hypothetical artificial agent managers

When we compare the temporal measures for our two artificial agent managers with those from our four human managers, we obtain the results (ranked from the highest value of D to the lowest) shown in Table 2.

Table 2. Human and artificial agent managers' work effort as characterized by fractal dimension (D), Hurst exponent (H), and availability (A)

Agent	D	H	A
Artificial Agent Manager A	0.999	0.001	99.4%
Human Manager A	0.962	0.038	49.1%
Artificial Agent Manager B	0.945	0.055	68.2%
Human Manager D	0.908	0.092	17.9%
Human Manager C	0.692	0.308	17.9%
Human Manager B	0.532	0.468	1.0%

Source: author's own calculations.

An examination of these results allows us to make the following observations:

1. The values for the two artificial agent managers described above further substantiate our assertion that the traditional measure of availability and our newly developed fractal measure yield non-duplicative, independently meaningful information about managers' temporal work patterns. For example, we note in the cases above that while a higher value for A is typically correlated with a higher value for D (i.e., higher availability is regularly correlated with greater antipersistence), there is no theoretical necessity that this always be the case. E.g., Human Manager A has a lower value of A than Artificial Agent Manager B but a higher value of D .

2. The hypothetical cases considered above suggest value in using a fractal temporal measure to compare the temporal patterns of specific human managers with those of specific artificial agents. If one relies solely on the measure of availability for such comparisons, one might find that – as a class – all artificial agent managers rank high in availability and all human managers rank significantly lower; the measure of availability is not well-suited for making more precise and meaningful comparisons between specific members of these two groups. Our fractal temporal measure, on the other hand, reveals more nuanced similarities and contrasts between particular human and artificial agents. For example, we see that the temporal work

patterns displayed by Human Manager A and Artificial Agent Manager A – as captured by their fractal temporal measure – are remarkably similar, despite the fact that their availability values differ greatly. While their availability values might lead an organizational designer, solution architect, or performance engineer to believe that Human Manager A and Artificial Agent Manager A have wildly different temporal performance characteristics – and are thus likely incapable of performing similar management functions with the same degree of effectiveness – the results of our fractal temporal measure force one to rethink that presumption and to consider more carefully whether Human Manager A and Artificial Agent Manager A actually possess similar strengths and weaknesses in their temporal work patterns that might allow them to perform the same management function interchangeably, with similar degrees of effectiveness.

5. Conclusions

Avenues for further research that we have identified to advance our understanding of these issues include gathering empirical data about temporal work dynamics from a sample of real-world human managers and artificial agent systems to verify the appropriateness and value of this fractal-dimension-based model. Analysis of such data could aid in predicting the temporal dynamics of future artificial agent systems (for which empirical data is not yet available) and designing more advanced artificial intelligence systems that will be capable of carrying out a wider range of business management roles. It would also prove worthwhile to identify correlations between the values of D and H for a particular manager's temporal dynamics with traits identified in established models of managerial motivation and behavior.

As described in this paper, the work that we have completed thus far has already demonstrated the fact that our fractal measure reveals unique information about the potential strengths and weaknesses of managers' temporal work patterns that cannot be obtained by looking at a traditional measure like that of availability, as well as the fact that our fractal measure can be applied to both artificial agent managers as well as human managers, allowing direct comparisons between the performance characteristics of the two. We hope that in some small way this fractal temporal measure can offer a new tool to practitioners of organizational design, solution architecture, and performance engineering, as they seek to create, maintain, and improve workplaces in which human personnel and sophisticated artificial agents share in carrying out effectively the most critical management functions of their enterprise.

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NARZĘDZIE DO PROJEKTOWANIA ORAZ OCENY MODELI PRACY CZŁOWIEKA I INTELIGENTNYCH AGENTÓW

Streszczenie: Miary dostępności używa się często do porównywania niezawodności systemów komputerowych. Jednakże jest to niedoskonała miara, w jakiej dwa systemy o takiej samej dostępności mogą wyświetlać diametralnie różne charakterystyki wydajności. Tutaj rozwijamy nową fraktalną, temporalną miarę dla nakładu pracy, która – używana obok dostępności – oferuje bogatszy wgląd do wydajności systemów komputerowych. Pokazujemy, że ta miara fraktalna może być stosowana do czasowego cyklu pracy zarówno ludzi, jak i inteligentnych agentów, umożliwiając bezpośrednie porównanie pomiędzy nimi. Analizując sześć hipotetycznych przypadków, pokazano, że ta nowa miara ujawnia unikatowe mocne i słabe strony w organizacji pracy człowieka i inteligentnych agentów, które nie są ujęte przez tradycyjne miary dostępności. Zidentyfikowano sytuacje, w których takie nowe narzędzie oceny porównawczej będzie coraz bardziej istotne dla projektantów i architektów rozwiązań organizacyjnych, a rozwój bardziej wyrafinowanych środków sztucznych stwarza sytuacje, w których poszczególne funkcje w organizacji mogą być przeprowadzane przez pracowników lub inteligentnych agentów.

Słowa kluczowe: analiza wydajności, wymiar fraktalny, zarządzanie obliczeniami i systemami informacji, godziny pracy, sztuczna inteligencja (łącznie z robotyką).