On the theory of system administration

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Abstract

This paper describes necessary elements for constructing theoretical models of network and system administration. Armed with a theoretical model it becomes possible to determine best practices and optimal strategies in a way which objectively relates policies and assumptions to results obtained. It is concluded that a mixture of automation and human, or other intelligent incursion is required to fully implement system policy with current technology. Some aspects of the author’s immunity model for automated system administration are explained, as an example. A theoretical framework makes the prediction that the optimal balance between resource availability and garbage collection strategies is encompassed by the immunity model.

1 Introduction

System administration is the realm of computer science which deals with the planning, configuration and maintenance of computer systems. It is presently a discipline founded mainly on the anecdotal experiences of system managers[1]. To date, no formal (mathematical) analyses of system administration have been undertaken, with the aim of making more scientific studies. This makes it difficult to express objective truths about the field, avoiding marketing assertions and the vested interests of companies and individuals, which are common in the commercial sector.

The aim of the present work is to establish a formal basis for the field, a way of formulating a framework for objective discussions about computer management. It will hopefully serve as a bridge between mathematical disciplines and system administrators. In this respect, the paper may be viewed mainly as a commentary, laying some foundations for future work, rather than providing immediate solutions.

In previous work, it has been shown how the average behaviour of systems of computers and users can be approximated by a blend of statistical models and thermodynamical ideas[2]. That work allows us to form a mathematical model of computer systems which can be used as a basis for modelling system administration. The study of computer behaviour has much in common with the physics of thermodynamics. From a coarse mathematical viewpoint, system
administration can be viewed in much the same way as thermodynamical experiments with pistons and engines, i.e. moving information and resources around in such a way as to change the state of the system. However this viewpoint is mainly useful in a calculational setting. System administration also has much in common with medicine. In many ways, system administration is medical science for computers: a somewhat simpler problem than that of human physiology, but nonetheless involving many of the same themes: nutrition, regulation, immunity and repair.

What then should a theory of system administration be about? The task of elucidating this sounds straightforward, but it is a slippery business. System administration, in reality, is based on mainly qualitative, high level concepts, which mix technical and sociological issues at many levels. Although it is clear to system administrators that there is a body of technical principles involved in the discipline, it remains somewhat intangible from the viewpoint of a scientist. It is hard to find anything of general, reproducible value on which to base a more quantitative theory.

One of the obstacles to formulating such a theory is the complexity of interaction between humans and computers. There are many variables in a computer system, which are controlled at distributed locations. Computer systems are complex in the sense of having many embedded causal relationships and controlling parameters. Computer behaviour is strongly affected by human social behaviour, which is often unpredictable. The task of identifying and completely specifying the ideal state is therefore a non-trivial one. It is nonetheless this task which this paper attempts to address. Can one formulate a quantitative theory of system administration, which is general enough to be widely applicable, but which is specific enough to admit analysis?

If this, already significant problem can be addressed in sufficient terms, one might then aim to look further towards general regulatory systems and approach more ambitious questions. It is not difficult to see many analogous questions in other areas of science, which could be applicable to system administration. For instance: what is the effectiveness of generalized immunity and repair systems? (automatic repair and regulation)? Is there an optimal strategy for error detection and correction? Is a system administrator’s human mind (playing the role of doctor/surgeon) better or worse than a mechanistic response or immune system? This last point is often a bone of contention in the system administration community. Should tasks be automated? Or should a human lawgiver always remain in manual control? What is more efficient? Biological systems point to the need for both types of management: at any given moment, a doctor’s intelligence and superior human cognition can compensate for a lack of adaptation in our programmed immune responses, but the automatic immune response is both faster and more capable than a doctor when its program is sufficient. Certainly the empirical evidence in biological information systems is compelling: after billions of years of evolution, nature has established immune systems in all vertebrates larger than a tadpole. Of course, this is no indication that the solution is optimal. No acceptable analysis has been used to demonstrate this yet. It could be that vertebrate evolution is merely poised on some
plateau between minima of much deeper importance.

The aim of this paper then is to elevate system administration from an expression of subjective opinion to a more objective, scientific level, hopefully without inflating it meaninglessly into pseudo-science or philosophy. In order to limit the length of this paper, solutions of the models and constraints will be kept to a minimum here. However, it will be possible to draw a few general conclusions, even without reference to specific models.

The outline of this paper is as follows. To begin the discussion it is necessary to establish some basic axioms. It is important to restrict the scope of what a theory of system administration encapsulates; without such a restriction, one ends up with either many disjointed pieces or only vague hand-waving notions. Having determined the ground rules, it is then appropriate to identify the basic operations which can be carried out within that scope. This identification is required in order to formulate a discussion of strategies for system management. Once this level of formality has been attained, strategies can be formulated, based on types of action and timing and the task of administrating a computer system can be described in precise game theoretical terms. This is the primary goal of this work.

2 The scope of system administration

One of the first obstacles in discussing the theory of system administration is defining its scope. System administrators are called upon to perform all manner of tasks as part of their duties. This battery of skills has no particular cohesion or structure to it, so it resists formalization. We must improve on this situation if we are to make progress in forming a theory of system administration. In particular, we must restrict its scope to encompass only core activities. These core activities will include insuring availability, efficiency, and security for all users, and finally fault diagnosis of the system. This includes issues such as software installation and upgrades, which can be classified under availability and efficiency. It also includes user management to a certain extent, though it will not be useful to address the issue of creation of user accounts in this context.

3 On scales

A well known feature of descriptions of complex systems is that a complete understanding is best organized as a unification of the partial understanding of the system at several different levels or scales. Complex systems are often so disparate at different scales that quite different descriptions are required to capture the full essence. A theory of system behaviour at, say the microscopic level of system calls, need not resemble a theory for the behaviour at a macroscopic scale of larger entities, such as patterns of user behaviour. Both are needed in order to understand the whole hierarchy of things going on.
If one is only interested in high level phenomena, then the details of low level phenomena are seldom directly relevant, to a good approximation. This is the principle of separation of scales. The principle states that, as one moves from microscopic to macroscopic scales, new behaviour can emerge as collective phenomena, which often depends only weakly on the microscopic details of the levels below. This is a simple idea, which is quite intuitive, but which has far reaching consequences. It can easily be appreciated with the help of a couple of examples.

A bridge, for instance, has the property of spanning a distance and carrying weight, regardless of whether it is made from steel or copper or wood. The choice of material and the microscopic arrangement of atoms in the metal or wood, of course, tells us something about the strength of the bridge, but perhaps not as much as the structure of the bridge at the scale of the whole thing. In other words, the construction of the bridge at the scale of the users of the bridge is far more important to its function than the microscopic construction of its pieces under a microscope.

Similarly, to an acceptable approximation, the behaviour and operation of a sales database, at the level of information transactions (their order and type), is more important to an information retrieval system than how those transactions are implemented through system calls (e.g. whether the system runs on Unix or on NT). The ability to retrieve information does not depend on whether the storage medium is, an IDE or a SCSI disk. The same job will be done regardless.

To summarize, a description of system behaviour at a high level is, for many purposes, independent of specific details of the lower levels. Computer systems can be modelled by generic computer systems with certain high level characteristics; similarly users can be modelled as idealized users, also with common characteristics. A theory of system administration will be most successful if it appeals to such generalities, rather than delving into unnecessary specifics.

4 Axioms of system administration

To begin a formal discussion, we need to establish a frame of reference, i.e. the ground rules for the discussion. In this section, a basic fundament is proposed with the aim of striking a balance between reality and suitability for analysis. It is also necessary to partially limit the scope of the discussion to avoid unnecessary complication. Although the aim of this presentation is not precise mathematical rigor, it is the aim to indicate that such a rigor is possible and to indicate how it can be provided. A secondary aim is to communicate the key elements of the discussion to a more theoretical audience; for these reasons, the language adopted is one which is meant to build bridges between system administration and more mathematical disciplines. Readers are asked to keep an open mind with regard to use of terms however, since technical disciplines often use words in meanings which are specific to those disciplines, and this could lead to confusion.

A computer system is analogous to a community composed of many in-
teracting and competing players: i.e. users and administrators. It can only properly be discussed in terms of the aims and activities of this collective and of individual members of that community. Not all the members of a community share the same objectives, as a general rule. Traugott and Huddleston have pointed out[5] that it is often pertinent to view a local computer community as a single virtual machine, rather than as a conglomeration of individual hosts. In this paper, the term computer system will be used to refer to the collective hosts of a local domain, or some appropriate logical unit of networked computers. It is taken for granted that there may be internal competition for resources and even conflict between competing parties.

In order to formulate a theory of system administration we must establish a set of possible goals, procedures and obstructions and state them in formal terms. The aims and intentions of each computer system are different; usually they are prescribed by a system policy, i.e. a formal statement of intent and allowed practice. The aim is then to postulate or derive strategies which best achieve those goals, given the essential constraints. From this viewpoint, one expects the language of constrained competition to play a role in a theory of system administration. Even if one could frame such a theory in formal terms, what would be the purpose of such an exercise? The principal benefit of such an attempt is to create a rigid protocol for discussing system administration, which is general enough to cover most of the actual problems and possibilities, but which is stringent enough to prevent its perversion by parties with vested interests in proving a certain point of view.

There is a number of stages in this programme. To begin with, one needs some basic axioms which all parties agree on, propositions which define the aims of system administration. Next one needs to abstract a model of a computer system which is sufficient to capture the dynamical interaction between all of the players, but which is sufficiently simple to be surrendered for analysis. Here we shall suppose that a computer’s resources (memory, CPU, disk etc) are divided into two parts,

\[ R = R_c \oplus R_m, \]

i.e. a part which determines the behavioural configuration parameters \( C \) of the system working resources, and a remainder part (the working resources themselves) which users of the system can change as a normal part of their interaction with the system. This remainder part can be observed over an appropriate time scale, giving a set of measurements \( M \) which indicate how the system is being used.

The different possible configurations of the system resources \( \{C\} \) are made up from the independent operation types \( \{T\} \) which lead to these configurations. From this definition one needs to be sure that a unique description is possible, i.e. eliminate points of contention about the description itself. Finally, one must be sure that the description is sufficiently complete, i.e. that there exists a mapping between policy and system configuration which is as complete as the problem itself. The purpose of this section is to introduce the key players in this description, in advance of a fuller description in the coming sections.
In order to state the purpose of system administration, we may take the basic tenet or principle to be the following:

**Basic assumption 1** The requirements and constraints of any computer system are defined at any time $t$ by an implementable system policy $P(t)$. This policy determines the actions or rules of play for a system administrator, but not necessarily the actions of users. It includes a specification of which and how many users are allowed to access the system.

The policy $P(t)$ is not usually a continuous function of time, but may change catastrophically (in the mathematical sense) over a time scale which is much longer than the time scale over which users act and make changes to the system. The nature of this policy is not yet determined.

In order to make a policy implementable, it must be possible to relate it to a complete configuration instruction for the system $C(t)$, through rules and constraints. These rules and constraints could be issued verbally to users, or could be programmed into configuration files of software components which form the system. A single complete configuration instruction for the system can be thought of as being a sum of two parts:

$$C = C_r \oplus C_u,$$

(2)

a specification of resource configurations $C_r$ which describe how the software and hardware landscape is configured, and a specification of user configurations $C_u$, which describes who is allowed to do what with the resources (this includes remote, network users who access services through local agents). A specification of user configurations $C_u$ (numbers of users and their rights to resources) could easily be separated from system policy conceptually, but it is convenient to view the policy as a complete specification of the system plus its intended and actual usage. The meaning of the symbol $\oplus$ is that of a heuristic union: configuration specifications take many forms (are objects of many types). They are most easily thought of as sets of more primitive objects, in which case the addition of sets implies their strict union.

A complete configuration instruction can be thought of geometrically as a point in a vector space, which is found by adding together instructions of linearly independent (orthogonal) types. One does this by introducing a set of primitive configuration instruction types $\{T^i\}$, and writing the complete configuration as a linear combination of these:

$$C = \sum_i c_i T^i,$$

(3)

with set-valued coefficients $c_i$. The basis of primitive configuration operations will be described later. A complete configuration usually contains instructions for the operators of the system also. The system administrator can also be viewed as part of this system for the sake of abstraction.

The set of all configurations $\{C\}$ contains much redundancy. Let us imagine that the mapping of complete configuration instructions to the final state of the
system is many to one, and that this multiplicity can be represented by a group of permutations and transformations $G$. Thus equivalent configurations could be formed by permuting configuration instructions, if ordering is unimportant, or by exchanging (transforming) one component of the configuration for another. An example of this is the following: the configuration of a World Wide Web service might be possible with several equivalent software systems, each with equivalent configuration files: in this case, these would form an equivalence class. Conversely, if even a minor detail distinguishes them, then they are inequivalent configurations.

Let us define an implementable policy $P(t)$ as being any representative member of the set of equivalent configurations $\{C(t)\}$

$$P(t) \equiv \{C(t)\}/G.$$  

(4)

A policy could naturally mean more than a configuration (or computer and its operators), but as long as other aspects of the policy cannot be implemented by either machine or human, they are irrelevant to the system. Having related policy to configuration instructions, the path is clear to define the state $S(t)$ of the system.

Let a state of the system describe a single configuration of users $C_u$, of system resources $C_r$ and a set of measured average metrics $M$ which summarizes the average usage of the system in relation to the users. The metrics $M$ represent a first order response (feedback interaction) between users and resources. The state is written, again, as a direct sum

$$S_p \equiv \left(\frac{C_r \oplus C_u}{G}\right) \oplus M(C_r, C_u)$$  

(5)

where the behavioural metrics $M(C_r, C_u)$ are functions of resources and user activity. One may now state the following provable hypothesis.

**Theorem 1** Any sufficiently complete system policy $P(t)$ specifies, by implication, a representative average ideal state $S_p(t)$, from an equivalence class of ideal states $\{S\}$ under $G$, for the computer system concerned, over user timescales $T_u$, provided that the rate of change of policy $dP/dt$ is much smaller than changes in user behaviour $dM/dt$, i.e. the policy changes on the order of weeks or months rather than hours or days.

**Corollary:** The ideal state can only be identified on average, since interactions with unpredictable user activity are constantly causing fluctuations $\delta S(t)$ in the state of the system. These fluctuations also occur at a rate $dM/dt \gg dP/dt$.

The existence of an ideal state has already been used in designing the author’s site **Configuration Engine (cfengine)**, but it has not previously been

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1The nature of this group could be fairly complicated and is not particularly important to the discussion. The fact that the redundancy, in principle, may be represented by a mathematical group is an idealization which is attainable in in theory. It is not an expression of the current state of affairs in the world of computers.
explained at length. The proof of this theorem is straightforward, from the definitions. Every computer system has a finite set of resources and configuration objects which is completely prescribed by a total configuration $C_p$. Each resource object may be in a state described by a finite length bit string, describing a distinct configuration $s_i \in C_r$. There is therefore a mapping from the configuration $C_p$ to the actual state

$$C_p \rightarrow \mathcal{S}_p + \delta S.$$  \hspace{1cm} (6)

This mapping is one to many, since $\delta S$ is a stochastic variable. The averaging operation eliminates the non-uniqueness by extinguishing $\delta S$, provided the averaging process is defined, i.e., $d\delta S/dt \gg dP/dt$. Thus any complete set of average measurements contributes to the average state in a well-defined manner.

The meaning of ‘sufficiently complete system policy’ is now clear. The covering of the policy domain must be as large as the domain of state one wishes to cover, since it follows from the above definitions that the association of policies to states is now one to one, after one factors out the equivalences $\mathcal{G}$. The uniqueness is secured by making the configuration instruction itself a part of the state. Without this, there would still be ambiguity, since there is no guarantee that a measurement $M(C_r, C_u)$ is a unique function of its arguments. This completes the proof.

This sufficiency referred to above has the corollary that an incomplete system policy $P_1$ cannot determine a unique state for the whole system, only a part of it. An incomplete policy divides the system into two or more parts, since the total policy is still in one to one correspondence with the states.

$$P_1 + P_2 + \ldots \rightarrow S_{p1} + S_{p2} + \ldots$$  \hspace{1cm} (7)

By the virtue of the fundamental theorem, we have the important conclusion that the necessary and sufficient condition for implementation a policy $P(t)$ (i.e. the ability to map it onto a system configuration over a period of time) is that the total average state $\mathcal{S}(t) = \mathcal{S}_p(t)$.

Let us take a moment to understand the structure and meaning of average ideal state. It is tempting to think of the system as being in an ideal state at some time $t_0$ and then deviating from it at later times. The precise state of the system at some reference time might seem to characterize an ideal to our subjective judgement, but the ideal state of configuration must change with time, since the computer system is, by nature, influenced by users whose activities are not completely secured by a policy. To freeze one’s view of the ideal in time, is to place unreasonable restrictions on the use of the system (we shall see this later in examples connected to the use of fixed disk quotas). A specification of resource and user boundary conditions is not the same as a specification of the ideal dynamical behaviour of the system, if users are allowed to act on the resources.

Given that the policy and user configurations are stable over the prescribed time-scales, one may take the average value (or distribution of values) for each metric which characterizes the response of system over shorter time-scales.
\( \overline{M}(C_r, C_u) \) as being representative of the state at time \( t \). This summarizes the effect of feedback of users on resources, or the statistical interaction between the users and the system. Since we have prescribed every bit string affecting the dynamics of the system at the outset as policy, and we have measured the average result of those prescriptions at time \( t \), we have a complete description of the system in terms of an implementable policy.

\[
\overline{S}_p = P \oplus \overline{M}(P).
\]  

(8)

Not surprisingly, this expression is directly analogous to linear response theory in the physics of time-varying systems. The policy plays the role of a constraint of the motion, while the statistical metric \( \overline{M} \), has the role of the integrated response of the evolved state at time \( t \). The ‘equations of motion’ which lead to the evolution of a system also have an analogue here: they are the operations carried out by the system software on the resources.

Figure 1: The existence of an ideal state. This picture shows the mapping of equivalent configurations of users \( C_u \) plus hardware \( C_r \) to a factored set \( C/\mathcal{G} \) which can be interpreted as the set of implementable policies \( P \). A unique configuration results in a measurable effect on the system \( \overline{M} \), i.e. the feedback resulting from the policy \( P \). The combination of the configuration with its average effect on the system defines a unique state \( \overline{S} \).

The permutation or invariance group \( \mathcal{G} \) is of no concern to this paper except as a matter of principle for the most pedantic. It is a heuristic representation of all of the involved details which are irrelevant to a theoretical formulation,
but which occur in practice. Nevertheless, it has a theoretical implication: the ideal state $S$ has a number of equivalent representations, e.g. those formed by permuting or swapping configuration details whose ordering or equivalence is unimportant. This multiplicity could be a benefit or a hazard to the task of implementation of policy. This remains to be determined.

Having established the existence of an ideal state, the second basic assumption is:

**Basic assumption 2** The long term aim of system administration is to optimize the policy $P(t)$ for maximum productivity, insofar as this is allowed by local constraints. The short term aim is to keep the system as close to the resulting ideal state $S_p(t)$ as possible, i.e. to minimize fluctuations $\delta S = S - S$.

One expects the average state $S_p$ to exhibit persistent behaviour however, i.e. be invariant for periods approaching the duration of the system policy. Note that, what we are essentially doing, by making the assertion of an ideal state, is to separate slowly varying changes from quickly varying changes.

$$S(t) = S_p(t) + \delta S(t).$$

(9)

Errors and misconfigurations (fluctuations $\delta S$) can accumulate over short periods of time, shorter than the time scale over which the average or ideal state changes. In terms of the relative rates of change:

$$\max \left| \frac{1}{\delta S} \frac{d}{dt} \delta S \right| \gg \max \left| \frac{1}{S_p} \frac{d}{dt} S_p \right|. \tag{10}$$

The business of system administration is therefore a problem in regulation, or in minimizing the effect of $\delta S$.

We arrive at the following: a theory of system administration would attempt to answer the questions:

*Is there an optimal strategy for keeping the system as close as possible to its ideal state, and maximize its productivity?*

To answer these questions, we must understand more deeply the meaning of the abstract formulation above. To begin, we backtrack and re-examine the underpinning concepts.

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2The fact that such details do indeed represent a set, indeed a group of permutations and transformations is clear from the empirical facts. The factoring of redundancy means picking only one representative member of each configuration which gives the same results, in the same manner that factor groups are formed in group theory. Indeed, it is a trivial technical point that the sets and equivalence classes in a computer system may all be represented by operations on a single binary string (a computing machine does precisely this on a finite, possibly disjointed binary string). The existence of transformations with closure is assured by extending a binary string to encompass all possibilities; the existence of an inverse is trivial for permutations, as is the existence of a null operation and associativity. That the formal factor group exists follows from the existence of heuristic equivalences with respect to system function.
5 A generic computer system

In order to elucidate the goals of computer configuration and maintenance, it will be necessary to identify the main characteristics of computer systems at a suitable level of abstraction. These include finding:

- Relevant variables,
- Invariances,
- Persistent structures,
- Sources of information loss or entropy,

which affect the principal goals. Several studies of computer systems have attempted to identify such qualities\[7, 2, 8\] and it is hypothesized that a suitably abstracted description can be built on the few simple principles identified by these authors.

The basic model of a computer is that of a dynamical community of processes and resources, coupled to an external environment (an external source or force). The source includes the stochastic influences of all of the users of the system, and any other computer systems which communicate with hosts within the perimeter of our own system. As pointed out in ref. [5], the issue of networking does not increase the complexity of the administration problem, only its localization and perhaps its magnitude. A set of networked hosts, sending external messages, is simply a single virtual host with internal inter-process communication.

The variables, important in characterizing the usage of a computer system, are measures of average behaviour, such as rate of work, numbers of processes, network connections and so forth\[2\]. Other measures, such as average service latencies, affect the system only at the level of the network. Latencies are very complex phenomena and are unlikely to be predictable by any simple model.

Invariances refer to the independence of qualities and values to changes. In the long run, there are no features of a computer system which are fully constant, but for long periods of time, certain things can be considered invariant. For instance, the software tools one uses to edit a file usually make no difference to the outcome, thus the outcome of an editing operation may be considered invariant with respect to differences in software used; the CPU efficiency of the software used makes no difference to the result in most cases. Invariance could also mean that a particular piece of software never changes (is never upgraded), or that the content of a configuration file is fixed with respect to other changes. In the space of changes, such invariances may be considered to be ignorable coordinates.

Persistent structures are, like invariances, values or qualities which do not change over appreciable periods of time. This includes checksums of important software, kernel profiles of software; it might also include numbers of user accounts. Persistent structures are not expected to change. Changes in these structures might be considered anomalous behaviour.
An important characteristic of computer systems is that they are strongly coupled to human users' behaviour patterns. The majority of human users follow strict daily and weekly work patterns and this is reflected in many measurements of system resource behaviour. A consequence of this is that measurements which are periodically constrained are distributed according to a Planck spectrum. The Planck spectrum can therefore be considered a general characteristic of computer statistics in many cases.

6 The scope of a theory of system administration

Even a limited theory of system administration should cover some key aspects of the problem:

- Policy determination,
- Strategic decisions about resource usage,
- Productivity considerations (the economics of the system),
- Empirical verification of strategies and policies,
- Efficiency of policy and of policy implementation,
- Efficiency of the system in doing its job.

More pragmatic details such as the need for software installation and upgrade have to be tackled at an abstract level, in terms of productivity, probability of failure, resource usage and so on. Software bugs can be addressed in terms of productivity or security. Security, in turn can be viewed as a contest for resources at the level of the system.

The benefits of automation versus human incursion are often discussed in system administration, sometimes as a bone of contention. This is one area that a theory of system administration can address objectively and have a real prospect of answering once and for all. An aspect of this will be discussed later as an example.

6.1 Measures and characters

As an empirical science, system administration suffers from many shortcomings. It has all of the problems associated with the social sciences: statistical measures are seldom forthcoming, experimental repeatability is a luxury, and sufficient repetition to obtain statistically meaningful samples is a near impossibility. The conditions under which measurements are made are constantly changing. The situation is somewhat analogous to that of non-equilibrium statistical mechanics in physics, but markedly less controlled.

The characteristics which are of interest to us refer to the actions and results which inter-weave in the dynamical behaviour of the system. These include
the quality of actions of the system administrator, in relation to the prescribed policy, a typical characterization of the environment which affects the system. The measurements which are most useful are those based on persistent variables, since these have a stable value. Other fluctuating values can be treated stochastically or averaged out into persistent values.

The following measures will be useful in formulating ‘pay-off’ matrices for administration models, as in the example to follow below. The accuracy with which a policy is implemented by an agent of system management (human or automatic system) can be gauged with the following ratio:

\[
\text{Accuracy} = \frac{\text{Number of policy actions}}{\text{All actions performed}}
\]

i.e. the fraction of work which is within prescribed guidelines. In algebraic terms:

\[
\alpha = \frac{N_p(t)}{N(t)} = \frac{\sum_{a \in P} N_a}{\sum_{(\forall a)} N_a}
\]

For humans \(\alpha \leq 1\). For any bug-free automatic system, \(\alpha = 1\). Similarly, one may define the efficiency of a system by its use of resources (memory and CPU share):

\[
\text{Efficiency} = \text{Accuracy} \times \left(1 - \frac{\text{Resources used}}{\text{Resources available}}\right)
\]

In algebraic terms:

\[
\varepsilon = \alpha \left(1 - \frac{\sum_{(a \in P)} r_a}{\sum_{(\forall a)} r_a}\right)
\]

i.e. the more resources which are consumed in implementing a policy, the less efficient it can be considered to be.

Other measures are more useful for describing the relationship of a computer system to its environment, or the influential forces which steer its dynamical evolution. The response of a computer system to its users is characterized by averages which fluctuate in time. Human society’s diurnal work pattern imposes a twenty four hour periodic character on these measurements\(^{3,4}\) and a also a weekly work pattern, which is dominant during weekdays and slight at weekends (at least in the Western world). The periodic topology implies that the distribution of resource usage takes on the special form of a Planck distribution with a Gaussian component, by analogy with statistical physics at temperature \(T\):

\[
D(\lambda) = A e^{-\left(\frac{\lambda - \lambda_0}{2\sigma}\right)^2} + \frac{B}{(\lambda - \lambda_0)^3(e^{1/(\lambda - \lambda_0)T} - 1)}.
\]
\( \lambda \) is the deviation of a measurement from its average value over a period. The values of the constants \( A, B, \lambda_0 \) and \( T \) may be chosen to fit the behaviour of any variable which is strongly coupled to periodic usage. Their absolute values have no significance, since there is no ‘standard candle’ computer system to compare to, but changes relative to the local norm could be interpreted as anomalies. Non-zero \( A \) allows for the presence of additional Gaussian noise in some measurements.

### 6.2 Interactions of time scales

The identification of suitable time-scales is of crucial importance to any dynamical problem. Time-scales control rates of competition which lead to balance, and also rates of change.

It is easy to show that human administrators only compete with automatic systems in speed and efficiency at times of the day when they have nothing pressing to do. Indeed, it is always possible to arrange for an automatic system to beat a human, provided it can run in overlapping instantiations. A straightforward comparison of the time-scales involved in automated maintenance, to those of manual human maintenance can be made for any operation which is programmable in an automatic system with available technology.

Alarm systems which merely notify humans of errors and then rely on a human response are intrinsically slower than automatic systems which repair errors, provided the alarms represent errors which can be corrected with current automation.

The response time \( t_{\text{auto}} \) of a automatic machine system \( M \), falls between two bounds (see figure 1)

\[
n T_p + T_e(A) \geq t_{\text{auto}} \geq T_e(A)
\]

where \( T_p \) is the scheduling period for regular execution of the system (e.g. the cron interval, typically half-hour to an hour), \( T_e(A) \) is the execution time of the automatic system (typically seconds). The integer \( n \geq 0 \) since the number of iterations of the automatic system required to fix a problem might be greater than one. The time required to make a decision about the correct course of action \( T_d(A) \) is negligible for the automatic system.

For a human being, making a decision based on a predecided policy, the response time \( t_{\text{human}} \) falls between the limits:

\[
\infty \geq t_{\text{human}} \geq T_w(H) + T_d(H) + T_e(H)
\]

\( T_d(H) \) is again the decision time, or time required to determine the correct policy response (typically seconds to minutes). \( T_e(H) \) is the time required for a human to execute the required remedy (typically seconds to minutes). \( T_w(H) \) is the time for which the human is busy or unavailable to respond to the request, i.e. the wait-time. The availability of human beings is limited by social and physiological considerations. In a simple way, one can expect this to follow a
pattern in which the response time is greatest during the night; simplistically, if one assumes that humans sleep 8 hours,

\[ T_w(H) > 4(1 + \sin(t/24)), \]

where time is measured in hours, whereas

\[ T_w(A) \approx 0. \]

We can note that human response times are usually much longer than the corresponding machine response times,

\[ T_d(A) \ll T_d(H) \]
\[ T_e(A) \ll T_e(H) \]

and that the periodic interval of execution of the automatic system is generally taken to be greater than the execution time of the automatic system

\[ T_p \geq T_e, \]

thus avoiding overlapping executions (though this is not necessarily a problem, see the discussion of adaptive locks[9]). It is always possible to choose the scheduling interval to be arbitrarily close to \( T_e(A) \) (i.e. as short as one likes). Then provided,

\[ T_w(H) > T_e(A) \]
the automatic system can always win over a human. This last inequality requires qualification however, since very long jobs (such as backups or file tree parses) increase exponentially in time with the size of the file tree concerned. This makes a prediction: it tells us that one should always arrange to allow such long jobs to be run last in a sequence of maintenance tasks, and also in overlappable threads. This means that long jobs will not hinder the rapid execution of a maintenance program.

Cfengine allows overlapping runs using its scheme of adaptive locks. Thus, by scheduling long jobs last in a cfengine program, it is virtually always possible for cfengine to beat a human, unless it is prevented from running, or the human is given the chance to respond with a head-start; this seldom happens by chance.

7 Primitive moves

Having identified the principle aims and methods of system administration, one is free to represent a model for these in any convenient calculational scheme. Almost immediately, one is confounded by the multiplicity, or non-uniqueness of the mapping between problem and solution: It is common-lore amongst system administrators, and it is to be expected logically in any causal web, that

- One problem can have several solutions.
- Several problems can be solved with a single solution.

How should one classify such mappings? By coarse-graining? Some degree of coarse classification is inevitable to make the analysis tractable, but it needs to be performed in a well-defined way. To some extent, we have already dealt with this problem in the factoring out of redundant expression in section 2. However the same problem returns in specifying the actions required to maintain the ideal state.

In order to unravel this situation as far as possible, it is reasonable to try to express problems and solutions in terms of linear combinations of primitive actions. The analysis of primitive operations has already been considered by Burgess in ref. in developing automated approach to system administration. There is little to add here, except to say that it is required that every implementable policy be decomposable as a combination of these primitives.

The available channels for action, i.e. the possible moves which a ‘player of the computer system game’ (user or administrator) can choose from, form a huge set if one views them at the level of the user. Formulating generic activity would be an intractable problem if one chose to consider every nuance of the system, viewed from a user perspective. Fortunately it is possible to break down the variety of activities available to users into a number of primitive actions. Any task can be considered as some linear combination of these few basic actions. The actions are:
| Primitive type $T^i$ | Comments/Examples |
|----------------------|--------------------|
| Create file          | Tidy garbage      |
| Delete file          | Disable            |
| Rename file          | Used in configuration |
| Edit file            | Permissions        |
| Access control       | Read/Mount         |
| Request resource     | Read/write         |
| Copy file            | Start/stop         |
| Process control      | Nice               |
| Process priority     |                    |
| Configure device     |                    |

We should be careful to distinguish between how functions are implemented and how they can be decomposed. The method of implementation is not necessarily relevant to the analysis. What is important is that there exists a finite number of primitive actions which can be used to express all others in combinations.

Are these primitives sufficient in themselves? Could we implement the following policy, for instance: downloading of pornographic material between the hours of 9:00 and 17:00 is forbidden? If such a policy is implementable by an automatic system, it must be possible to filter content-specific data. Such a filter would need a configuration file which would need to be edited. The time-dependent behaviour could be handled by a scheduler, also configured by a text file. These configuration details are all implementable with file editing and process control. The ability of software to perform the task has to be assumed. This has nothing to do with management of the system. If the same job is to be carried out by a human, then the model of the management system must be extended to include humans, in which case job control and job definition require the analogous concepts to file editing and process control, for human brains. In other words, when humans are involved in a theory of manual work, they must be considered a part of the computer system.

8 The ideal average state

In order to have a chance of repairing damage, or maintaining a detailed balance of resources, we need to be able to trace the development or history of the system, from an ideal average state at an initial time, to a less than ideal state at a later time. In accordance with the axioms laid out at the beginning of the paper, it is assumed that the ideal state is determined as a matter of policy, by local considerations.

Many minor changes take place all the time in a computer system; these are healthy. Programs are started and stopped, files are created and destroyed: this is part of the work done by the system. However, certain features of the system should not change greatly (they should be persistent, at least on average). For instance, resources like disks and network services should be available to users...
at all times. If a crucial service falls out, then it affects other changes in the system.

Some changes are important to operation of the system, others are unimportant. For instance, it would be unimportant if one swapped the process ID’s of two programs. The process ID is just a label which has no bearing on the performance of the system or the productivity of users. However, if one process stopped running prematurely, this would be a change of state.

If we know what changes have taken place to move the system away from the ideal state, it should be possible to undo them, provided these do not involve the destruction of useful work. To accomplish this tracking of changes, in formal terms, we need to quantify the state of the system with respect to specific changes. Suppose one considers system administration as a game, framed on a lattice of \( n \)-dimensions, and suppose that the system has an ideal state located at the origin of this lattice, based on a policy and described in terms of primitive system variables. Each node of the lattice is a new state of the system. Let us suppose that the aim of the game is to remain as close as possible to the ideal state, i.e. the origin of this discrete space. How can one formulate such a game? How many dimensions does the lattice extend into, and what do they represent? These questions are central to formulating an analysis.

In a general sense, a computer system is a dynamical system like any other, and it must follow the same basic principles as any set of variables which changes in time. Let \( \phi_i(t) \), where \( i = 1, 2, \ldots N \) be the set of measurable variables which can be associated with a computer system. A canonically complete dynamical system can be associated with the set of phase-space variables, \( q_i(t), \dot{q}_i(t) \), i.e. the variables and their time derivatives. Not all variables can be considered differentiable functions of time, but it will be possible to give the derivative a meaning even for discrete variables, so this may be regarded symbolically for the present. Given that the values of these variables can change statistically with time (the nature of this variation will be qualified later), at any time \( t \), we can decompose the value of \( q(t) \) into a local average and a fluctuating piece.

\[
q(t) = \overline{q}(t) + \delta q(t).
\]  

This means essentially decomposing \( q(t) \) into fast and slowly changing variables. The average value \( \overline{q}(t) \) varies only slowly with time, but many rapid changes \( \delta q(t) \) fluctuate about the average value. The average may be defined by

\[
\overline{q}_i(t) = \frac{1}{t - t_i} \int_{t_i}^{t} q_i(t') \, dt',
\]

\[3\] Note that, while one is interested in tracking changes in principle, in order to formulate the theory of system changes, this does not imply memorizing changes in a system is a desirable thing to do. Some system administration tools attempt to do this, often unsuccessfully, but as a counter-example one has cfengine which simply acts as a generic counter-force, pushing the system towards the ideal state, regardless of what specific historical chain the system follow.
where \( t - t_i \) is the interval over which the average is taken, and it is assumed that

\[
t - t_i < t - t_0,
\]

(25)

where \( t_0 \) is the ‘zeroth’ time at which the system was in the ideal state. The rate at which variables are changing \( \dot{q}(t) \) can also be measured. A similar procedure can be implemented for the \( N \) derivatives and their local average values.

For the sake of characterizing the state of the system, one is interested in change in the average values since some ideal zeroth time \( t_0 \):

\[
d_i \equiv \{ \overline{q_i}(t) - \overline{q_i}(t_0), \overline{\dot{q}_i}(t) - \overline{\dot{q}_i}(t_0) \}.
\]

(26)

In terms of the deviations \( d_i \) in key system variables, one may postulate a \( 2N \)-dimensional lattice whose independent, orthogonal axes are the \( n = 2N \) variables of the phase space \( d_i \), for \( i = 1 \ldots n \). Positions on this lattice are denoted by the vector of these component deviations. It is collectively denoted \( \vec{d} \).

Suppose now that the system has deviated from the ideal state at \( \vec{0} \) and has reached a point \( \vec{d} \) on the lattice (see figure 2). The number of equivalent paths \( H(\vec{d}) \) back to the ideal state, is

\[
H(\vec{d}) = \frac{(\sum_{j=1}^{n} d_j) !}{\prod_{k=1}^{n} (d_k)!}
\]

(27)

This grows rapidly with the Euclidean distance \( |\vec{d}| \)

\[
|\vec{d}| \equiv d = \sqrt{\sum_{i=1}^{n} (d_i)^2}.
\]

(28)

\( H(\vec{d}) \) may be considered as a measure of the entropy, or disorder in the system. The entropy may be thought of as measuring the ‘hopelessness’ of finding the original route which led to the deviation. If all the paths are equivalent, i.e. the particular route by which the current state was achieved was not important, then it measures the number of equivalent ways in which the deviation can be fixed.

If the path is important then a different interpretation is more appropriate. In common with its analogue from physics, \( H \) may be thought of as a measure of the amount of potential work has been lost to the system as a result of its deviation from the ideal state. Or conversely, here it may be considered a measure of the amount of work which would have to be expended in order to return the system to its ideal state. To gauge how quickly this grows with distance, one
Figure 3: Deviations from the ideal state may be visualized as a random walk through a lattice of \( n \)-dimensions (here only two). The number of paths of equal length by which one can return to the origin increases rapidly with the distance.
may compute the rate of increase in numbers of paths as $\vec{d}$ increases. Define

$$\frac{d_i}{\nabla} H(\vec{d}) = \frac{H(\vec{d} + \Delta\vec{d}) - H(\vec{d})}{|\Delta\vec{d}|} = H(d_1, ..., d_i + 1, ..., d_n) - H(d_1, ..., d_i, ..., d_n)$$

(29)

Thus we define the rate of increase on the discrete lattice by,

$$\frac{d_i}{\nabla} H(\vec{d}) = \frac{H(d_1, ..., d_i + 1, ..., d_n) - H(d_1, ..., d_i, ..., d_n)}{(d_i + 1) \sum_{j \neq i} d_j \gg 1.}$$

(30)

This shows that the increase is in fact approximately proportional to the distance. In other words, the rate of increase is approximately exponential. Clearly, this simple quantification of cumulative system error indicates that deviations from an ideal state should be dealt with as quickly as possible, since it becomes increasingly difficult to make corrections as the errors are compounded.

The ideal state itself needs to be characterized in terms of reasonable tolerances in system variables. The important variables include the availability of resources (ability to create new files and processes) as well as the level of activity. In dynamical terms one considers a set of variables and their rates of change:

$$q(t), \frac{dq(t)}{dt}.$$  

If the system is a complete characterization of every possible influence and change in the system, then these form a simplectic algebra and the behaviour of the system is, at least in principle, completely deterministic, if not exactly predictable. In most cases there are influences which are not completely known, or may be regarded as random. In that case, one moves from simple mechanical systems into to realm of statistical mechanics and non-equilibrium studies.

These underlying variables are only indirectly linked to the ideal state, through averaging.

The above view is quite simplistic. In reality there might not be only one ideal state, but a set of equivalent ideal states. These can all be formulated as direct sums or quotients of a simply-connected state space however, so these need not be of concern to the principle of the argument. Having identified an ideal state as a point in a vector space, or lattice, one is now free to discuss how changes in the forces or influences on the system lead to movements through the lattice.

9 Game theory and the contest for the ideal state

There are two separable issues in the ideal-state view of system administration. The distinction concerns the perceived intelligence behind the changes which
lead to a degradation of the ideal state. We may classify changes as either random (stochastic) or as intentional (strategic) depending on the nature of the adversary.

This distinction is partly artificial: all changes can be traced back to the actions of humans at some level, but it is not always pertinent to do so. Not all users act in response to a specific provocation, or with a specific aim in mind. It just happens that their actions lead to a general degradation of the ideal state, no malice intended. This strikes back to the fundamental principle of detail, namely that high level effects wash out the specifics of low-level origins. Thus there is a part of the spectrum of changes which averages out to a kind of faceless background noise. The details of who did what are of no concern. Random influences have been analyzed in ref. [2] and are found to follow a number of well-known statistical distributions. Their study is part of the problem to be solved, but not all of it.

The other part of the problem is the case of actions which may be regarded as being more carefully calculated, or following a systematic behavioural pattern. These are caused by conflicts of interest between system policy and user wishes. A suitable framework for analyzing conflicts of interest, in a closed system, is the theory of games [10, 11]. Game theory is about introducing players, with goals and aims, into a scheme of rules and then analyzing how much a player can win, according to those restrictions. Each move in a game affords the player a characteristic value, often referred to as the ‘payoff’. Game theory has been applied to warfare, to economics (commercial warfare) and many other situations. In this case, the game takes place on the n-dimensional board, spanned by the $\vec{d}$ vectors.

There are many types or classifications of game. Some games are trivial: one-person games of chance, for example, are not analyzable in terms of strategies, since the actions of the player are irrelevant to the outcome. In a sense, these are related to the first kind of deviation referred to above. Some situations in system administration fit this scenario. More interesting, is the case in which the outcome of the game can be determined by a specific choice of strategy on the part of the players. The most basic model for such a game is that of a two-person zero-sum game, or a game in which there are two players, and where the losses of one player are the gains of the other. ‘Zero sum’ is the law of conservation of currency (current).

Many games can be stated in terms of this basic model, although this is often a simplification of reality. Games in complex systems are rarely true zero-sum games: energy leaks out, money gets burned or printed and thus there is no exact zero-sum conservation.

9.1 Models

The basic valuables of system administration are the system resources: file space, CPU share, memory share and network share. The theory of system administration can be viewed as a competition for these resources and for user privileges. The central obstacle in formulating a scenario in terms of game
theory is the classification of strategies and their evaluation in terms of a characteristic (payoff) matrix.

- As a zero sum, two person game system administration is a game between the collective users and the system administrator. The aim of the users is to consume all of the system resources, while the aim of the administrator is to keep the system as close as possible to its ideal state. Ideally, the system administrators strategies should always bring the system closer to the ideal state. This is the property of convergence referred to in ref. [6, 3]. The ideal outcome of this game is a stalemate, or equilibrium somewhere close to the ideal state.

This game is often one with perfect information since all the important moves are visible to both players, however both sides can engage in bluffing. Clearly the administrator can win, either by limiting or reducing the consumption of resources and by extending the resources of the system. A user can ‘win’ in a certain pessimistic sense by moving the ideal state so far from the ideal that the system crashes and thus the game ends.

- A more optimistic variant of the above, is to view the aim of users as being to produce as much useful work as possible. This is a more complicated aim, since users can now impede their own progress by consuming too many resources, thus impairing the system as a whole and preventing themselves from being able to work (users need to be environmentally friendly). Experience from reality shows that most users do not concern themselves with this aspect however; they see it as the system administrators job to deal with such problems when they arise.

- As a zero sum, N-person game one can make a more detailed model, in which users compete against one another in addition to the system administrator. The system administrator’s task then becomes to act as a kind of Robin Hood character, preventing any one user’s consumption of all resources, trying to distribute resources fairly. Again, the aim of the administrator is to maximize the duration of the game by keeping the system as close to the ideal state as possible.

9.2 Payoffs and work

The next obstacle concerns the level at which we decide to address the behaviour of the system. Appropriate measures can be defined at various levels.

In order to formulate the characteristic matrix (often called the pay-off matrix) we must identify the book-keeping parameters and aims by which one hopes to win the game. What is the currency of this system? In social systems one has money as the book-keeping parameter for transactions. In physical systems, one has energy as the book-keeping parameter. These quantities count resources, in some well-defined sense. An analogous quantity is needed in system administration.
• The aim of the system administrator is to keep the system alive and running so that users can perform useful work.

• The aim of benign users is to produce useful work using the system. The aim of malicious users is often to maximize their control over system resources.

In a community, games are not necessarily cut and dried zero-sum engagements. We are faced with a Nash problem, or prisoner’s dilemma, which often ends in a Nash equilibrium[12].

A user of the system who pursues solely private interests, does not necessarily promote the best interest of the community as a whole.

In other words, users can shoot themselves in the proverbial foot by using up all the available resources on a finite system. This affects them as much as anyone else. The empirical evidence suggests that, on average, users consume resources at a rate which is periodic and polynomial in time[7, 2].

\[ W(t) \propto \sin(\Omega t) \sum_{n} c_n t^n \]  

(32)

A definition of work is required in order to quantify the production of useful work in a non-prejudicial manner. Clearly the term ‘useful work’ spans a wide variety of activities. Clearly work can increase and decrease (work can be lost through accidents), but this is not really germane to the problem at hand. The work generated by a user (physical and mental work and then computationally assisted results) is a function of the information input into the system by the user. Since the amount of computation resulting from a single input might be infinite, in practice, the function is an unknown.

In general, the pay-off in not just a scalar value, but a vector. This indicates that a game might actually be decomposable into a number of parallel but interacting games.

What is the value of a game? How much can a user or an attacker hope to win? The system administrator, or embodiment of system policy, is not interested in winning the game, but rather in confounding the game for users who gain too much control. The system administrator plays a similar role to that of a police force. In some vague sense, the administrator’s jobs is to make sure that resources are distributed fairly, according to the policies laid down for the computer society.

9.3 Strategy expression

In a realistic situation one expects both parties in the two-person game to use mixed strategies. The formulation of the game theoretical pay-off matrix requires one to consider the strategies which the players can adopt. Again, the number of possible strategies is huge and the scope for strategic contrivance is almost infinite. In order to limit the formulation of the problem, it is necessary
to break down strategies into linear combinations of primitives again. What is a strategy?

- A set of operations
- A schedule of operations
- Rules for counter-moves

In addition to simple strategies, there can be meta-strategies, or long-term goals. For instance, a nominal community strategy might be to:

- Maximize productivity or generation of work.
- Gain the largest feasible share of resources.

An attack strategy might be to

- Consume as many resources as possible.
- Destroy key resources.

Other strategies for attaining intermediate goals might include covert strategies such as bluffing (falsely naming files). Defensive strategies might involve taking out an attacker, counter attacking, or evasion (concealment), exploitation, trickery, antagonization, incessant complaint (spam), revenge etc. Security and privilege, levels of access, integrity and trust must be woven into algebraic measures for the pay-off. A means of expressing these devices must be formulated within a language which can be understood by system administrators, but which is primitive enough to enable the problem to be analyzed in an unambiguous fashion.

9.4 Stable and dominant strategies

It has been argued here, and in earlier papers, that computer systems can be viewed as fluctuating around statistically stable configurations, for the most part. This assumes that both users and system administration mechanisms are in approximate balance. Game theory is suited to finding equilibria, or stable superiorities in a set of strategies. Let us consider how game theory can be used to frame system behaviour as a contest for control of the system’s resources.

The simplest case of a two-person, zero-sum game is chosen.

We are interested in determining whether any optimal strategies can be adopted by the system (and its administrator) in order to maintain control of the system, i.e. in order to prevent users from winning control of the system. This situation is analogous to the analysis of dominant evolutionary strategies, considered by Hamilton and Maynard-Smith. These so-called Evolutionary Stable Strategies are the winning strategies favoured by natural selection mechanisms in the animal or plant kingdom. In our case, we are simply interested in strategies which are clear winners over all other strategies. If we consider the
characteristic matrix, or pay-off matrix, as a function of strategies for attack and defense \( \pi(\sigma_a, \sigma_d) \), then one may characterize a dominant attack-strategy \( \sigma_a^* \) by the criterion:

\[
\pi(\sigma_a^*, \sigma_d) > \pi(\sigma_a, \sigma_d)
\] (33)
i.e. \( \sigma_a^* \) must be a better move than any other strategy against an arbitrary counter-move \( \sigma_d \). If this is the case, then there exists at least one pure strategy which is optimal for the attacker. Similarly, an optimal defensive strategy \( \sigma_d^* \) is characterized by:

\[
\pi(\sigma_a, \sigma_d^*) > \pi(\sigma_a, \sigma_d)
\] (34)

A more general situation is that one can find a winning mixture of strategies \( \Sigma \) (a linear combination of pure strategies)

\[
\Sigma = \frac{1}{N} \sum_i^N c_i \sigma_i.
\] (35)

Then if the dominant mixture of strategies \( \Sigma_a^* \) satisfies,

\[
\pi(\Sigma_a^*, \Sigma_d) > \pi(\Sigma_a, \Sigma_d)
\] (36)
then the attacker must win, but if some optimal mixture of strategies \( \Sigma_d^* \) satisfies,

\[
\pi(\Sigma_a, \Sigma_d^*) > \pi(\Sigma_a, \Sigma_d),
\] (37)
then the defender must prevail. It is this final solution which one hopes to find in order to secure a stable computer environment.

To illustrate this idea, consider an example of some importance, namely the issue of garbage collection. The need for forced garbage collection has been argued on several occasions[14, 6, 9], but the value of this strategy to system rule has not been analyzed previously.

The first issue is to determine the currency of this game. What payment will be transferred from one player to the other in play? Here, there are three relevant measurements to take into account: (i) the amount of resources consumed by the attacker (or freed by the defender), and sociological rewards: (ii) ‘goodwill’ or (iii) ‘privilege’ which are conferred as a result of sticking to the policy rules. These latter rewards can most easily be combined into an effective variable ‘satisfaction’. Then the player who can’t get no satisfaction is the poorer one. A satisfaction measure is needed in order to balance the situation in which the system administrator prevents users from using any resources at all. This is clearly not a defensible use of the system, thus the system defenses should be penalized for restricting users too much. The characteristic matrix now has two contributions,

\[
\pi = \pi_r(\text{resources}) + \pi_s(\text{satisfaction}).
\] (38)
It is convenient to define
\[ \pi_r \equiv \pi(\text{resources}) = \frac{1}{2} \left( \frac{\text{Resources won}}{\text{Total resources}} \right). \] (39)

Satisfaction \( \pi_s \) is assigned arbitrarily from values from plus to minus one half, such that,
\[-\frac{1}{2} \leq \pi_r \leq +\frac{1}{2},\]
\[-\frac{1}{2} \leq \pi_s \leq +\frac{1}{2},\]
\[-1 \leq \pi \leq +1.\] (40)

The pay-off is related to the movements made through the lattice \( \vec{d} \). The different strategies can now be regarded as duels, or games of timing.

| Users/System         | Ask to tidy | Tidy by date | Tidy above Threshold | Quotas |
|----------------------|-------------|--------------|----------------------|--------|
| Tidy when asked      | \( \pi(1,1) \) | \( \pi(1,2) \) | \( \pi(1,3) \) | \( \pi(1,4) \) |
| Never tidy           | \( \pi(2,1) \) | \( \pi(2,2) \) | \( \pi(2,3) \) | \( \pi(2,4) \) |
| Conceal files        | \( \pi(3,1) \) | \( \pi(3,2) \) | \( \pi(3,3) \) | \( \pi(3,4) \) |
| Change timestamps    | \( \pi(4,1) \) | \( \pi(4,2) \) | \( \pi(4,3) \) | \( \pi(4,4) \) |

The elements of the characteristic matrix must now be modelled by suitable algebraic or constant terms. The rate at which users produce files may be written
\[ r_u = \frac{n_b r_b + n_g r_g}{n_b + n_g}, \] (41)

where \( r_b \) is the rate for bad users and \( r_g \) is the rate for good users. The total number of users \( n_u = n_b + n_g \). From the authors experience, the ratio \( n_b/n_g \) is about one percent. The rate can be expressed as a scaled number between zero and one, for convenience, so that \( r_b = 1 - r_g \).

The payoff in terms of the consumption of resources by users, to the users themselves, is then
\[ \pi_u = \frac{1}{2} \int_0^T dt \frac{r_u (\sin(2\pi t/24) + 1)}{R_{\text{tot}}}, \] (42)

where the factor of 24 is the human daily rhythm, measured in hours, and \( R_{\text{tot}} \) is the total amount of resources to be consumed. Note that, by considering only good user or bad users, one has a corresponding expression for \( \pi_g \) and \( \pi_b \), with \( r_u \) replaced by \( r_g \) or \( r_b \) respectively. An automatic garbage collection system results in a negative pay-off to users, i.e. a pay-off to the system administrator. This may be written
\[ \pi_a = -\frac{1}{2} \int_0^T dt \frac{r_a (\sin(2\pi t/T_p) + 1)}{R_{\text{tot}}}, \] (43)
where $T_p$ is the period of execution for the automatic system, considered earlier. This is typically hourly or more often, so the frequency of the automatic cycle is some twenty times greater than that of the human cycle. The rate of resource-freeing $r_a$ is also greater than $r_u$, since file deletion takes little time compared to file creation, and also an automated system will be faster than a human. The quota payoff yields a fixed allocation of resources, which are assumed to be distributed equally amongst users and thus each quota slice assumed to be unavailable to other users. The users are nonchalant, so $\pi_s = 0$ here, but the quota yields

$$\pi_q = +\frac{1}{2} \left( \frac{1}{n_b + n_g} \right). \quad (44)$$

The matrix elements are expressed in terms of these.

\(\pi(1, 1)\): Here $\pi_s = -\frac{1}{2}$ since the system administrator is maximally satisfied by the users’ behaviour. $\pi_r$ is the rate of file creation by good users $\pi_g$, i.e. only legal files are produced. Comparing the strategies, it is clear that $\pi(1, 1) = \pi(1, 2) = \pi(1, 3)$.

\(\pi(1, 4)\): Here $\pi_s = 0$ since the users are dissatisfied by the quotas, but the system administrator must be penalized for restricting the functionality of the system. With fixed quotas, users cannot generate large temporary files. $\pi_q$ is the fixed quota payoff, a fair slice of the resources. Clearly $\pi(4, 1) = \pi(4, 2) = \pi(4, 3) = \pi(4, 4)$. This tells us that quotas put a straight-jacket on the system. The game has a fixed value if this strategy is adopted by system administrators. However, it does not mean that this is the best strategy, according to the rules of the game, since the system administrator loses points for restrictive practices. This is yet to be determined.

\(\pi(2, 1)\): Here $\pi_s = \frac{1}{2}$ since the system administrator is maximally dissatisfied with users’ refusal to tidy their files. The pay-off for users is also maximal in taking control of resources, since the system administrator does nothing to prevent this, thus $\pi_r = \pi_u$. Examining the strategies, one find that $\pi(2, 1) = \pi(3, 1) = \pi(3, 2) = \pi(3, 3) = \pi(4, 1) = \pi(4, 2)$.

\(\pi(2, 2)\): Here $\pi_s = \frac{1}{4}$ since the system administrator is maximally dissatisfied with users’ refusal to tidy their files. The pay-off for users is now mitigated by the action of the automatic system which works in competition, thus $\pi_r = \pi_u - \pi_a$. The automatic system is invalidated by user bluffing (file concealment).

\(\pi(2, 3)\): Here $\pi_s = \frac{1}{4}$ since the system administrator is maximally dissatisfied with users’ refusal to tidy their files. The pay-off for users is mitigated by the automatic system, but this does not activate until some threshold time is reached, i.e. until $t > t_0$. Since changing the date cannot conceal files from the automatic system, when they are tidied above threshold, we have $\pi(2, 3) = \pi(4, 3)$. 

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Figure 4: The absolute values of pay-off contributions as a function of time (in hours). For daily tidying $T_p = 24$. User numbers are set in the ratio $(n_g, n_b) = (99, 1)$, based on rough ratios from the author’s College environment, i.e. one percent of users are considered mischievous. The filling rates are in the same ratio: $r_b/R_{tot} = 0.99, r_g/R_{tot} = 0.01, r_a/R_{tot} = 0.1$. The flat dot-slashed line is $|\pi_q|$, the quota pay-off. The lower wavy line is the cumulative pay-off resulting from good users, while the upper line represents the pay-off from bad users. The upper line doubles as the magnitude of the pay-off $|\pi_a| \geq |\pi_u|$, if we apply the restriction that an automatic system can never win back more than users have already taken. Without this restriction, $|\pi_a|$ would be steeper.
Thus, in summary, the characteristic matrix is given by:

\[
\pi(u, s) = \begin{pmatrix}
-\frac{1}{2} + \pi_g(t) & -\frac{1}{2} + \pi_g(t) & -\frac{1}{2} + \pi_g(t) & \pi_q \\
\frac{1}{2} + \pi_u(t) & \frac{1}{2} + \pi_u(t) + \pi_u(t) & \frac{1}{2} + \pi_u(t) + \pi_u(t) \theta(t_0 - t) & \pi_q \\
\frac{1}{2} + \pi_u(t) & \frac{1}{2} + \pi_u(t) & \frac{1}{2} + \pi_u(t) & \pi_q \\
\frac{1}{2} + \pi_u(t) & \frac{1}{2} + \pi_u(t) & \frac{1}{2} + \pi_u(t) & \pi_q \\
\end{pmatrix}, \tag{45}
\]

where the step function is defined by,

\[
\theta(t_0 - t) = \begin{cases}
1 & (t \geq t_0) \\
0 & (t < t_0)
\end{cases}, \tag{46}
\]

and represents the time-delay in starting the automatic tidying system in the case of tidy-above-threshold.

It is possible to make several remarks about the relative sizes of these contributions. The automatic system works at least as fast as any human so, by design, in this simple model we have

\[
\frac{1}{2} \geq |\pi_a| \geq |\pi_u| \geq |\pi_g| \geq 0, \tag{47}
\]

for all times. In addition, for short times \( \pi_q > \pi_u \), but users can quickly fill their quota and overtake this. In a zero-sum game, the automatic system can never tidy garbage faster than users can create it, so the first inequality is always saturated. From the nature of the cumulative pay-offs, we can also say that

\[
\left(\frac{1}{2} + \pi_u\right) \geq \left(\frac{1}{2} + \pi_u + \pi_u \theta(t_0 - t)\right) \geq \left(\frac{1}{2} + \pi_u + \pi_a\right), \tag{48}
\]

and

\[
\left|\frac{1}{2} + \pi_u\right| \geq |\pi_g - \frac{1}{2}|. \tag{49}
\]

Let us now apply these results to a modest strategy of automatic tidying, of garbage, once per day, in order to illustrate the utility of the game formulation. The first step is to compute the pay-off rate contributions. Referring to figure 4, one sees that the automatic system can always match users’ moves. As drawn, the daily ripples of the automatic system are in phase with the users’ activity. This is not realistic, since tidying would normally be done at night when user activity is low, however such details need not concern us in this illustrative example.

The policy we have created in setting up the rules of play for the game, penalizes the system administrator for employing strict quota shares. Even so, users do not gain much from this, because quotas are constant for all time. A quota is a severe handicap to users in the game, except for very short times before users reach their quota limits. Quotas could be considered cheating in such a game, since they determine the outcome even before play commences. There is no longer a contest. Moreover, comparing the values in the figure,
it is possible to see how resource inefficient quotas are. Users cannot create temporary files which exceed these hard and fast quotas. An immunity type model which allows fluctuations is a considerably more resource efficient strategy, since it allows users to span all the available resources for short periods of time, without consuming them for ever.

Any two-person zero-sum game has a solution, either in terms of a pair of optimal pure strategies or as a pair of optimal mixed strategies. This result is known as the minimax theorem and was proved by Von Neumann. The solution is found as the balance between one player’s attempt to maximize his pay-off and the other player’s attempting to minimize the opponent’s result.

In general one can say of the pay-off matrix that

\[
\max_{\downarrow} \min_{\rightarrow} \pi_{rc} \leq \min_{\downarrow} \max_{\rightarrow} \pi_{rc},
\]

where the arrows refer to the directions of increasing rows (\(\downarrow\)) and columns (\(\rightarrow\)). The left hand side is the least users can hope to win (or conversely the most that the system administrator can hope to keep) and the right is the most users can hope to win (or conversely the least the system admin can hope to keep).

If we have

\[
\max_{\downarrow} \min_{\rightarrow} \pi_{rc} = \min_{\downarrow} \max_{\rightarrow} \pi_{rc},
\]

it implies the existence of a pair of single, pure strategies \((r^*, c^*)\) which are optimal for both players, regardless of what the other does. If the equality is not satisfied, then the minimax theorem tells us that there exist optimal mixtures of strategies, where each player selects at random from a number of pure strategies with a certain probability weight.

The situation for our time-dependent example matrix is different for small \(t\) and for large \(t\). The distinction depends on whether users have had time to exceed fixed quotas or not; thus ‘small \(t\)’ refers to times when users are not impeded by the imposition of quotas.

For small \(t\), we have:

\[
\max_{\downarrow} \min_{\rightarrow} \pi_{rc} = \max_{\downarrow} \left( \frac{\pi_g - \frac{1}{2}}{\frac{1}{2} + \pi_u + \pi_a} \right) \left( \frac{\frac{1}{2} + \pi_u}{\frac{1}{2} + \pi_u + \pi_a} \right) \left( \frac{\frac{1}{2} + \pi_u}{\frac{1}{2} + \pi_u + \pi_a \theta(t_0 - t)} \right) = \frac{1}{2} + \pi_u.
\]

The ordering of sizes in the above minimum vector is:

\[
\frac{1}{2} + \pi_u \geq \frac{1}{2} + \pi_u + \pi_a \theta(t_0 - t) \geq \pi_u + \pi_a \theta(t_0 - t) \geq \pi_g - \frac{1}{2}
\]

This is useful to know, if we should examine what happens when certain strategies are eliminated. For the opponent’s endeavours we have

\[
\min_{\rightarrow} \max_{\downarrow} \pi_{rc} = \min_{\rightarrow} \left( \frac{1}{2} + \pi_u, \frac{1}{2} + \pi_u, \frac{1}{2} + \pi_u, \pi_g \right)
\]
\[ \pi_{rc} = \min_{\pi_u} \max_{\pi_r} \pi_{rc} = \pi_q. \quad (55) \]

This indicates that the equality in eqn. (54) is satisfied and there exists at least one pair of pure strategies which is optimal for both players. In this case, the pair is for users to conceal files, and for the system administrator to tidy by any means (these all contribute the same weight in eqn (54)). Thus for small times, the users are always winning the game if we assume that they are allowed to bluff by concealment. If the possibility of concealment or bluffing is removed (perhaps through an improved technology used by the administrator), then the next best strategy is for users to bluff by changing the date. In that case, the best system administrator strategy is to tidy at threshold.

These results make qualitative sense and tally well with the author’s experience. The result also makes a prediction for system administration tools like cfengine. Cfengine must be able to see through attempts at bluffing if it is to be an effective opponent against the worst users.

For large times (when system resources are becoming or have become scarce), then the situation looks different. In this case one finds that

\[ \max_{\pi_u} \min_{\pi_r} \pi_{rc} = \min_{\pi_u} \max_{\pi_r} \pi_{rc} = \pi_q. \quad (55) \]

In other words, the quota solution determines the outcome of the game for any user strategy. As already commented, this might be considered cheating or poor use of resources, at the very least. If one eliminates quotas from the game, then the results for small times hold also at large times.

This simple example of system administration as a strategic game between users and administrators was not intended to be as realistic as possible, rather it was intended as an illustration of the principles involved. Nevertheless, it is already clear that user bluffing and system quotas are strategies which are to be avoided in an efficient system. By following this basic plan, it should be possible to analyze more complex situations in future work.

### 9.5 The policy \( P(t) \) and the pay-off matrix \( \pi(t) \)

At the beginning of this paper, we referred to a central axiom which involved the changing system policy \( P(t) \). The characteristic (pay-off) matrix \( \pi_{rc}(t) \) must clearly be related to this policy.

Let us suppose that the pay-off matrix is a \( u \times s \) matrix, with \( u \) user strategies and \( s \) system strategies. The administrators strategies are limited by the policy, and the rewards are also limited, so both the dimension \( s \) and form of the pay-off matrix are functions of the policy. The user’s strategies cannot be assumed to be limited by policy however, since ‘criminal’ users will ignore policy for personal gain. Although one may think of the dimension \( s[P(t)] \) as being a functional of the policy, it would not be correct to think of \( u \) as being a functional of the policy, since there can be no restriction on what users will try, simply as a result of law-giving. User’s actions can only be restricted by applying counter-measures
within the

\[
\pi = \pi_{rs}[P(t)](P(t)).
\]  

(56)

It should be noted, however, that there can be no unique mapping between policy and pay-off matrix.

### 9.6 Change and future models

Expressing deterministic changes in generic computer systems would be a huge undertaking unless one restricted ambitions to general features and trends. Dynamical systems are difficult to trace, even in the simplest of cases, so one cannot expect to get very far without making significant simplifications. The aim of considering a dynamical theory is thus to characterize the significant trends of change which might occur, owing to idealized influences. A full discussion of this topic is beyond the scope of the present paper, however based on the axioms and deliberations presented here, it is possible to outline the way forward in studying them.

The expression of strategies in the previous section is too general to be useful for a fully general, dynamical theory. Taking account of every strategic detail would be a vast undertaking. Instead, one can analyze the development at the level of a generic computer system undergoing generic changes as a matter of principle. The purpose of such a vague preliminary investigation is to elucidate the relationship between the system administration game and the lattice description of the ideal state, presented in section 8.

Once a strategy mixture has been decided, one must address the fact that, in real-world games, the speed of information is finite. It will take a finite amount of time for a response to develop after a strategy is implemented. Moves and counter-moves do not follow a rigid time-plan as in games like chess. This kind of delay leads to races and duels for superiority between competing players. Delay is the province of linear response theory.

The aim, then, is to express the causal structure of system development in the foregoing mathematical language. In order to reduce the dynamical game to algebra we must express each of these in terms of basic primitives. Causality is about relating actions to outcomes, or changes of state \( \delta S \). A general action \( A(t) \) is built up from a number of primitive action-types \( T_a \) (called the generators for the action transformation) in a linear combination

\[
A(t) = \sum_i a_i(t) T_i
\]  

(57)

where \( a_i(t) \) are functions of time (not necessarily differentiable, often step-like) and \( i \) takes values which number the full spectrum of primitive actions. The \( T^i \) are orthogonal vectors or matrices (indices suppressed), one for each primitive action type, which span an abstract vector space. This vector space is the chequerboard on which the game takes place.
Each complete action $A(t)$, results in a change in the state of the system, which may be denoted $\delta S$. An action can also be a causal chain of sub-actions, characterizing a sequence of changes in the state. This type of causal relationship is summarized by a Green function, propagator, or response-function formulation [15, 16]:

$$\delta S(t) = \int dt' G(t, t') A(t'),$$

(58)

where $G(t, t')$ is the two-point response function, as yet unspecified. If the rules of the game are independent of time, then $G(t, t') = G(t - t')$; if the rules change over time, then $G(t, t') = G(t - t', t + t')$. In this language of dynamical systems, an action plays the role of a source or driving force for the system. The equation above may be inverted to provide an inhomogeneous differential equation for the changing state of the system. If one formally introduces a differential operator $D_t$ which is the inverse of the response function:

$$\int dt' D_t G(t, t') = 1,$$

(59)

then the differential equation may be written, schematically:

$$D_t S(t) = A(t),$$

(60)

where, as ad hoc an example one might have,

$$D_t \equiv \frac{d^2}{dt^2} + i\gamma \frac{d}{dt} + \omega_0^2,$$

(61)

for an approximately periodic system which degrades over time, like a damped harmonic oscillator. Each action $A(t)$ thus leads to a response or change of state; this in turn implies that the state of the system must be a linear combination of the same action types:

$$S(t) = \sum_i s_i(t) T_i.$$

(62)

The state is thus defined on the same lattice, or checkerboard as the actions themselves. Differential (difference) characterizations of state have been studied in ref. [7]; this type of description is interesting, since it leads often to rich dynamics. Alternating periods of change and stability (riffles and pools in the flow of the system) might be best described by a difference representation.

Returning to the idea of the contest as a game, one writes a strategy as a statistical mixture of actions (i.e. moves in the game) $A(t)$, applied over an interval of time. This stochastic mixture specifies the boundary conditions under which the actions are applied. It may be formed as a linear combination of basic actions $A_n$, with probability weights $w_n$:

$$J(t) = \sum_n w_n A_n(t) = \sum_i p_i T_i,$$

(63)
The strategy vector \( J_i \) is the vector of probabilities for each primitive action, given the chosen mixture of full actions \( A_n \) for \( J \). In other words, \( J_i \) are the components of the decomposition of the strategy \( J(t) \) on the space of primitive actions.

\[
J_i = \sum_n w_n. \tag{64}
\]

It is easy to normalize these so as to be actual probabilities which sum to unity

\[
\sum_i p_i = 1. \tag{65}
\]

Notice that the specific representation of basis generators \( T_i \) does not affect the strategy vector, since it only serves to label the lattice-work of independent actions. There is no unique labelling. The components with respect to the basis must be related by a response function \( \Pi_{ij}(t, t') \)

\[
\delta S_i = \int dt' \ \Pi_{ij}(t, t') J_j(t'). \tag{66}
\]

The matrix value distribution is related to the pay-off matrix, and a basis of so-called ladder operators, also called creation and annihilation operator. The represent do-action/undo-action operations of the users and system administrator.

\[
\Pi(t, t') \sim \pi_{ij} \otimes \langle \vec{d} | \hat{S}_+ (t) \hat{S}_- (t') | \vec{d} \rangle \tag{67}
\]

where \( \hat{S}_\pm \) are operators which annihilate a configuration state at \( t' \) and create a new configuration at time \( t \). This is the generic mechanism by which the system develops. This form of description might seem unnecessarily formal, but it is actually highly useful, since the continuous generalization of this kind of dynamical system has been widely studied in statistical field theory. By picking out universal features of statistical models and restricting the scope of the computer system, there is a real chance of being able to build toy models which have qualitative, predictive power. However, this is no trivial undertaking and will be considered in a later paper. \[17\]

Since the actions which configure a computer system form a lattice, and these primitive action types do not necessarily commute with one another, one concludes that a suitable idealization of the system administration’s stochastic dynamics is found in non-Abelian, statistical field theories. This line of study would be suitable for modelling resource availabilities for large numbers of users, in which all users behave approximately equally on average (like an ideal gas). This approach promises therefore to be relevant to the problem of anomaly detection \[8\] and will be returned to in later work.
10 Summary

The aim of this paper has been to formulate a trustworthy framework for analyzing models of system administration. There is good cause to view computers as dynamical systems, approximated by mechanistic rules developing in time, with idealized properties which can be summarized by a finite state lattice. The theory of games has been employed in order to select between alternative strategies in a contest for machine resources, moving the state of the system through the lattice, as if on a chequerboard. It has been shown that it is possible to see system administration as the effort to keep the system close to an ideal state, by introducing countermeasures in the face of competitive resource consumption. This is the formal basis which opens the way for objective analyses in the field.

It is important to understand that, even an answer obtained with the assistance of a mathematical formalism is not necessarily the last word on the subject. Mathematics is only a tool for relating assumptions to conclusions, in an impartial way. With a mathematical approach, it becomes easier to see through personal opinions and vested interests when assumptions and methods are clearly and rigorously appraised. However, one can only distinguish between those possibilities which are taken into account. That means that every relevant strategy, or alternative, has to be considered, or else one could miss the crucial combination which wins the game. This is the limitation of game theory. It is not generally possible to determine strategies without creative input; this means that human intelligence will be required for the foreseeable future. There can be no zero-maintenance computer system. With this caution, how can one know that the ideal state of a system can be reached? How can one know that the system will not run away in an unstable spiral to catastrophe?

Two things are clear from the limited analysis here. The first is that purely dumb automatic systems are inadequate to perform every task in system administration today. Intelligent incursions are required to solve complex problems, to extend or adjust the strategies of the automatic system. Interestingly, this is the approach by which evolution has solved the immunity problem: the automatic responses of lymphocytes only go so far; the emergence of intelligence in humans has enabled us to develop medical research and develop drugs and other treatments against damage and disease. It seems naive to believe that any simple mechanistic system would be able to do any better than this; we can expect to require the assistance of humans at least until alternative machine intelligences have been developed.

The second point is that the use of quotas is a highly inefficient way of counteracting the effects of selfish users. A quota strategy can never approach the same level of productivity as one which is based on competitive counterforce. The optimal strategies for garbage collection are rather found to lie in the realm of the immunity model. However, it is a sobering thought that a persistent user, who is able to bluff the immune system into disregarding it, (like a cancer) will always win against the resource battle. The need for new technologies which can see through bluffs will be an ever present reality in the future. With the ability of encryption and compression systems to obscure file contents, this is a
contest which will not be easily won by system administrators.

There is plenty of work to be done on the theory of system administration. This paper is merely a small push in the direction of progress.

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