Gray Networking

a step towards next generation computer networks

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ABSTRACT

Modern networks are very complex. It is highly desirable to reduce management complexity in next generation networks design. Researchers have been seeking inspiration in natural observations to help better manage the ever increasing complexity of modern networks. Bio-inspired and cognitive networks have shown tremendous promise towards better adapting networks to local stimuli intelligently, and to some extent without human intervention.

In this paper, we discuss why the human brain is an excellent model for designing next generation smart networks. Insights gained into macro-behavior of human brain and its structural organization in the last decade are discussed. We identify features that can be adapted for network modeling. We then propose a network design model based on our understanding of the mind, how cognition is achieved, how memory is formed, etc. We end this paper with a real life network design problem we address using the proposed general model.

Categories and Subject Descriptors

C.2.1 [**Network Architecture and Design**]: Distributed Networks; A.1 [**General Literature**]: INTRODUCTORY AND SURVEY

General Terms

Cognitive Networks

Keywords

Bio inspired computing, Nature inspired computing, Cognitive networks, Gray networking

1. INTRODUCTION

Neuroscience research has advanced at an exhilarating pace over the last three decades. With modern technologies coming to their aid (EEG, EMG, fMRI, and PET scans to name some), neuroscientists today have a much better understanding of organization and functioning of various parts of human brain. No doubt, more complex questions such as what constitutes consciousness still remain a mystery. Studies being conducted worldwide on stroke survivors and epileptic patients have started answering questions related to memory, vision, etc.

Network researchers recently have started looking at natural phenomena in hopes of better managing the increasing complexity of modern networks. Ant behavior [1] [4] in locating food sources, virus spread models, epidemics [5] [7] [3] and many other similar natural patterns are being studied with the hope of using lessons learned from such studies in ushering in next generation of smart networks. We believe our own human brain organization might have the key to solve some major issues in such networks. It is generally thought that our brains are the most complex organs found in our planet. With its billions of neuron interconnections, yet functionally very efficient, our brain could provide some answers long sought by the networking community.

In the past researchers in the field of AI have made some significant progress towards making computers appear intelligent, but most of these approaches are purely algorithmic in the sense that given some external input, the algorithm behavior can be modeled as a state machine. The approach we take in this paper is very different as we try to model the architecture and behavior of a large network, with individual nodes interacting and behaving using some peer-to-peer overlay semantics.

At this point we should state that, although one can envision a global Internet wide network modeled after our proposal, this would be challenging to achieve in reality. Security concerns, inter-organization transit/relay restrictions, and several political concerns make such a large scale intelligent, self-configuring, overlay network deployment essentially a non starter! Hence the ideas presented in this paper will be applicable mostly in any large network deployment where all participating nodes belong to the same organization.

The main contribution of this paper is a network design model that mimics the human brain with major focus on adaptability and reliability. We first document some neural observations discovered in the past decade by neuroscientists, and compare those to some of the already known and frequently used principles in communications and networks research. Then we argue for the feasibility of using such a model for future network designs and propose what could be construed as a skeletal model for complex network designs.

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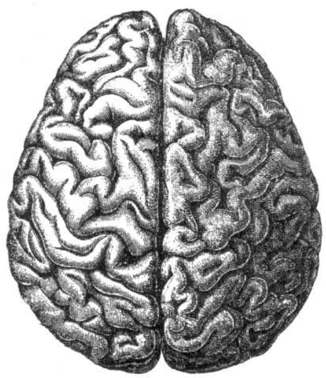

Figure 1: The human brain

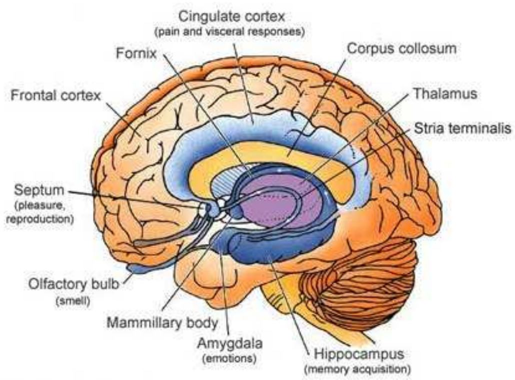

Figure 2: The limbic system

We call it 'GRAY NETWORKING' model. The reference 'gray' is inspired by the 'gray matter' which is a major component of our central nervous system[1] and consists of neurons, dendrites, and axons. This model will undoubtedly undergo several revisions in future as and when we know more about our brain. This paper represents the start of this process.

2. THE HUMAN BRAIN

In the past decade, studies conducted on numerous epileptic and stroke patients have uncovered functional and structural components of the human brain previously unknown. Research conducted in areas like phantom limbs, mind-body therapy, functional and sensory mapping, e.g., have helped us answer some of the fundamental questions about our brain. Figure (1) shows the typical walnut-like shape of the human brain. It shows the two halves separated by a thin membrane (corpus callosum) that often acts as a filtering mechanism for neural signals transmitted between the two halves. Each half typically controls the action of the opposite half of the human body. The sensory receptors from various body parts are received and processed by somatosensory system of the brain. Using functional MRI tests (fMRI), scientists have been able to map the various sections of the brain that correspond to sensations produced by different body parts. Figure (2) shows the human limbic system[2].

[1]Gray matter: http://en.wikipedia.org/wiki/Grey_matter

[2]source: http://www.alinenewton.com/neuroscience.htm

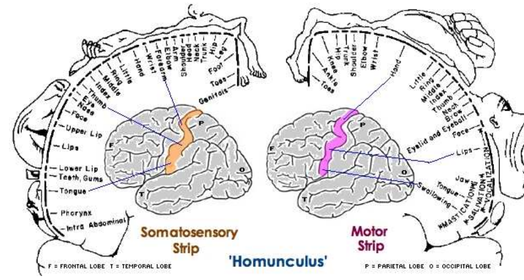

Figure 3: The somatosensory map

The limbic system forms the inner structure of brain's cortex. It takes part in several higher level functions, including forming of memory, emotions, sense of smell, etc. Figure (3) shows the brain's somatosensory map[3]. The relative significance of each organ determined by the size of the area of the mapping corresponding to it, is generally shown using 'to scale' drawing of that body part, in a human-like figure referred as homonculus (little man). This is also shown in the figure.

The above paragraph gives a sketch of some of the major components of human brain. In the next section we associate some well known computing principles with the way our brain is believed to work. Building on this, we then propose an initial model of network design that generally mirrors our brain.

3. COMPUTING PRINCIPLES ANALOGY

The way different components of our brain coordinate in order to analyze external stimuli provides a deep insight into principles that govern such behavior. As we expect, most of these principles are in line with what research communities have already proposed for efficient computing across several disciplines. So the next question that arises naturally is, "Can we tap these insights into designing a more efficient and intelligent systems?" In this section we present some of the recent findings on brain behavior by neuroscientists. We correlate these findings with some well-known and widely used engineering principles.

3.1 Observed characteristics

In his book [10], V. S. Ramachandran presents several case studies involving stroke patients. Based on his own observations and those of several other colleagues, he explains several abnormal behavioral patterns seen in these case studies. His own research dealing with medical condition in amputees, where they experience pain in their amputated limb, termed "phantom" limbs has uncovered several interesting facts on how our brain functions.

One very interesting observation is that every person is born with a blind spot in each eye. This phenomena is in fact very easy to observe[4]. Even though our both eyes have blind spots in their view area, we do not see a weird black hole when we see. The reason for this is that blind-spots for the left and right eyes do not overlap, enabling our brain to fill the missing details with sensory input from the other eye. This is very similar to '***redundancy***' principle. In fact in

[3]source: colorado.edu/intphys/Class/IPHY3730/image/figure5-7.jpg

[4]http://www.blindspottest.com/

this case our brain exhibits ***complementary redundancy***. When we do the test for blind spots with one eye closed, we still don't see the blind spot region as a void, as the brain fills in the missing details based on the sensory data of the surrounding area. This shows ***probability based analysis*** by our brain. Our brain fills in the missing data using what seems to be the most likely to be present in our blind spot using visual data of area surrounding our blind spots.

'***Compartmentalization***' is another well known feature of our brain. Scientists now generally agree that different regions of our brain are responsible to different actions. Left and right hemispheres in our brain perform different and highly specialized functions. They are connected by a very thin conductive membrane (corpus callosum) that acts as a sieve for signals crossing from one hemisphere to another. Stray signals that are not expected by the other hemisphere or impulses that may be harmful are filtered out. This exhibits the ***selective filtration*** ability of our brain. In fact it can also use ***selective fusion*** of different data channels to achieve some desired goal. We will see more about this later.

Another important behavior that became apparent while studying "phantom" limbs patients was the existence of both feed-back as well as feed-forward control loops in our brain. Our brain sends commands to multiple locations; one set of commands is sent to the body parts for which the intended action impulse is meant, and another set is sent to a monitoring area in the brain. The monitoring region takes appropriate actions if the actuators (or our body parts) deviate from the intended action.

Feed-back and feed-forward path can also be thought as bottom-up or top-down action pathways. The feed-back and feed-forward paths play a very important role and often these act as supplementary information pathways as well. For instance, if there are some missing data for brain to act upon, it tries to fill the void by using long term data that comes from the higher functional centers of our brain. Priority is always given to the bottom-up data channel over the top-down data channel, as these data are the real-time data sent up by the sensory mechanisms of our body. The absence of a feed-back path in patients with stroke related damage to the visual cortex of their brain resulted in hallucinations in these patients. In a normal person, the feed-forward data are generally vetoed by the feed-back sensory impulse data, which keeps the hallucinations in check. This shows that our brain uses a complex ***multi-level feedback*** architecture. In fact one can argue that our brain employs *combination of feedback paths along with selective filtration* to perform many of its tasks.

Studies on memory formation have revealed several interesting facts. Short term memory and its transition to long term stored memory has been used for many years now in AI and machine learning research. How exactly a memory is formed is still unknown, but scientists now know that we have different types of memory. There is a suggestion of division of memory depending on tasks, e.g., existence of visual memory and linguistic memory, episodic memory and semantic memory, and several others[5]. All these preliminary research data suggest existence of a complex, multi-level memory structure.

Vision researchers have found that brain does visual processing in a highly optimized fashion. More processing is done for vision regions that contain non-uniform, unstructured details than on regions that have regular features. For instance, the brain gives more processing attention to visual impulses that correspond to edges of a table than the top smooth surface of the same table. A likely reason for this is that the table top surface most likely will have smooth and gradual changes to color and texture. This is corresponds to ***data entropy*** where uniform data have low information content whereas nonuniform data have more information.

Looking at these preceding observations, we see that our brain employs several optimized methodologies in its functioning. Given that our brain is one of the most complex organs known to biology, it would only be appropriate to employ the known operational knowledge of our brain in design of next generation smart, self-managing computer networks.

[5]Memory: http://en.wikipedia.org/wiki/Memory

4. GRAY-NETWORKING MODEL

We propose general design guidelines that follow the major structural and functional observations made on the human brain. We refer to this guideline as the ***Gray Networking Model***. This model will be updated as and when new facts are known about human brain.

Any computing design model can be claimed to fall under 'Gray-Networking' model if it incorporates majority of these listed features:

- incorporates functional compartmentalization using clearly defined functional components
- filters inter-component/inter-module communication using customizable filters
- incorporates a separate learning module and associated logic
- allows for criteria-based graduation of learned facts into long term stable memory
- incorporates multiple and multilevel feedback / corrective / control loops in design
- uses multiple sensors to gauge real-time network conditions and other system parameters
- intelligently fills in missing data (see: top-down data path) to achieve some task (policy based)
- deploys ample redundancy to allow for partial failures and subsequent recovery (network plasticity)

In a human body, the brain along with the nervous system is primary controller organ and therefore nature through the course of evolution has provided for its protection (example: hard skull). Similarly, the vital components in our design must be protected from external as well as internal threats to the system. Furthermore, we believe it is very important that we incorporate human-in-the-loop in our design. There is always the possibility that in course of time a self-managing network may get stuck in some bad configuration. Our ability to reset the system and gain control will be very helpful and needed in such a scenario.

Thus these additional features should also be incorporated irrespective of the original design goal:

- security provisions against both external and internal threats

- mechanisms in place to keep a human in the loop

These are some of the major high level design features associated with 'Gray-Networking.' We later give a hypothetical high level design of a plausible network using the above guidelines and present arguments in favor of the proposed design. The following subsections attempt to throw more light on some of the above mentioned guidelines.

4.1 Communication Filters

The motivation behind this feature is the brain's central membrane that partitions left and the right hemisphere and acts as a filter between the impulses being exchanged between these hemispheres. Rogue and dangerous impulses are often filtered out here. Similarly, in the 'Gray-Networking' model, each module should have an incoming message filter that first tries to filter out unnecessary or potentially detrimental messages arriving from external modules. Ideally, this is done in conjunction with feedback and fusion handling.

4.2 Learning Module

Event postprocessing coupled with vital network parameters at the time of the event occurrence can lead to significant knowledge generation that the network can use to adapt more effectively in future. Hence use of a dedicated knowledge generation and learning module is a major feature of this model. This learned behavior may be stored in a short term memory, or may transition to a long term memory for future use depending on graduation criteria set up during the design phase (which themselves may be subject to adaptation). The learning subsystem may be centralized or distributed depending on the design goals. The existence of a top-down data path generally necessitates the use of a long term memory module. The content of the long term memory may be populated using either a learning algorithm or guided by organizational long term goals, or a combination of both. In [6] the authors present a scheme for long-term memory, mental models with respect to situation awareness that could be used as a guideline to develop a memory subsystem under ***GRAY NETWORKING*** model.

4.3 Ability to gauge Network Conditions

In order to minimize system administration burdens, next generation computer networks have to be smart, self-healing, and self-managing with auto configurability features built in, leaving system administrators to do higher level analysis and design per organizational computing goals. Since network operating conditions may change dramatically at short notice, one of the requirements of this model is to incorporate the use of sensors to determine real-time network conditions. This will allow the network components to readjust their working parameters in order to satisfy the higher level organizational goals and services guarantees it is designed to deliver. Sensors are also necessary for self generation of event driven knowledge as mentioned in the previous subsection.

A sensor node could be any typical network node configured to perform specific measurements on some network data. A sensor node (host) could perform traffic sensing by performing packet inspection and report the measurements periodically to some other node (part of higher control plane). Another example of a sensor node could be taken from honeypot [9] research. A node could be setup as a honeypot node to attract malicious attacks to itself, thereby sensing the state of mal-activity in the network. In a critical network one would need to use multilevel and possibly a hierarchical sensor organization to achieve the desired goals.

4.4 Top-Down Vs Bottom Up Data-Path

Our brain has the capability to fill in missing impulse data using data from higher cognition centers. Information flows both bottom-up from actual sensors such as nerve endings, eyes, ears to the brain, as well as top-down from higher processing centers in the brain to muscles and other body parts. Both these information channels aid each other in construction a ***consistent and complete*** picture of the external and internal environments.

The same principle can be incorporated in next generation network design. The capability to fill in missing information chunks from statistical data stored in long term storage to complete some critical task in the face of partial corruption or an incomplete service request can prove a very powerful tool in improving the end user perceived quality of service. On the other hand, this feature could prove to be an Achilles heel where strong security is desired. A fine balance between usability and security then becomes a matter of correctly defining the system policies. One important observation to make here is the fact that if there ever arises a situation where there are competing data values from both bottom-up channel and top-down channel, the bottom-up data vetoes the top down channel value, since the bottom-up data value represents the actual value whereas the top down value is statistical data from several past observations.

4.5 Network Plasticity

Neuro-plasticity [8] in our brain is well documented. Even though the tasks of two hemispheres are now generally known, it has been observed that in some scenarios, our brain, with proper training can adapt and rewire itself in the face of tissue damages. In such cases it has been observed that the neural impulses that were processed by say the left hemisphere before brain cell damage were later processed by regions in the right hemisphere after training. In a recent study [2] scientists have found evidence of brain rewiring in test subjects that led to congenitally blind patients being able to see. These studies suggest that the human brain's functional compartmentalization is not static but plastic in nature, and our brain has the capability to rewire itself.

This concept of plasticity can be used in designing critical service networks. With ample redundancy and smart logic built into the network, we can design the next generation critical networks to be able to survive infrastructure outages, that is, ***self-heal*** by re-routing and re-orienting, i.e., ***reconfiguring*** its services via alternate paths.

We would like to disambiguate the plasticity behavior from internet path rerouting in the face of link failures. Although network link rerouting is indeed a valid form of plasticity, from a neural viewpoint it could be viewed as an alternate path for neural impulses using a different sets of neurons, hence such plasticity is at a much lower level. Here we are referring to migration of services and responsibilities from a failed component (node) to another node. This could be achieved using solicitations by a higher layer node from participating nodes or even active recruiting. An example could be a failed sensor node which may trigger the monitor (in the higher plane) to recruit some other nodes in the overlay network to take on the task of the failed sensor. This could be achieved if a network design has *provisions for ample redundancy and has associated logic to perform reconfiguration*.

Benefits and Issues

Now that we have explained our model in some detail, we will demonstrate its usefulness by modeling a real network task based on 'Gray Networking' model. As will become clear from the example architecture below, several of current network tasks that are challenging to implement, can be designed and implemented based on the proposed model. But before that, let us look into possible benefits and drawbacks of our proposal.

Possible Benefits

A main aim of this model is to reduce the network management burden. This could be achieved by incorporating intelligence into the network. Furthermore exploiting adaptiveness of a network to achieve high degree of robustness becomes possible. A network that is self healing and self configuring can handle minor failures on its own, thereby improving system availability. Our model also introduces the notion of combining reconfiguration and redundancy, and introduces the idea of coupling feedback and filtration. Ultimately, the hope is that this model could be seen as presenting a new paradigm in network design.

Possible Drawbacks

Since we are proposing a design guidelines based on a structure (our brain) that itself is not fully understood, the design guidelines will undergo several revisions as we gain new understanding of our brain. From the design phase itself, one must take care to address threats to the critical components. One must take both external and internal threats into consideration. A critical component if compromised could lead to widespread service disruptions.

5. AN EXAMPLE NETWORK DESIGN

Figure (4) shows a simple organizational network incorporating our model guidelines. The example design is in no way exhaustive, but it shows how using the model we proposed above, one can quickly and with ease come up with a design scenario for an intelligent network. The objective of such a design is to demonstrate how using some of the ideas mentioned in this paper, one can proceed to design a smart network. The example network shows various high level components that one may want to install.

The network schematic shows several nodes labeled 'TA' and 'HP'. These nodes form a part of the *sensor nodes organization*. Nodes labeled 'TA' are traffic analyzers. They perform packet inspection and may also report the network load in their own neighborhood. The nodes labeled 'HP' are honeypot [9] elements. These nodes form a part of the honeypot network whose primary role is to analyze the threat level to the organizational network. The traffic analyzers report periodically to the 'Resource Manager' and the 'HP' nodes report to the 'Intrusion Detection' subsystem. An autonomous self-tuning intrusion detection system [11] can be used. The 'Resource Manager' and the 'Intrusion Detection' subsystem, both report to the 'Configuration Generator'. 'Configuration Generator' has access to the list that has entries on all the network components installed along with their capabilities. It uses these data to generate each component's configuration parameters in such a manner so as to achieve the larger organizational goals.

Sensor nodes report their own working status to 'Component Status' monitor. In case a critical node fails, the 'Task Reassigner' may delegate the responsibilities to some other node in the network. It may float a volunteering request among the online nodes or it may draft some nodes to perform the tasks of the failed nodes. This behavior demonstrates how reconfiguration management and redundancy could be coupled. Ample redundancy will generally make the task of reconfiguration manager easier. The task binary store could house several different types of functionality enablers (binary codes, maybe) and depending on nodes being recruited by task-reassigner, it may securely deliver the enabler module to volunteering nodes in the network.

The nodes then have to be designed in such a way that they are capable of handling multiple and varied tasks assigned to them. This can be achieved if the application stack is designed to allow a module to be replaced on the fly. These binary chunks from *task store* then would get stacked in the application layer of the destination node and depending on the type of code or parameters installed on them, their behavior could be changed in real time. This demonstrates smart *reconfiguration in the face of failures*.

Another component shown is the 'Authentication Subsystem'. It may authenticate user login requests for the entire session, or it can also be configured to authenticate them on a per access request. It monitors the type of requests against each user and reports this fact to the 'User Access History' manager. The memory management logic may then decide whether to keep the information in the working memory or transition it to the long term storage. Long term user access history may also be linked to the 'Intrusion Detection Subsystem' (IDS), which could allow it to function more efficiently. This also would then form a feedback path into the IDS subsystem, and along with the feedback provided by the *sensor organization* mentioned earlier would form a *multi-level feedback* sub-system. The IDS subsystem would have its own data filters tuned to sieve relevant data chunk from multiple feedback loops. This demonstrates how *feedbacks and smart filtration* could be coupled. Having this coupling would simplify the design of sensor nodes. Sensors could be designed to provide a wide array of data which would be filtered by different network modules differently depending on the needs and tasks performed by such modules.

The general 'network state' statistics over a period of time could be stored in a long term memory subsystem. Let us assume that periodically our 'intelligent' network accesses the configuration parameters of all active components. And depending on the 'traffic analysis' report and network 'intrusion' threat, it may realign the components' configuration. But say for some reason the most recent 'traffic analysis' report has not been generated, maybe due to 'TA' system failures. In that scenario the missing data (i.e. the 'traffic analysis' report) could be substituted using the statistical traffic analysis data stored in the long term memory. In fact, long term memory becomes necessary if a feed-forward data path is incorporated in the network design.

The above high level sample network design incorporates many features from our proposal. It demonstrates 'plasticity', uses short term and long term 'memory manage-

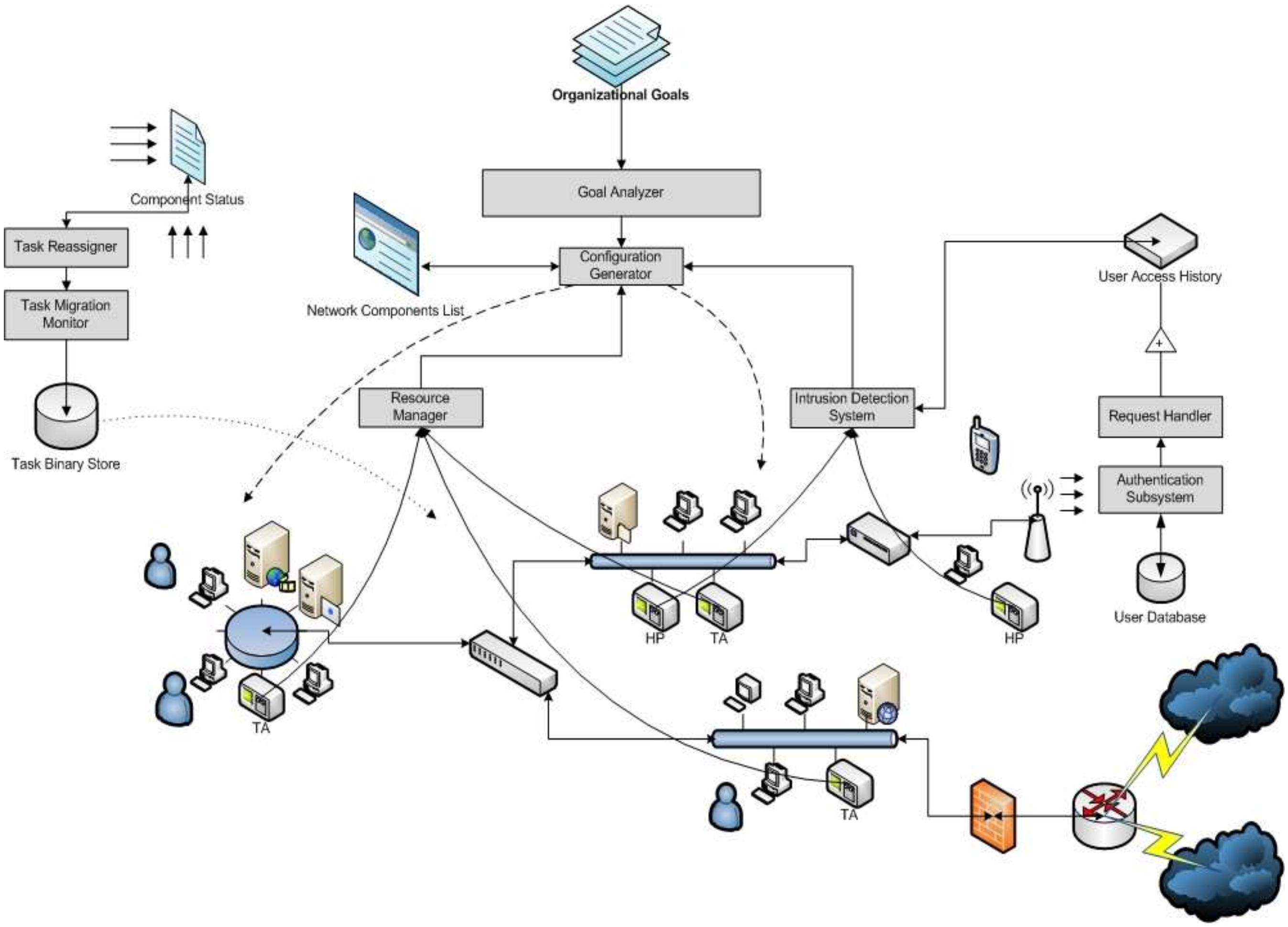

Figure 4: A sample network design

ment,' has clear functional compartmentalization, uses feedback and feed-forward data loops, and makes use of sensors to assess the network state. Each subsystem we referred to in our example could itself be designed (recursively) on the proposed model.

6. CONCLUSIONS

In this paper we have proposed a bio-inspired network design model which is based largely on macro-functional insights into a human brain. Hopefully using the guidelines provided in this paper one can at least get a general sense of a direction to think before designing the self-configuring, self-healing, smart networks of tomorrow. This paper is a small step in this direction. We will continue to update our model as we gather more insights into the human brain. We also presented an example network design demonstrating some of the guidelines proposed in this paper.

7. FUTURE RESEARCH DIRECTION

This paper represents a first step toward *gray networking* at best. We are working hard towards finalizing a validation model and formalizing design objectives. Each component of the *gray networking* model will require further research. We believe the next several years will be very exciting and will see influx of many innovative ideas into *gray computing* and nature-inspired networking in general.

8. ACKNOWLEDGMENTS

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