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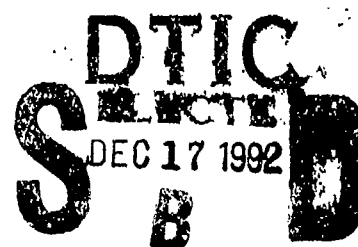
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NAMRL Special Report 92-1

**USING CONSTRAINT
SATISFACTION NETWORKS TO
STUDY AIRCREW SELECTION FOR
ADVANCED COCKPITS**

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SUMMARY PAGE

THE PROBLEM

Pilot selection techniques for the U.S. Navy must meet the challenges offered by the next generation of aircraft. One specific technological advance is likely to be the introduction of machine intelligence into the cockpit to assist pilots in their assigned tasks. We presently do not have any psychological tests in our selection toolkit to measure the cognitive skills needed to interact optimally with machine intelligence. This research has the goal of developing psychological tests, together with the accompanying mathematical models, to measure individual differences in pilot candidates with regard to cooperative human-machine problem solving.

FINDINGS

The groundwork for a constraint satisfaction network (CSN) approach to cooperative human-machine problem solving was laid down. The details and terminology of a simple CSN were explained. An algorithm to calculate the minimum energy of a CSN was explored in great depth. This algorithm is important because it is the basis for a numerical solution to the mathematical model underlying the CSN. I showed how this algorithm generated probability mass functions, which will be extremely helpful in practical experiments where human-machine performance needs to be quantified.

RECOMMENDATIONS

This research project should be continued forward to its next phase. The next step would be to look at larger CSNs as practical models for the cooperative human-machine problem solving endeavor. Experiments with pilot candidates on a simple problem solving task will provide the data to assign weights, or constraints, to a CSN. This will mark the starting point of an effort to measure individual differences using such a model.

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INTRODUCTION

Aircrew selection must continuously attempt to keep pace with the changes wrought by advances in technology. A highly significant example of a breakthrough in computer technology is the introduction of artificial intelligence into the cockpit. The Air Force's *Pilot's Associate* program is a harbinger of such advances. The present medical selection criteria can, and should be, augmented with results arising from research on the salient psychological characteristics of the potential aviators who are expected to fly these aircraft of the 21st century.

Previous research directed towards naval aviator selection [1] has tended to emphasize psychomotor skills, spatial/perceptual skills, and personality traits. The investigation of these skills was appropriate when the Navy (and the Navy's adversaries) flew slower aircraft so that pilots relied more extensively on visual, auditory, and vestibular cues. In this situation, superb psychomotor skills could effectively explore the outer fringes of the aircraft's operating envelope. It is my contention that the next-generation aircraft will place less premium on these particular psychological skills.

Instead, the pilot will function more as a monitor of various systems onboard the aircraft and will, in addition, rely on the assistance from intelligent components of the overall weapons system in order to fly the aircraft to its maximum capabilities. As the overall manager of this complex weapons system, the pilot must blend in and interact with other intelligent components. It is an unanswered question as to what psychological makeup is required for such an integration to take place.

The purpose of this paper is to present the scientific model that will be used to investigate cooperative problem solving between a human pilot and machine intelligence. The general outline of the model will be discussed, and some numerical examples will be explored. In addition, the algorithm used to find numerical solutions to the questions posed will be examined in some detail. The goal, then, of this initial effort is to begin developing a metric to assess individual differences in pilot candidates with regard to some of the cognitive tasks they will be asked to perform in future aircraft.

CONSTRAINT SATISFACTION NETWORKS

Both human and machine intelligence will be represented by a set of processing units. These units will be highly interconnected as demanded by neural network theory. We want to see how these units can cooperate to solve a problem. One way of analyzing such cooperative problem solving behavior is through a constraint satisfaction network, or CSN [2].

Constraints are expressed locally as weights between some restricted set of processing units. The idea is that the CSN exhibits emergent computational properties. That is, solutions to problems can be achieved when local constraints are satisfied in the best

possible fashion. Therefore, the hope is that human intelligence and machine intelligence can interact to satisfy the maximum number of constraints. The end result of this emergent activity would achieve the goal of solving some tactical air problem.

The states in the numerical example refer to activation values that the various processing units can assume. The energy refers to the mathematically defined relationship between the activation values of the processing units and the weights connecting those units. This energy function captures the constraints imposed on our system, and in some sense, it can also be considered to embody the knowledge implicit in the network [3].

For our purposes, energy is defined as

$$E = - \sum_{i < j} w_{ij} a_i a_j + \sum_i \theta_i a_i$$

where w_{ij} represents the modifiable connection strength between two processing units i and j , and a_i and a_j are the activation values of processing units i and j [4]. In our example the activation values can take on only two values, 1 and 0. The θ s represent threshold values for each unit. They indicate, in some sense, the constraints in the network for having a particular unit turned on in the absence of any other contributing evidence. As such, the thresholds represent the *a priori* knowledge for considering a particular hypothesis to be true.

If both units assume a value of 1, then the contribution to the overall energy is w_{ij} . If one of the units has an activation value of 0 or both have a value of 0, then the contribution to the overall energy of these two units i and j will be 0. If w_{ij} happens to be negative, then this latter situation disallows a decrease in the overall energy. Decreasing the overall energy is what the system is striving to do to reach a problem solution. The point is, whether unit i assumes an activation value of 1 or 0 could be good or bad depending on the sign of the connection strength with unit j .

The network is divided into three kinds of units:

1. input units
2. hypothesis units
3. output units

The input units are where the network interfaces with the environment. The particular problem presented to the network will be coded into activation values for the input units. Input units retain the values imposed by the problem solving environment; they are not allowed to change. As the name implies, the hypothesis units represent the activation of particular hypotheses, which either the human or the machine is considering to be true, based on the particular problem input. An activation value of 1 for an hypothesis unit indicates that the hypothesis is currently being considered to be true; an activation value of 0 indicates that the hypothesis is currently considered to be false. The hypothesis units are themselves divided into two groups: 1) those dedicated to the human decision maker and 2) those dedicated to the machine decision maker. These activation values

are allowed to change during the course of finding the minimum energy. That is, these units "turn on" or "turn off" hypotheses in an attempt to best satisfy the constraints (or equivalently, the knowledge) embedded in the CSN. The final set of units constituting the network are the output units. All the hypothesis units feed into the output units, and once the hypothesis units *settle* or *relax* into the best solution, the result is fed into the output units for the coded solution to the particular problem presented at the input units. (see Fig. 1)

FURTHER DETAILS OF A CONSTRAINT SATISFACTION NETWORK

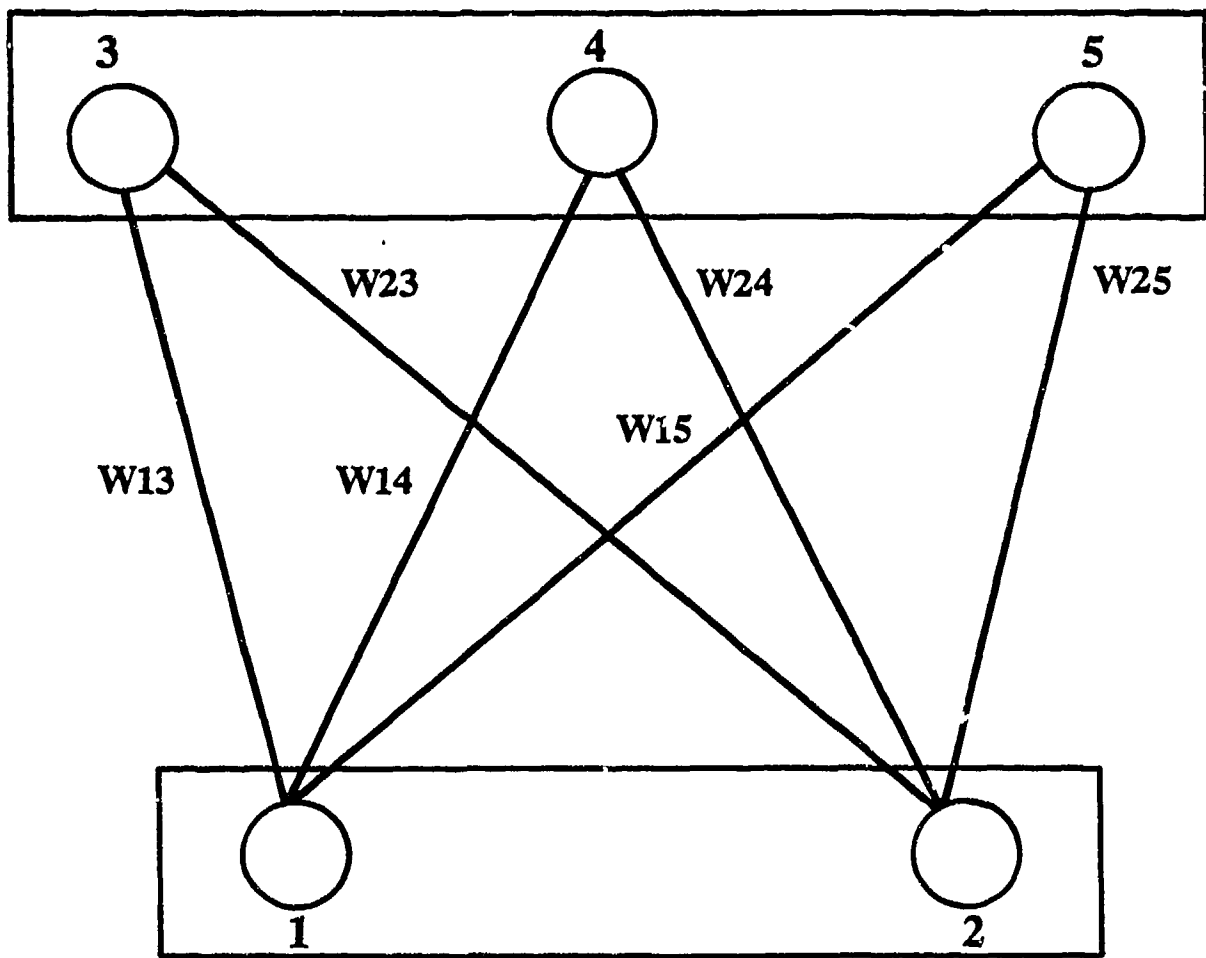
Figure 1 shows a portion of a constraint satisfaction network with five hypothesis units. Assume that the two units in the bottom layer are machine hypothesis units and the three units in the upper layer are pilot hypothesis units. Further, ignore for the time being the input units and the output units and concentrate solely on the hypothesis units. The units are fully interconnected, that is, there is a constraint represented as a weight between each of the two machine hypothesis units and each of the three human hypothesis units. These constraints and the thresholds take on the values given in Table 1, which are assigned arbitrarily for the purpose of working out numerical examples.

TABLE 1. The Connection Strengths and Thresholds for the Example Network of Figure 1.

Connection Strengths	Thresholds
$w_{13} = +1$	$\theta_1 = 1$
$w_{14} = +2$	$\theta_2 = 0$
$w_{15} = -2$	$\theta_3 = 2$
$w_{23} = +3$	$\theta_4 = 2$
$w_{24} = -1$	$\theta_5 = 0$
$w_{25} = -3$	

Given that we have five units, each of which can take on the value of 0 or 1, a total of $2^5 = 32$ situations are possible. We will call these possible situations a "state". Each state has an energy value attached to it. All 32 states and associated energies are listed in Table 2.

Human Hypothesis Units



Machine Hypothesis Units

Figure 1: A portion of a constraint satisfaction network showing the human and machine hypothesis units. The units are labelled numerically from 1 to 5. The weights representing the connection strengths between units are shown in Table 1.

TABLE 2. The Binary Representation and Energy of all 32 States.

State	Unit Activation Values	Energy
S_1	00000	0
S_2	00001	0
S_3	00010	-2
S_4	00011	-2
S_5	00100	-2
S_6	00101	-2
S_7	00110	-4
S_8	00111	-4
S_9	01000	0
S_{10}	01001	+3
S_{11}	01010	-1
S_{12}	01011	+2
S_{13}	01100	-5
S_{14}	01101	-2
S_{15}	01110	-6
S_{16}	01111	-3
S_{17}	10000	-1
S_{18}	10001	+1
S_{19}	10010	-5
S_{20}	10011	-3
S_{21}	10100	-4
S_{22}	10101	-2
S_{23}	10110	-8
S_{24}	10111	-6
S_{25}	11000	-1
S_{26}	11001	+4
S_{27}	11010	-4
S_{28}	11011	+1
S_{29}	11100	-7
S_{30}	11101	-2
S_{31}	11110	-10
S_{32}	11111	-5

An example is the calculation of the maximum energy state, S_{26} , where $E = +4$, and the minimum energy state, S_{31} , where $E = -10$. The state S_{26} occurs when the network has units 1, 2, and 5 turned on and units 3 and 4 turned off. This pattern is coded as 11001. Using the formula for the energy,

$$\begin{aligned}
\text{Energy (State 26)} &= -\{w_{13}a_1a_3 + w_{14}a_1a_4 + w_{15}a_1a_5 \\
&\quad + w_{23}a_2a_3 + w_{24}a_2a_4 + w_{25}a_2a_5 \\
&\quad + \theta_1a_1 + \theta_2a_2 + \theta_3a_3 + \theta_4a_4 + \theta_5a_5\} \\
\text{Energy (State 26)} &= -\{w_{15} + w_{25} + \theta_1 + \theta_2 + \theta_5\} \\
&= -\{(-2) + (-3) + (+1) + (0) + (0)\} \\
&= +4
\end{aligned}$$

Because units 1 and 5 are both on and units 2 and 5 are both on they are the only weights that are counted.

On the other hand, S_{31} is characterized by having units 1, 2, 3, and 4 on and unit 5 off. The energy in this case is

$$\begin{aligned}
\text{Energy (State 31)} &= -\{w_{13}a_1a_3 + w_{14}a_1a_4 + w_{15}a_1a_5 \\
&\quad + w_{23}a_2a_3 + w_{24}a_2a_4 + w_{25}a_2a_5 \\
&\quad + \theta_1a_1 + \theta_2a_2 + \theta_3a_3 + \theta_4a_4 + \theta_5a_5\} \\
\text{Energy (State 31)} &= -\{w_{13} + w_{14} + w_{23} + w_{24} + \theta_1 + \theta_2 + \theta_3 + \theta_4\} \\
&= -\{(+1) + (+2) + (+3) + (-1) + (+1) + (0) + (2) + (2)\} \\
&= -10
\end{aligned}$$

The state that satisfies the constraints inherent in the network to the best degree possible is the state with the minimum energy configuration. By inspection of Table 2, S_{31} , which we just calculated, has an energy value of -10. With positive weights between units 1 and 3 and positive weights between units 1 and 4, the network will try to turn these units on. With negative weights between units 1 and 5 and negative weights between units 2 and 5 the network is "happiest" when unit 5 is off as it is in S_{31} . Not all of the constraints specified in the weights connecting the units can be satisfied simultaneously though. The network would like units 2 and 4 to be off, but this constraint cannot be satisfied in S_{31} . So the constraint satisfaction network will be content with satisfying as many constraints as possible. Such a network solves optimization problems with so called *weak* constraints.

FINDING MINIMUM ENERGY STATES OF MUCH LARGER NETWORKS

With only five units, it is relatively easy to calculate, as we did in Table 2, all possible activation states of the units and inspect for the state with the minimum energy. It

is equally obvious that this technique becomes impossible with any reasonably sized network. Combinatorial explosion sets in and there are just too many states to enumerate, not to mention calculating the energy function for each state.

An analogous problem exists in trying to integrate a multidimensional integral that does not yield to an analytical solution. Numerical methods have been invented which "sample" the integrand at "important" places in order to estimate an answer. These methods are usually lumped under the rubric of Monte Carlo solutions. Physicists and chemists were faced with the same problem when they attempted to study the macroscopic behavior of physical systems made up of a huge number of atoms [5].

A Monte Carlo solution to these problems was proposed by Metropolis *et al.* [6]. An algorithm they proposed has come to be called the Metropolis algorithm and is the cornerstone of a numerical technique to find the minimum energy states of a constraint satisfaction network. The Metropolis algorithm works as follows: [7]

1. The algorithm starts with the network in some arbitrarily chosen state. For example, the algorithm might start out in S_5 where unit 3 is turned on and units 1, 2, 4, and 5 are turned off. This state has an energy of -2 .

2. A new state of the network is generated by applying a set of moves to the network. One possible set of moves is to consider "flipping" the activation value of a randomly chosen unit from a 1 to a 0 or from a 0 to a 1. An example is given in Table 3. From step 1 we know that the network is in S_5 . The first column of Table 3 shows each unit being considered, from unit 1 to unit 5 in turn, for a flip. The second column indicates the new state that the flip has caused. The final column indicates the change in energy caused by the move.

3. A new state is entered according to the above strategy by generating a random number. If the random number is between 0 and .20, then flip unit 1; if the random number is between .20 and .40, then flip unit 2, and so on.

4. The difference in energy (called ΔE) between the new state just entered and the old state where the move was initiated is calculated. For example, if the random number was .37, a move into S_{13} is called for. From Table 3,

$$\Delta E = E(\text{final}) - E(\text{initial}) = -5 - (-2) = -3$$

If the random number had been .59, then we would have flipped unit 3 and moved into S_1 . In this case,

$$\Delta E = E(\text{final}) - E(\text{initial}) = 0 - (-2) = +2$$

5. If $\Delta E \leq 0$, then accept the move into the new state. In the case where we moved into S_{13} , $\Delta E \leq 0$, so we would accept this move.

6. If $\Delta E > 0$, then accept the move into the new state with the probability $e^{-\Delta E/T}$. In the case where we moved into S_1 , $\Delta E > 0$. The probability of accepting this

move is $e^{-2/T}$ where T is a parameter called *temperature*. The meaning of this parameter will be explained more fully below. If $T = 4$, the probability of accepting the move equals

$$e^{-\Delta E/T} = e^{-1/2} = .6065.$$

We generate another random number, and if this number is less than .6065, we accept the move. Otherwise, we reject this move into the new state.

7. Move from state to state by following the above procedure for a long series of trials. After this long series of trials, the process will lose memory of the states in which it started out and eventually reach an equilibrium condition. Statistics of interest can then be gathered that reflect the behavior of the entire network even though only a sample of the total possibilities the network could assume has been realized. In our case, we might calculate an estimate of the minimum energy and the states where this minimum is achieved.

TABLE 3. The Possible Transitions to a New State of the Network From a Given State and Resulting Change in Energy.

Unit Activation Values	State Transition	ΔE
00100 $\rightarrow$ 10100	$S_5 \rightarrow S_{21}$	$-4 - (-2) = -2$
00100 $\rightarrow$ 01100	$S_5 \rightarrow S_{13}$	$-5 - (-2) = -3$
00100 $\rightarrow$ 00000	$S_5 \rightarrow S_1$	$0 - (-2) = +2$
00100 $\rightarrow$ 00110	$S_5 \rightarrow S_7$	$-4 - (-2) = -2$
00100 $\rightarrow$ 00101	$S_5 \rightarrow S_6$	$-2 - (-2) = 0$

The essential utility of the Metropolis algorithm is that it enables us to answer key questions concerning large constraint satisfaction networks. Among other things, it allows us to find the configuration of activation values that has the lowest energy. This is the configuration that satisfies the constraints in the best possible manner, or in other words, makes best use of the prior knowledge embedded within the network. The Metropolis algorithm is a general heuristic technique which has some mathematical guarantees for finding answers to optimization problems. Specifically in our case, it is a useful computational device for finding energy minima in constraint satisfaction networks.

In step 6 above we mentioned a temperature parameter. The addition of this parameter is an enhancement to the Metropolis algorithm. Starting the process at high values of the temperature parameter and then very slowly decreasing the temperature by a set schedule will yield estimates of the minimum value of the function we are trying to minimize. This technique is called *simulated annealing* because of its analogy to the physical process of

heating materials, like glass, to high temperatures, and then slowly cooling to a ground state where imperfections in the material are reduced [8].

SIMULATED ANNEALING

Table 4 shows how simulated annealing works on the simple constraint satisfaction network we have been using as an example. It follows the same steps outlined in the previous section with the explicit addition of a temperature parameter.

TABLE 4. Representative Trials From the Metropolis Algorithm at High and Low Temperatures.

Trial	Proposed Transition	ΔE	RN	$e^{-\Delta E/T}$	Accept
<i>Temperature = 100</i>					
⋮	⋮	⋮	⋮	⋮	⋮
11	10110 → 11110	-8 → -10 = -2	***	***	Yes
12	11110 → 11100	-10 → -7 = +3	.99	.97	No
13	11110 → 01110	-10 → -6 = +4	.53	.96	Yes
⋮	⋮	⋮	⋮	⋮	⋮
<i>Temperature = .8</i>					
⋮	⋮	⋮	⋮	⋮	⋮
6	11110 → 10110	-10 → -8 = +2	.05	.08	Yes
7	10110 → 10100	-8 → -4 = +4	.64	.01	No
8	10110 → 00110	-8 → -4 = +4	.37	.01	No
⋮	⋮	⋮	⋮	⋮	⋮
14	10110 → 11110	-8 → -10 = -2	***	***	Yes
⋮	11110 → 01110	⋮	⋮	⋮	⋮
20	11110 → 11011	⋮	⋮	⋮	⋮

The upper part of Table 4 shows what typically happens at a high temperature. At the beginning of trial #11 the network is in S_{23} with units 1, 3, and 4 on and units 2 and 5 off. Unit 2 was randomly chosen for a flip, in this case from 0 to 1 ("off" to "on"). The second column shows this proposed transition from S_{23} to S_{31} . This transition results in a movement to a region of lower energy seen in the ΔE column. Any $\Delta E \leq 0$ is automatically accepted. Therefore, recording in the last column that this transition has been accepted, we flip unit 2 from "off" to "on." (0 to 1).

With one trial of the Metropolis algorithm completed at a given temperature, we can proceed to trial #12. From the previous move, we start out in S_{31} with units 1, 2, 3, and 4 on and unit 5 off. Unit 4 was randomly chosen for a flip from 1 to 0. In this move to a region of higher energy, ($\Delta E = +3$), we must generate a random number to compare to $e^{-3/100} = .97$. The random number turns out to be .99, which is greater than .97, so we do *not* accept this proposed transition. Unit 4 is not changed, and we remain in the same state as at the start of the trial.

At trial #13, we are again trying to move from S_{31} , which we know is the minimum energy state with an energy of -10, to a different state. Here unit 1 has been randomly chosen for a flip from 1 to 0, and, as in trial #12, we must be moving from a region of low energy to a region of relatively higher energy. This is confirmed by checking that $\Delta E = +4$. Contrary to the previous trial, the random number .53 is smaller than $e^{-4/100} = .96$. This proposed move is acceptable, even though it is to a region of higher energy. Unit 1 is turned off, and the subsequent trials at this temperature continue in similar fashion.

We now turn our attention to the lower part of Table 4 where the temperature has been considerably lowered. Trial #6 begins with the network again in S_{31} . A proposed transition involves flipping unit 2 which implies an increase in energy. We will accept this move with probability $e^{-2/.8} = .08$. A random number less than .08 is drawn so we accept this move. So we find ourselves at trial #7 in S_{23} contemplating a flip of unit 4. This move represents an energy increase of 4 which will probably not be accepted at this low temperature. In fact, less than 1% of such moves would be accepted. This is reflected in trials #7 and #8 where proposed transitions with an energy increase this large are not accepted. Compare this with trial #13 in the upper part of the table where, at a temperature of 100, a proposed transition with an energy increase of 4 would have been accepted 96% of the time. Eventually, a proposed transition will result in decreasing the energy as happens at trial #14. In this case, the network falls into the lowest energy configuration, and spends most of its time in this low energy configuration because it is so very unlikely that a proposed transition will be accepted. As illustrated with the rest of the trials in the table low energy configurations of the network are sampled more and more often as the temperature decreases. This is the objective of the simulated annealing algorithm [9].

An examination of the frequency distribution of all 32 states at decreasing temperatures reveals how the simulated annealing algorithm converges upon the minimum energy state. This information is provided in Table 5. The table should be scanned by first fixing on the leftmost temperature column (i.e., where temperature=100) and then reading down over the rows representing the states. 100 trials of the Metropolis algorithm were conducted at each temperature so each column will sum to a total of 100.

TABLE 5. The Frequency Distribution of All 32 States at Decreasing Temperatures.

State	Temperature									
	100	10	5	4	3	2	1	.9	.8	.7
1	3	2	1	2	0	0	0	0	0	0
2	3	1	0	1	0	0	0	0	0	0
3	1	3	3	3	1	0	0	0	0	0
4	1	5	2	0	0	0	0	0	0	0
5	7	2	1	2	1	3	0	0	0	0
6	9	1	0	1	2	1	0	0	0	0
7	4	3	2	7	6	0	0	0	0	0
8	6	3	2	5	1	0	0	1	0	0
9	3	0	1	3	0	0	0	0	0	0
10	1	1	0	0	0	0	0	0	0	0
11	1	0	4	5	0	0	0	0	0	0
12	1	2	1	0	0	0	0	0	0	0
13	2	1	4	4	5	5	0	0	0	0
14	2	0	0	2	3	2	0	0	0	0
15	3	5	6	6	9	3	0	0	0	0
16	2	4	0	1	0	1	0	0	0	0
17	2	3	3	1	0	1	0	0	0	0
18	4	4	2	0	0	0	0	0	0	0
19	5	4	7	9	4	9	0	0	0	0
20	6	4	5	2	0	1	0	0	0	0
21	4	4	4	6	3	10	0	0	0	0
22	5	7	1	0	1	1	0	0	0	0
23	4	13	7	6	21	21	13	8	7	4
24	3	5	3	0	4	1	1	9	3	0
25	1	2	3	1	0	0	0	0	0	0
26	4	2	1	0	0	0	0	0	0	0
27	1	6	7	8	4	2	0	0	0	0
28	3	1	1	0	0	0	0	0	0	0
29	1	4	11	10	9	7	15	6	0	4
30	3	1	0	3	0	2	0	0	0	0
31	4	6	17	9	26	26	71	74	90	92
32	1	1	1	3	0	4	0	2	0	0

At the highest temperature the distribution among states is fairly uniform. At high temperatures all states are visited at random with no particular preference given to low energy states. As the temperature drops, we begin to notice some departures from uniformity. Some states seem to be accumulating higher counts and there are more zeroes for other states. The pattern, at this point, is still a little murky. As the temperature continues to drop, the pattern comes into sharper focus. At $T = 1$ only four states, S_{23} , S_{24} , S_{29} , and S_{31} , have been visited by the algorithm. All of these states are low energy states, and

most importantly, S_{31} , the minimum energy state, has been visited most often. By the time we stop this process at $T = .7$, the pattern is quite clear. Only the lowest energy states have been visited, and S_{31} predominates, because it accumulated 92% of all visits. If we were to calculate any function based on this final low temperature distribution, such as the average energy of the CSN, then S_{31} would have contributed extensively to the calculation. This simple numerical example depicts exactly what simulated annealing is designed for.

CONCLUSIONS

The fundamental elements of a CSN have been defined in this report. The connection between energy configurations and constraint satisfaction was explored. The Metropolis algorithm was examined in some detail. Finally, a stepwise numerical example demonstrated that simulated annealing can find minimum energy configurations.

The research proposed here seeks to explore different cognitive domains that may be more relevant for the advanced aircraft of the 1990s. The human performance to be measured will center on decision-making, problem solving, and information transfer skills. The human pilot and the assistance he receives from machines will together form a complex system whose performance will depend greatly on the pattern of interaction between the human and the machine. The goal should be to develop and identify those qualities in a pilot candidate that optimize this pattern of interaction so that the combined human/machine performance exceeds what either one could have achieved singly. In conclusion, the Navy needs factual data on how to select pilot candidates who can best integrate their decision making and problem solving skills with similar problem solving capabilities afforded by machine intelligence in the advanced crew stations of the future.

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