



NAVAL POSTGRADUATE SCHOOL

MONTEREY, CALIFORNIA

**HUMAN SYSTEMS INTEGRATION DOMAIN
TRADE-OFFS IN OPTIMIZED MANNING:
THE TASK EFFECTIVENESS SCHEDULING TOOL**

by

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September 2010

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Prepared for: 711th Human Performance Integration Directorate
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ABSTRACT

The Sleep, Activity, Fatigue, and Task Effectiveness (SAFTE) model is a biomathematical model that uses information about sleep history, duration of wakefulness, and circadian phase to forecast an individual's future task effectiveness. It has seen practical application in the Defense Department within the Fatigue Avoidance Scheduling Tool (FAST). At present, given a personnel duty schedule with work and sleep periods, it is possible to obtain future predicted task effectiveness using FAST. It is not possible, however, to directly address the inverse question: given a task effectiveness threshold, what is the optimal schedule in terms of the time of sleep-wake periods and the assignment of performance sensitive duties? Such questions can now be addressed by importing data generated from FAST simulations into the Task Effectiveness Scheduling Tool (TEST). TEST is a mixed integer program that assigns persons to wake-sleep cycles and variable duty periods to provide coverage of a system function using the minimum quantity of personnel, while simultaneously ensuring individuals exceed a specified task effectiveness criterion during duty periods. The program then ensures that the temporal scheduling of duty periods maximizes averaged predicted task effectiveness over a 24-hour period. Accordingly, TEST allows analysts to mathematically determine optimal staffing and shift scheduling solutions via a deterministic model.

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I. INTRODUCTION

Pretending to be superhuman is very dangerous. In a well-led military, the self-maintenance of the commander, the interests of his or her country, and the good of the troops are incommensurable only when the enemy succeeds in making them so. It is time to critically reexamine our love affair with stoic self-denial If an adversary can turn our commanders into sleepwalking zombies, from a moral point of view the adversary has done nothing fundamentally different than destroying supplies of food, water, or ammunition. Such could be the outcome, despite our best efforts to counter it. But we must stop doing it to ourselves and handing the enemy a dangerous and unearned advantage (Shay, 1998, p. 104).

A. BACKGROUND

The first mathematical models of sleep and circadian processes were developed more than 20 years ago in an effort to explain the timing of the human sleep-wake activity cycle. In the intervening years, a number of applied biomathematical models of fatigue and performance have been developed from the first generation of models of sleep-wake cycles. These applied biomathematical models typically use information about sleep history, duration of wakefulness, and circadian phase to predict performance capability and risk. They are currently used to assess the potential contribution of fatigue to performance degradation at specific points in time, to develop and evaluate work/rest schedules, to plan work and sleep in operational missions, and to determine the timing of fatigue countermeasures to anticipated performance decrements (Neri, 2004). The March 2004 edition of the journal, *Aviation, Space, and Environmental Medicine*, provides a comprehensive review and model-to-data comparisons of seven of the current biomathematical models of human fatigue and performance. Those interested in more information on the biomathematical modeling of fatigue and performance should reference this resource and the bibliographies contained within.

The U.S. Defense Department has long pursued applied research concerning fatigue in military operations and has developed several biomathematical fatigue models. One of these models, known as the Sleep, Activity, Fatigue, and Task Effectiveness (SAFTE) Model, has achieved relatively wide acceptance and seen practical application within the Fatigue Avoidance Scheduling Tool (FAST) (Hursh, Redmond, Johnson,

Thorne, Belenky, Balkin, et al., 2004). FAST is used by various military occupational communities in conjunction with rule-based heuristics (e.g., shift-work guidelines, hours-of-service rules, etc.) to develop plans for staffing system functions or missions. FAST is also beginning to be used by the system development community, again as an augmentation of other heuristics, to develop and refine manpower estimates in light of predictions of human performance. For instance, organizational planners may use rule-based heuristics to determine staffing needs, while ignoring potential constraints, and then iteratively refine the solution, using heuristics and FAST, to then attempt to meet constraints and satisfy objectives. The result is necessarily a trial-and-error approach that attempts to take manpower and performance into account, but does not systematically minimize manpower or maximize performance.

Such instances beg the question: do current, commercially available implementations of biomathematical models of fatigue, with FAST being an archetype, answer the questions being asked by organizational planners? In essence, the current instantiation of FAST requires the user to provide a schedule for which the software computes predicted task effectiveness over some time period of interest. Thus, given a schedule, one can get a forecast for future task effectiveness. But what about the inverse question: given a desired threshold or lower limit for task effectiveness, what is the *optimal* schedule in terms of the timing of sleep-wake periods and the assignment of performance-sensitive duties? And by extension, there is the corollary question, how many people are needed to achieve sustained performance above the desired threshold? The operational relevance of these questions should be self-evident given the current emphasis on minimal manning paradigms for many military weapon systems.

In current vernacular, FAST is a point solution because it is tailored to provide a forecast of task effectiveness for a particular schedule. As such, it cannot directly answer the aforementioned questions that are most germane to organizational planners—that is, it does not allow for a systematic exploration of a solution space to determine an optimal solution in terms of manning, schedule, or both. Consequently, the question taken up here is the feasibility of reconciling this problem within the self-imposed constraint of using the existing implementation of the SAFTE model in FAST.

B. PROBLEM STATEMENT

To illustrate an approach to solving this problem, consider the general dynamic system represented by the block diagram in Figure 1. The system is subject to both exogenous inputs, d , which enter the system as filtered disturbances, w , as well as control inputs, u . The system responds by a measurable system output, y , which results in some performance of the system, z . A system controller, K , is present to supervise the system and make inputs as necessary to ensure system performance conforms to organizational objectives. Many systems can be described using this simple notation, although the exact form of the transfer functions G_i , G_{sys} , and G_o may not always be known. For our purposes here, we will assume that the system operates continuously and the controller, K , is an individual human operator. Such a system description might represent an operator controlling an unmanned aircraft system or the officer of the deck standing watch on the bridge of ship. Thus, our problem is to determine the minimum number of individuals that are needed to staff the function, K , with the constraint that their predicted task effectiveness must be above some *a priori* threshold. Additionally, it would be desirable, once this minimum number of individuals has been established, to determine how to schedule their duty periods such that their overall average predicted task effectiveness is maximized.

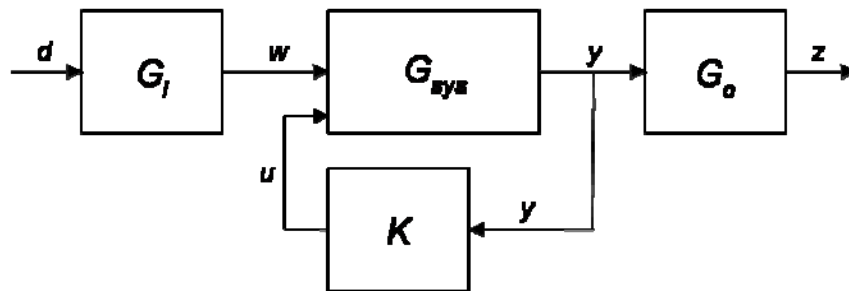


Figure 1. Block diagram of a generic dynamic system.

C. THE SLEEP, ACTIVITY, FATIGUE, AND TASK EFFECTIVENESS (SAFTE) MODEL

The SAFTE model is shown emblematically in Figure 2 using a system dynamics modeling stock and flow diagram. The conceptual architecture of the SAFTE model centers on a sleep reservoir, representing sleep-dependent processes that govern the

capacity to perform cognitive work. Using the language of system dynamics modeling, the stock of this reservoir is cognitive work capacity. Sleep is a replenishing flow into the reservoir, while wakefulness is a depleting flow out of the reservoir. Replenishment, in terms of sleep accumulation, is determined by information about the time-of-day of sleep, reservoir level (i.e., sleep debt), and sleep quality (i.e., sleep fragmentation). The system modeled in Figure 2 provides output in terms of performance effectiveness, which is simultaneously modulated by circadian effects and the level of the reservoir (Hursh et al., 2004).

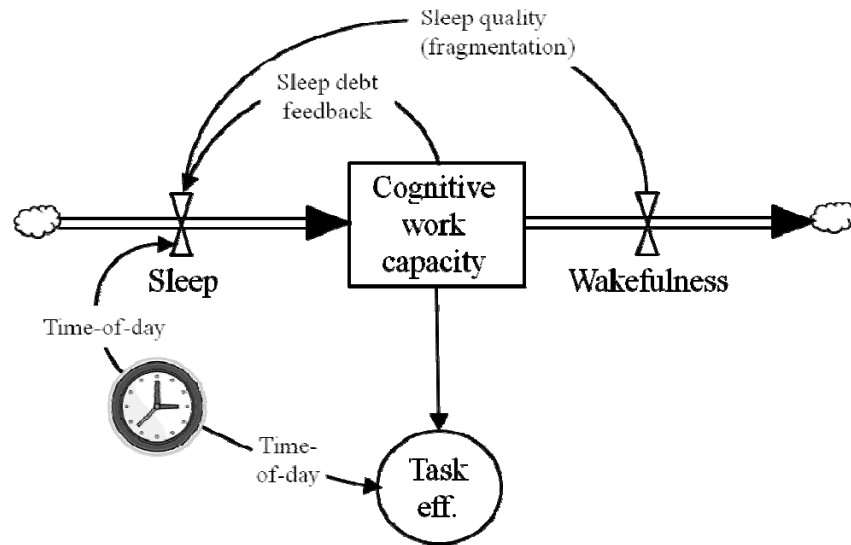


Figure 2. Stock and flow diagram of the SAFTE model.

The SAFTE model has been shown to predict changes in cognitive capacity, as measured by standard laboratory tests of cognitive performance, with reported coefficients of determination ranging from 89%-94%. It is presumed these cognitive tasks measure changes in the fundamental capacity to perform a variety of real-world tasks that rely on such cognitive skills as discrimination, reaction time, mental processing, reasoning, and language comprehension and production. Although specific military tasks may vary in their reliance on these skills, Hursh and colleagues (2004) assert that it is reasonable to assume that changes in military task performance will correlate with changes in the underlying cognitive capacity. Hence, there is an expected monotonic relationship between measured changes in cognitive capacity and military task performance.

Based on the structure of the SAFTE model, the reservoir or stock of cognitive work capability, shown emblematically in Figure 2, will remain within some finite range if an individual maintains a constant wake-sleep schedule—that is, the reservoir will exhibit a time-averaged equilibrium state. The stock and flow diagram also shows that sleep accumulation is dependent on information regarding “sleep quality,” which is modeled as the contiguity, or conversely, fragmentation of sleep. The software implementation of the SAFTE model (i.e., FAST), addresses sleep quality in terms of the sleep environment and the average number of interruptions to sleep expected in that environment. The FAST software provides the following ordinal scale for describing sleep environments:

- *Excellent:* 0 interruptions per hour
- *Good:* 1-2 interruptions per hour
- *Fair:* 3-5 interruptions per hour
- *Poor:* 6 or more interruptions per hour

These values are equated to 60, 50, 40, and 30 minutes of effective sleep per hour, respectively.

Given the implications of the SAFTE model structure, it is clear that two classes of variables must be considered: schedule and sleep environment. The schedule determines the timing and duration of sleep and wakefulness, and in conjunction with sleep quality, determines the equilibrium state of the reservoir. In principle, the equilibrium state of the reservoir correlates inversely to the degree to which an individual is fatigued, the latter being a direct concern of the survivability domain of HSI. Likewise, the sleep environment is a determinant of sleep quality, which modulates sleep accumulation, and in turn, the equilibrium state of the reservoir. Since the sleep environment is shaped by the physical environment of sleeping or berthing areas (e.g., adequate space, temperature and lighting control, noise attenuation, etc.), it is a direct consideration of the habitability domain of Human Systems Integration (HSI).

D. AN OPERATIONS RESEARCH PERSPECTIVE

The operations research community focuses on the formulation of mathematical models of complex engineering or management problems and how to analyze them to gain insight about possible solutions. The three fundamental concerns in forming operations research models are the decisions open to decision makers, the constraints limiting decision choices, and the objectives that serve as criteria for rating the relative preference of decision choices. Optimization models, which are also called mathematical programs, are a class of operations research models that represent problem choices as decision variables, which maximize or minimize objective functions of the decision variables subject to constraints on variable values expressing the limits on possible decision choices. Once a problem has been formulated as an optimization model, one can systematically search for optimal solutions, the latter being feasible solutions that achieve objective function values as good as those of any other feasible solution (Rardin, 1998).

Part of the art of constructing mathematical formulations of complex problems is to see past the unique circumstances of the individual problem and recognize general problem types, even if by analogy. The present problem clearly resembles a shift scheduling and staff planning model, where the work is already fixed and we need to plan the resources to accomplish it. The main element in any staff planning model is the covering constraint, which assures that the work periods chosen provide enough worker output to cover requirements over each time period (Rardin, 1998); that is,

$$\sum_{\text{shifts}} (\text{output/worker}) \cdot (\text{number on duty}) \geq \text{period requirement} .$$

In this case, we express the period requirement in terms of predicted task effectiveness, and we consider shifts in terms of organizationally permissible sleep-wake cycles. Next, without intending to sound dehumanizing, we contemplate a worker on a shift as being a metaphorical vessel containing a reservoir of cognitive work capacity, such as is depicted in Figure 2. For each worker, periods of wakefulness are associated with a discharging flow from the reservoir and periods of sleep are associated with a recharging flow into the reservoir. The output for a worker during a particular period,

again expressed in terms of task effectiveness, will be a combined function of the state of their reservoir and their intrinsic diurnal cycle.

If we limit the number of workers on duty during any particular period to unity, we are forced to select a worker from some shift whose predicted task effectiveness meets or exceeds the period requirement for each and every period. Since a decision to use a worker from a particular shift equates to gaining that person in the organization, the objective is simply one of minimizing the number of shifts used to cover all work periods. Solving this staff planning model will yield the manpower optimal solution. However, we may extend this problem one step further by repeating the analysis, but this time restraining ourselves to use no more than the optimal number of shifts and seeking the objective of maximizing the average task effectiveness over all periods. In essence, we are looking for the best arrangement of duty periods given the minimum number of workers. Solving this secondary problem will yield a constrained (in terms of manpower) optimal solution for average task effectiveness. In sum, this is the central logic underlying the optimization programming method described in the following section.

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II. MODEL FORMULATION

The Task Effectiveness Scheduling Tool (TEST) is a modest mixed integer program that assigns persons to wake-sleep cycles and variable duty periods in an attempt to provide coverage of some continuous system function using the minimum quantity of personnel, while simultaneously ensuring individuals exceed an *a priori* predicted task effectiveness criterion during duty periods. The program then ensures that the temporal scheduling of duty periods maximizes average predicted task effectiveness over a 24-hour period. This section presents the formulation of the model with data given in lowercase symbols and decision variables in uppercase symbols.

A. INDICES AND [CARDINALITY]

$q \in Q$ — set of ordinal ratings of sleep quality [~4].

$s \in S$ — set of wake-sleep schedules [~72].

$t \in T$ — set of time periods [~48].

B. DATA AND [UNITS]

req_eff — required human task effectiveness [%].

$saft_e_data_{s,t}^q$ — predicted task effectiveness for time period t when following schedule s with sleep quality q [%].

$work_rule$ — organizational limit on maximum hours of service [periods].

Data on predicted task effectiveness is provided in a matrix with 72 rows and 48 columns. Each row corresponds to a unique schedule, s , consisting of a 6-, 7-, or 8-hour continuous sleep period and a corresponding continuous wake period. Each column corresponds to a time period, $t = 0000, 0030, 0100, \dots, 2330$, where each t is a 30-minute interval and $t = 0000$ begins at midnight. Wake periods start on a subset of the collection of time periods, $t' \in T$, corresponding to the integer hours of the day, which is to say that $t' = 0000, 0100, 0200, \dots, 2300$. Thus, S is an exhaustive combinatorial collection of permitted continuous sleep and wake periods. Each schedule, s , in the collection of possible schedules, S , was simulated in FAST version 1.6 over a 30-day period, and the

predicted task effectiveness for each time period, t , on the 30th day of the simulation, is recorded in the matrix. Predicted task effectiveness is set to zero during time periods of sleep. Additionally, task effectiveness is set to zero for the 60 minutes prior to and after the sleep period to account for hygiene and other preparatory activities, which would necessarily make an individual unavailable for assignment.

FAST provides for the ability to set an ordinal rating of sleep quality (i.e., excellent, good, fair, or poor) during the sleep period, which impacts the predicted task effectiveness. It is possible to enlarge the matrix of predicted task effectiveness to consider a quadruplet of schedules, varying in terms of sleep quality, for each primary schedule, s , in the collection of possible schedules, S : $s = \langle s_{\text{excellent}}, s_{\text{good}}, s_{\text{fair}}, s_{\text{poor}} \rangle | s \in S$.

However, this approach adds little to the model, as any attempt to optimize task effectiveness will naturally lead to a choice of $s_{\text{excellent}}$ in the absence of some penalty function. Thus, the other elements in the quadruplet will not be selected, but the larger matrix will drive a correspondingly larger decision matrix, and in turn, unnecessarily increase computational burden—a reasonable concern when dealing with integer programs. From a more pragmatic perspective, sleep quality can be ascribed as a function of the environment in which sleep is attempted. Consequently, sleep quality may be fixed *a priori* based on the habitability considerations present within the problem context for which a schedule is being sought.

For the aforementioned reasons, the second approach is used in the subsequent model formulation. Accordingly, separate predicted task effectiveness matrices are developed for each ordinal rating of sleep quality, q . The choice of q is fixed at q' , where $q' \in Q$, and the corresponding predicted task effectiveness matrix, $\text{saft}_e_data_{s,t}^{q'}$, is incorporated in the model as data. The ensuing sections will suppress further reference to sleep quality for the purpose of economy of notation.

C. VARIABLES

$ASSIGN_{s,t}$ — binary decision variable to assign a person following schedule s to cover time period t .

$D_{s,t}$ — difference variable used to determine a change in the state (i.e., on or off duty) of a person following schedule s at time period t .

$MANPOWER_s$ — binary decision variable to utilize a person on schedule s .

D. CONSTRAINTS

$$(C1) \sum_s ASSIGN_{s,t} = 1 \quad \forall t.$$

$$(C2) \sum_t ASSIGN_{s,t} \leq work_rule \quad \forall s.$$

$$(C3) \sum_s safte_data_{s,t} ASSIGN_{s,t} \geq req_eff \quad \forall t.$$

$$(C4) D_{s,t} \geq ASSIGN_{s,t} - ASSIGN_{s,t-1} \quad \forall s, t > 1.$$

$$(C5) D_{s,t} \geq -ASSIGN_{s,t} + ASSIGN_{s,t-1} \quad \forall s, t > 1.$$

$$(C6) \sum_{t|t>1} D_{s,t} \leq 2 \quad \forall s.$$

$$(C7) MANPOWER_s \geq ASSIGN_{s,t} \quad \forall t, s.$$

$$(C8) ASSIGN_{s,t} \in \{0,1\} \quad \forall t, s.$$

$$(C9) MANPOWER_s \in \{0,1\} \quad \forall s.$$

$$(C10) 0 \leq D_{s,t} \leq 1 \quad \forall s, t > 1.$$

E. OBJECTIVE

$$\text{Minimize } Z = \sum_s MANPOWER_s.$$

Once the value of the manpower objective is minimized (that is, Z^* is determined), a new constraint is created

$$(C11) Z^* \geq \sum_s MANPOWER_s.$$

The program is then solved for the following objective:

$$\text{Maximize } \frac{\sum_s \sum_t safte_data_{s,t} ASSIGN_{s,t}}{48}.$$

Solving the first objective establishes the minimum number of persons required to provide coverage of some continuous system function while simultaneously ensuring individuals exceed an *a priori* predicted task effectiveness criterion during duty periods. Solving the second objective seeks to maximize the average predicted task effectiveness of this minimum number of individuals. Thus, the program first establishes the optimal quantity for manpower to satisfy performance requirements, and then it determines how to optimize performance given this now constrained quantity of manpower.

Constraint (C1) is a set partitioning constraint requiring that exactly one person from the collection of wake-sleep schedules, S , belongs to a solution for time period t . Constraint (C2) tallies the number of time periods an individual on schedule s is assigned to provide coverage of a function and enforces organizational hours of service rules. The special case where an organization has no hours of service rules can be simply addressed by setting *work_rule* to 48, which corresponds to the maximum number of time periods in the predicted task effectiveness data matrix. Constraint (C3) enforces the requirement that the predicted task effectiveness of an individual following schedule s assigned for duty during time period t meets or exceeds some prespecified criterion; alternatively, for each time period, t , one could use a filter to only consider the subset of schedules, s' , where $s' \in S$, for which predicted task effectiveness meets or exceeds the criterion.

Constraints (C4) and (C5) assess whether a change in assignment status occurs for a person following schedule s between time period $t-1$ and period t . Constraint (C6) enforces an upper limit on the number of changes in assignment status that can occur for a person following schedule s . By setting this limit at two, assigned duty periods are forced to be continuous. This avoids the undesirable result where individuals are assigned to multiple, disjoint time periods. Constraint (C7) acts as a manpower counter: it is set to unity for a person on schedule s if they are assigned for any time period, t .

Constraints (C8) and (C9) establish the binary decision variables. Constraint (C10) fixes the upper bounds on the nonnegative variable, $D_{s,t}$, at unity.

III. RESULTS AND DISCUSSION

A. CASE 1: HIGH TASK EFFECTIVENESS CRITERION

When inadequate attention is paid by system developers to human factors engineering considerations, a potential outcome is “human factors high drivers” (Directorate of Human Performance Integration, n.d., p. 43). Such drivers include tasks that require very high levels of sustained human performance, whether that is in terms of vigilance and monitoring, cognitive workload, or physical exertion. This case examines the trade-off between the human factors engineering and manpower domains of HSI that occurs when a requirement is generated that necessitates a high degree of sustained task effectiveness.

Figure 3 illustrates the TEST results when the required task effectiveness criterion is set to 95% and sleep quality is assumed to be good—that is, reasonable attention is paid to habitability domain considerations. Each row in the figure corresponds to a single person following a fixed wake-sleep cycle.

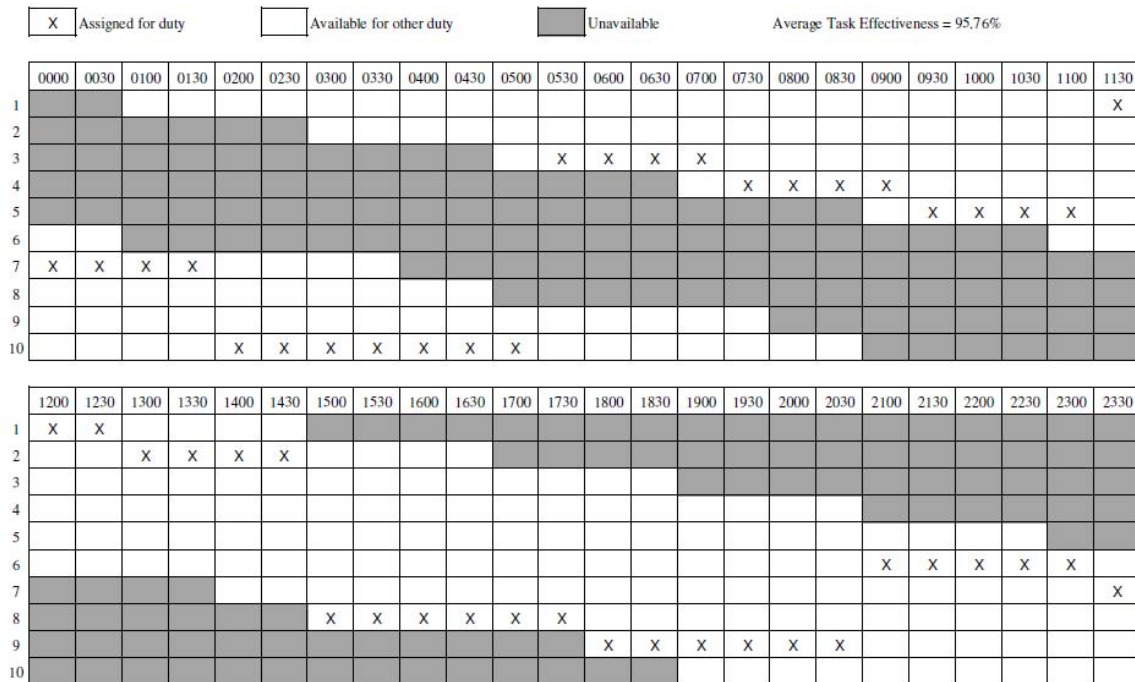


Figure 3. Task Effectiveness Scheduling Tool results when the predicted task effectiveness criterion is set to 95% and sleep quality is rated as good.

The shaded boxes in Figure 3 are indicative of time periods where a person is unavailable: the first two periods (i.e., 1 hour) for hygiene and preparatory activities, the next 16 time periods (i.e., 8 hours) for sleep, and the last two periods for hygiene and preparatory activities. The nonshaded boxes marked with an “X” are indicative of those time periods when an individual’s predicted task effectiveness meets or exceeds the criterion and they are scheduled to cover the high driver task. The other empty, nonshaded boxes are time periods where a person is available to work, but their predicted task effectiveness is below the criterion. Thus, this time can be allocated to working on less demanding tasks and other personal activities.

What is readily apparent from Figure 3 is that human factors high-drivers can lead to excessive manpower requirements—in this case, 10 people—to provide sufficient human cognitive resources for the task at hand. Since physiologically-based manpower modeling is seldom used in current practice, it is quite likely that individuals charged with developing the system manpower estimate would allocate far fewer than 10 people to cover such a high-driver task. What then results is an unrecognized or implicit trade-off, whereby decreased or more variable performance is accepted, increased systems safety risks are entertained, or both.

Figure 4 illustrates the dramatic impact on manpower that can be achieved by mitigating human factors high-drivers during systems development. In this case, the predicted task effectiveness criterion is reduced to 90% and sleep quality is unchanged. While the change in criterion appears relatively modest, the corresponding change in required manpower is dramatic. What previously necessitated 10 people, working no greater than 6.5-hour duty periods, is now accomplished using only two people, working 12-hour shifts.

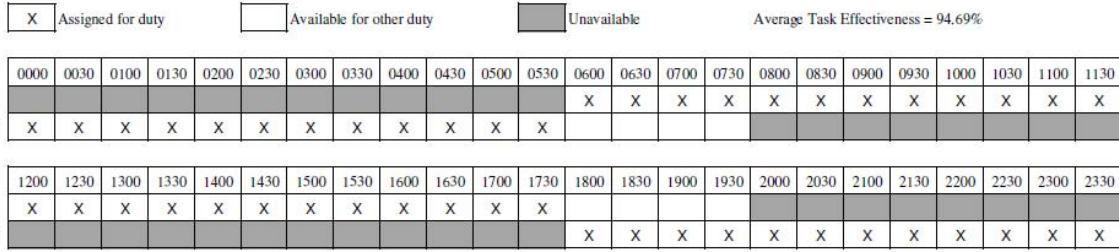


Figure 4. Task Effectiveness Scheduling Tool results when the predicted task effectiveness criterion is set to 90% and sleep quality is rated as good.

B. CASE 2: ORGANIZATIONAL HOURS-OF-WORK RULES

Sometimes it is the case that individuals performing major system functions belong to professions that are governed by regulatory policies that dictate maximum work periods and minimum rest periods (Miller, Matsangas, & Shattuck, 2007). Often these policies are influenced by nonphysiological considerations such as personnel availability, mission requirements, and organizational standard operating procedures. Figure 5 illustrates the impact of enforcing an hours-of-work rule limiting duty periods to no greater than 10 hours. With the exception of the constraint on hours-of-work, there are no differences in the settings of the model parameters used in the analysis displayed in Figure 4 and that shown in Figure 5. While the task could be done effectively by two people (Figure 4), organizational constraints require that a third person be added to the manpower estimate (Figure 5). There is no operationally significant improvement in average predicted task effectiveness (94.69% versus 94.64%) between the two manpower models, but one would expect there to be significant differences in terms of system life-cycle costs. Observations such as this should, at minimum, prompt questions regarding the rationale for the hours-of-work rule.

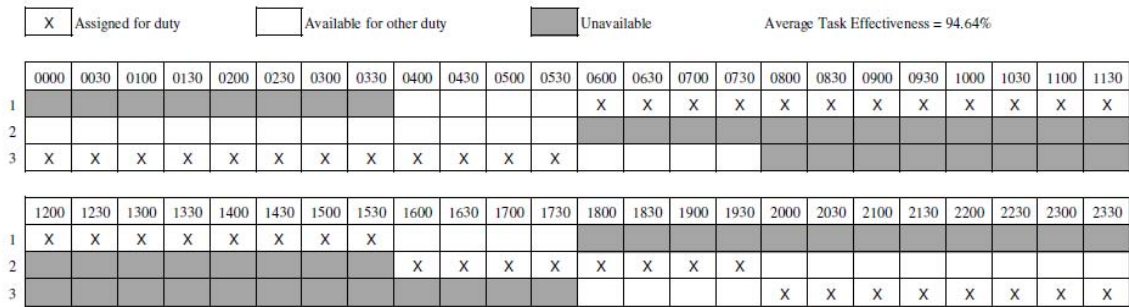


Figure 5. Task Effectiveness Scheduling Tool results when the predicted task effectiveness criterion is set to 90%, sleep quality is rated as good, and a 10 hours-of-work rule is enforced.

It is also worth noting in Figure 5 that the maximum average task effectiveness is obtained using nonuniform duty periods. The traditional, heuristically-based approach to scheduling shift work would lead managers to establish three 8-hour shifts based on the principle of equity (Miller, 2006). In contrast, a physiologically-based approach leads to a 10/4/10-hour, 3-shift system. Thus, this case illustrates nicely the disadvantage of using simple scheduling heuristics.

C. CASE 3: SLEEP QUALITY

It is generally acknowledged by HSI practitioners and system users that habitability domain considerations are important in sustaining human performance. It is also well recognized by these same individuals that senior decision makers tend to be reluctant to accept or vigorously advocate for system requirements that can be said to be focused on “comfort.” Even when such requirements are accepted, they are often the first to be sacrificed when issues of system development cost, schedule, or performance surface.

Figure 6 illustrates the case where habitability domain considerations are not given due diligence with regard to their impact on human performance. In this scenario, sleep quality is set at poor and the predicted task effectiveness criterion is relaxed to 77.5%, which corresponds to the threshold for the “criterion line” on the current FAST graphical display. The FAST criterion line equates to the performance of a person following loss of an entire night’s sleep. It provides yet another planning heuristic for determining whether a particular schedule is acceptable. However, the validity of this

heuristic is certainly questionable, particularly if, for example, a system was designed under the assumption that the operator would perform with a task effectiveness of at least 90%. Nevertheless, even with the reduction in the task effectiveness criterion, it takes eight people—some only suitable for 2 hours per day—to provide effectual coverage. Contrast this with the observation from the first case that two people can provide more than effectual coverage when sleep quality is set at good. The difference of six individuals between the two scenarios, which can be entirely attributed to the change in the model setting for sleep quality, is quite significant when considered in terms of system life-cycle costs. To summarize, comfort pays!

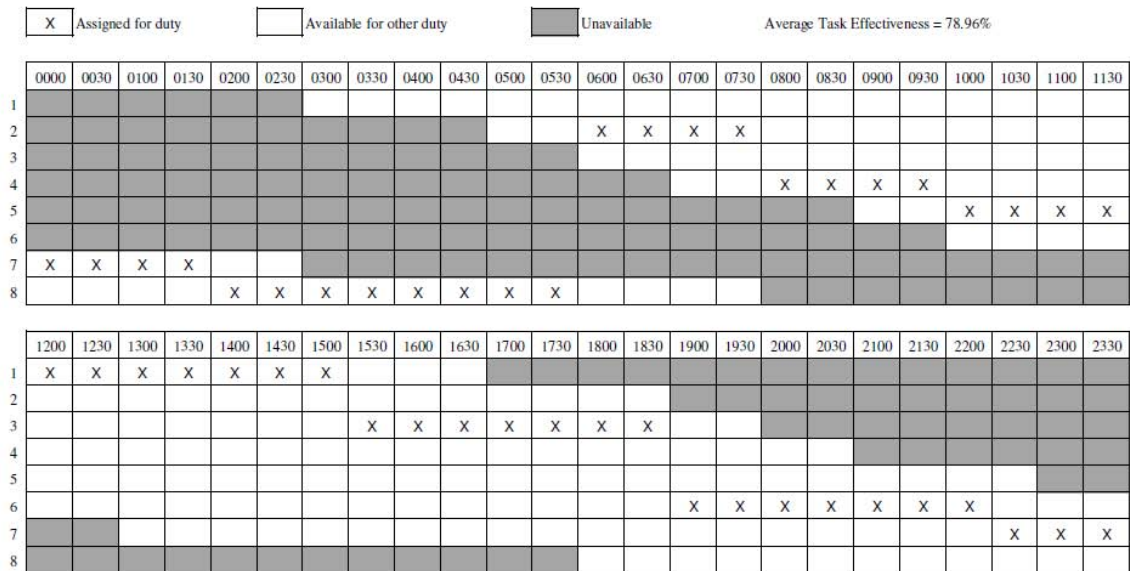


Figure 6. Task Effectiveness Scheduling Tool results when the predicted task effectiveness criterion is relaxed to the FAST criterion line of 77.5% and sleep quality is rated as poor.

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IV. CONCLUSION

In this report, we developed a novel approach to staffing and shift schedule planning that offers two key advantages over conventional approaches. First, it allows organizational planners to import data generated from FAST simulations—in essence, the results of individual simulation experiments—into an analytic model, whereby answers to the question of optimality can be found by mathematical techniques. Thus, reaching the optimal staffing and shift scheduling solution becomes a less elusive and more deterministic process. Second, it recognizes the inflexible boundary of human capacity and makes explicit the imperative to acknowledge human limitations in the design of staffing and shift schedule solutions. This process should help foster a more holistic approach to designing solutions, thereby taking advantage of the potential trade space that exists between the manpower, survivability, habitability, and human factors engineering domains of HSI. These domains, in turn, involve consideration of issues related to personnel quantity, fatigue (and inversely, the availability of cognitive resources) and its impact on personnel quality, sleep quality and the opportunity for recovery of cognitive resources, and task demands for cognitive resources, respectively.

By and large, the approach demonstrated here involves nothing uniquely new, either in terms of the biomathematical modeling of fatigue or optimization programming. Rather, it is a new way of using data from biomathematical models of fatigue to systematically find optimal staffing and shift schedule solutions—a way that should be appealing to system developers and force planners. While the model formulation used in this report specifically optimizes in terms of manpower, many alternative formulations are possible with minimal modification of the kernel of the model. Similarly, while the model was formulated to address staffing for a single system function (e.g., function K in Figure 1) requiring a single human controller, it is a simple matter to scale up the model for more complex systems. For instance, incorporating more than one system function would primarily involve the addition of an index set, f , to the model formulation where $f = \{K_1, K_2, \dots, K_n\}$. Likewise, the number of individuals required to simultaneously

perform the controller function, K , may be easily changed by modifying the right-hand side of the assignment constraint (C1).

To summarize, we expect that coupling biomathematical fatigue models and optimization programming will prove useful in developing physiologically balanced staffing and shift scheduling plans. Further work on this topic should examine the tractability of more complex shift schedule options such as rotating-shift solutions. Additionally, given the potential computational burden of even relatively simple-appearing discrete optimization problems, consideration should be given to the applicability of data filtering, linear programming (LP) relaxations, or both on the analysis of TEST-derived discrete models. Finally, it would be useful to consider how the human systems integration domain trade-offs that were demonstrated to be inherent in this approach may be incorporated into larger systems analyses.

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