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Dynamic resource allocation using adaptive networks

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Abstract. A hybrid approach is described which combines the strengths of adaptive networks and behavioral economics to optimize the allocation of resources. Several applications have already been developed using this approach and the BANKET software which implements it—these are briefly described.

1. Introduction to resource allocation problems

Adaptive networks, also known as Artificial Neural Systems (ANS), have desirable computational features which suggest their widespread use in coming years. As the technical capabilities of modern network architectures continue to improve, there is a rush to apply these systems to more and more interesting problems which defy conventional solution. Adaptive network solutions to problems of pattern recognition [7], signal processing [33], and associative memory [18] have been well documented. This paper will discuss a broad class of problems where the objective is to find an optimal solution to the allocation of one or more finite resources within a domain that is unstable—a class of problems that Wasserman [31] has called *nonlinear optimization* problems.

In terms used within the artificial intelligence research community, these more complex resource allocation problems are a type of "planning in uncertainty". Simpler resource allocation problems, like the "traveling salesman problem" [8, 17], lack some of the essential elements of planning, such as the definition of response elements and their sequential dependencies. Langlotz and Shortliffe [19], Hutchison [10] and Skinner [26] have contrasted two general approaches to planning problems—symbolic logic (which can be first order or nonmonotonic) and decision theoretic. Research into nonmonotonic logic ("default reasoning" which may require inferences and conclusions to be withdrawn as default values are replaced) seems most applicable when the goal is constructed of a new plan which complies with a set of constraints. Rule-based expert systems are a favored approach by the proponents of symbolic logic in problem solving. While logical inference can search a solution space for a plan which meets a set of logical constraints, these methods are poor at exerting preference for one course of action over another. Decision theory, on the other hand, offers a method of choosing between courses of action on the basis of the probability and value of certain outcomes. In fact, Langlotz, Shortliffe, and Fagan [20] have shown that decision theory concepts are implicit (but may be approximate) in rule-based systems. For the above reasons, we prefer a decision theory approach to planning problems in general, and resource optimization problems in particular.

Optimal resource allocation involves the management of resources (e.g., manpower, time, equipment) in a process such that some definable outcome is maximized (i.e., the value of the outcome is compared to the cost of the resources). The process may be anything that consumes resources in order to produce a desirable product. Manufacturing, training, marketing, and project management are all examples of this kind of process. It is difficult enough to produce an optimal solution to a complex resource allocation problem when the problem environment is stable. When the resource pool or the resource-consuming process is altered, the previously optimal but static solution must often be discarded, and a new optimal solution derived. This is typically expensive in terms of time, effort, and computing resources. An efficient, yet adaptive solution is therefore desirable in these kinds of situations.

BehavHeuristics has successfully developed solutions to several different resource allocation problems, using a hybrid approach that makes use of adaptive network systems within a decision theory context. These solutions have three elements in common: a causal model of the process based on a trained adaptive network, a method for determining the value or utility of a solution, and a method for optimally managing the allocation of resources to the process.

Each of these solutions were developed using BehavHeuristics' proprietary adaptive network software known as BANKET™ (BehavHeuristic Adaptive Network Knowledge Engineering Toolkit). Below, we will discuss the general features of BANKET and how it relates to behavioral economics and decision theory. We then will describe how an adaptive approach has been applied to the problem of selective discounting of airline seat inventory (i.e., revenue or "yield" management) and to a complex scheduling problem with multiple constraints.

2. BANKET

BANKET is the result of several years of independent research and development [10, 12]. It is a shell structure for developing and supporting adaptive networks, and is currently hosted within the Smalltalk-80™ Objectworks™ environment from ParcPlace systems. Smalltalk is an object-oriented programming and delivery system, and therefore supports a style of system development known as exploratory programming or rapid prototyping [25]. Smalltalk (and BANKET) will run on a large number of computers, including the IBM PC, AT and 386 systems (and their clones), the Macintosh II, and workstations from Sun, Tektronix, DEC and Apollo. It can be integrated with databases and local area networks. This software environment offers many practical advantages which are beyond the scope of the present paper.

BANKET is the embodiment of a theoretical viewpoint on adaptive behavior which combines the fields of behavioral science and behavioral systems analysis with the viewpoints of several other scientific disciplines which study adaptive systems [11]. A behavioral view of adaptive networks has been proposed by Hutchison [12] and Hutchison and Stephens [13], and similar viewpoints have recently been reviewed by Donahoe and Palmer [5] and Kehoe [16]. Many issues which are now of interest to adaptive software developers have been studied in the behavioral literature: learning, control over system behavior by complex inputs, models of choice between behavioral alternatives, and the integration of symbolic and distributed knowledge within intelligent systems [14].

BANKET is an adaptive network software environment that has been and is being used by BehavHeuristics in the development of a number of practical applications. It includes a number of features that are consistent with the behavioral approach to intelligent systems [28]. According to this approach, there are three major components to the contingencies of reinforcement and punishment which govern operant behavior: responses, consequent stimuli, and antecedent stimuli. Responses are the actions of the system that are designed to effectively solve the problem. Consequent stimuli are sources of feedback from the environment that indicate how satisfactorily the problem has been solved: this often involves the use of a utility function (see below). Antecedent stimuli are the environmental events and signals that serve as inputs to a network model. BANKET provides methods for representing environmental antecedent stimuli, including preprocessing and automatic/adaptive scaling to capture nonlinear stimulus effects. It has the ability to maintain a "sparse matrix" of connections to hidden units, and to automatically insert or remove these units as needed during training to optimally fit the domain. It provides, where appropriate, various learning acceleration processes including noise injection such as simulated annealing and forced random responding. It also contains methods for representing interresponse dependencies and control by temporal processes, essential for scheduling and other time-dynamic resource allocation solutions.

2.1. *Behavioral economics and BANKET*

Much of the power of BANKET in producing real-world applications comes from the integration of the adaptive network approach with another important methodology—an implementation of behavioral economics [9, 22, 27]. Networks need feedback in order to learn, but in most real-world problems the outcome of interest is not unidimensional. For example, in a training program the objectives are to maximize learning, minimize cost, minimize idle time, maximize student satisfaction, etc. Since these cannot generally all be optimized simultaneously, a function must be developed which combines them [24]. BANKET contains a set of procedures for developing such functions, which correspond to the "primarily utility functions" of dynamic programming. This function can be used in network learning through "temporal differences" methods described by Barto, Sutton, and Anderson [1], implementing an approximation to dynamic programming [32]. Since conventional dynamic programming is computationally intractable for most complex problems, the availability of a primary utility function provides an exciting building block for resource allocation.

The method of temporal differences is implemented in BANKET to provide feedback for learning during the course of an extended process, rather than waiting until process completion for learning to occur. The temporal differences method was identified by Sutton [29] who acknowledged its basis in Rescorla and Wagner's [23] behavioral theory of conditioning. In fact, the concept of temporal differences is related to an entire body of research on higher-order conditioning (cf. [6]): the primary utility function corresponds to primary reinforcement, while the secondary utility function corresponds to secondary, or "conditioned" reinforcement.

In some applications, algorithms can be mathematically derived to serve as utility functions; this is a major function of knowledge engineering in these cases. In other application areas where the utility function cannot be described directly, BANKET generates scenarios for a human expert to judge on the basis of "situational value" [2]. The database of judgments thus elicited can be used to train a separate network to match the human judgments of overall utility. Utility functions can be based on the best judgments of a single expert, or can be an aggregate of the judgments of multiple experts. BANKET can also discount future values and derive net present values of outcomes, and can integrate probabilistic events.

All of these features make BANKET amenable to optimal resource allocation by decision theory. Since it can effectively forecast event probabilities (if it can be trained with appropriate data), and since it can use a utility function that has either been provided algorithmically or derived through human judgments, it is ideally suited to compute expected values of outcomes. In resource allocation problems, different outcome actions compete with each other; the action with the highest expected value will be chosen.

3. Airline revenue management

The BehavHeuristics product family called the

Airline Marketing Tactician^{TM} (AMT) was initially described by Hutchison and Stephens [15]. Since then, the product has been enhanced considerably and has been providing excellent results in its installation at Nationair Canada. It is currently being evaluated by several major US and international carriers.

Revenue management represents a significant opportunity to increase profitability for airlines, hotels, rental car agencies, broadcasters, utilities, and manufacturers, among others [21]. What these industries have in common is that they market a perishable commodity which can be flexibly priced to reach different market segments. In the case of airlines, the commodity is the seat on a flight departure. The problem is one of servicing all available high-yield traffic (late-booking business travelers) while avoiding empty seats (by early sales of just the right amount of discount seats to discretionary leisure travelers). It is also valuable to overbook by just the right amount to compensate for no-shows and cancellations. To manage the process effectively, it is first necessary to forecast a number of parameters of consumer behavior, including demand for each fare class product and the likely no-show rates, many months in advance. This is, of course, not an easy task, since each departure exists in an almost unique marketing environment. The data and time of departure, the origin-destination market, the competition, and a host of other factors all affect the demand profile across fare classes.

An expert revenue analyst (one who has worked long enough with a particular flight in a variety of marketing scenarios) is able to make good estimates of demand if given plenty of information and time. However, since the policy of many carriers is to look far in advance at every departure, the workload of the typical analyst demands some automated assistance. The complex pattern of interacting factors, however, makes it difficult for the expert to articulate the factors that influence a subjective forecast of demand. This, combined with the large number of potential interactions and nonlinear contributions of the decision factors, makes the problem an unnatural fit to the production rule approach of a typical expert system solution. Even if the experienced analyst could identify all the determinants of her judgment, the rule base needed to represent this knowledge would be large and unwieldy. The same difficulties also pose severe problems to standard statistical and operations research methodologies.

The heart of AMT's forecasting module is an adaptive network. It is trained using historical data from the airline's reservation system, supplemented with input from the analyst regarding competitive position and special events. BANKET's self-configuring abilities construct a network structure which maintains only those "hidden layer" nodes that represent significant interactions. Since the network is trained with all readily available data which may play a part in determining demand, it represents a causal model of consumer behavior and the booking process. Each airline's competitive environment is unique, so an individualized forecasting network is developed, using available historical data, for each installation of the product. The utility function for AMT can be adjusted to include subjective input from key decision makers in the organization. In this way, it captures and retains corporate values and policies.

An adaptive system which self-configures requires very few *a priori* assumptions. And, since it can be incrementally retrained with most recent data, it is a dynamic model which can track evolving trends in the marketplace as they occur. Because the BANKET system incorporates the temporal differences method, updating the model can occur from one review horizon to the next, instead of waiting until the actual outcome of the flight departure is provided by the postflight audit. This forecasting method has proven to be extremely accurate—recent unpublished data trials have shown remarkable increases in forecasting accuracy over traditional methods.

The first generation of this product controlled the entire allocation process by an adaptive network, and it is certainly possible to train a network to make a fare class allocation decision given a certain business scenario. The traditional method of choice for solving optimization problems is often linear programming, but when there are many variables which may not be linear and which interact with each other, linear programming methods become computationally intensive and impractical. For these reasons, the adaptive network solution is preferable to linear programming. However, BehavHeuristics has since found a hybrid system more closely approaches optimality in an efficient way, and enables users to have the intermediate results (the demand forecasts). An algorithm based on marginal economics known as Expected Marginal Seat Revenue (EMSR) conducts a seat-by-seat bidding process to give each seat to the fare class with the greatest expected value (the product of fare and probability of booking the seat in the particular class). It is interesting to note that the network, in the first generation of AMT, automatically implemented EMSR. BehavHeuristics then derived and split the processes—independently arriving at the EMSR algorithm before it was described in detail by Belobaba [4].

4. Scheduling

BehavHeuristics views scheduling as a variation on the concepts represented in AMT, which could be said to "schedule" seats in fare classes. Yet, true scheduling is difficult for several reasons. Schedules must usually satisfy many constraints at once. There will typically be a large number of alternative legal schedules possible. The final quality of a schedule can usually not be evaluated until the entire schedule—which may be very long—has been constructed. If multiple events can occur in parallel and may compete for resources, the desirability of scheduling each event will depend on which other events are scheduled at the same time. Events may occur during the life of the schedule which will disrupt the original plan.

BehavHeuristics conceptualizes scheduling problems within a project management framework in which there is a set of activities. Each activity has a given duration; some activities have prerequisites; each activity requires resources; each resource is available according to a given calendar; each resource has certain fixed and variable costs. Numerous other constraints are often in effect. The "resource leveling" capabilities that many project management packages now offer merely enforce constraint checking, often leading to suboptimal resource allocation in schedules.

Using BANKET, BehavHeuristics developed a prototype scheduler for Link Flight Simulation, a division of CAE-Link Corporation, which demonstrates the feasibility of applying adaptive network software to resource allocation problems of this type. Called ANATS (Adaptive Network Aircrew Training Scheduler), the prototype demonstrated that the characteristics of adaptive networking techniques fit these applications extremely well and are able to produce correct and near-optimal schedules [3].

ANATS focused on scheduling aircrew training for pilots, copilots, flight engineers and loadmasters. In one example, several months were scheduled for up to 200 students at a time, with up to 100 training activities each, requiring numerous resources to be applied in various combinations, and with training plans having varying start dates and degrees of complexity.

Instructional systems present a complex scheduling problem, and thus provided a good test of the adaptive network approach. Resources, such as classrooms, instructors, and computer-based facilities, need to be allocated efficiently to avoid unnecessary costs. The same resource pool may be needed to teach different student cohorts (a cohort is a group of students with the same training requirements, e.g., pilots), each of whom are completing separate academic objectives. Course design may require students to participate within their own cohort, as a member of a mixed group of cohorts, or according to a self-paced format. Many additional constraints must be satisfied: length of the training day depending on type of activity, when "breaks" can or must be scheduled, how much time should be devoted to different activity types, how many students can participate in an activity at once, etc.

ANATS operates on data files that define the training scenario to be scheduled. This includes the characteristics of each cohort, the activities each cohort will complete and the sequential dependencies among these activities, and the pool of available resources to be used for completing these activities. A schedule is created by considering each hour in sequence, beginning with a given start date and time, and assigning activities to all students who are available for training at that hour. Activities are assigned according to the availability of needed resources and the relative value of possible activities for each cohort (defining these values is the first task of the network). When different cohorts compete for the same resources, assignment is made to cohorts such that the overall schedule will be optimized (this optimization is the second task of the network). The schedule is complete when all students have been assigned resources for their required activities. As in the airline seat allocation example, networks were provided the ability to generate optimal schedules by first defining a primary utility function, then by integrating temporal differences methods which allowed them to learn how to optimize over time.

A major challenge to optimal scheduling is that disruptions are inevitable; for example, a resource may fail at any time. Specific failures cannot be predicted, but general failure characteristics of resources are known. ANATS takes into consideration each resource's "failure model" in order to minimize these kind of disruptions. The adaptive network is trained in a simulated scheduling environment where resources become unavailable according to their respective models, so the resulting schedule is optimal not for a fictitious ideal world, but for the real world. Thus, ANATS schedules in such a way that failures are least likely to produce a state in which no other activity can be performed.

After a schedule has been created it can be examined according to resources or students, either for single days or for a week at a time. Changes to the schedule can be effected by swapping resources, by adding special events (e.g., unscheduled maintenance), and by rescheduling from some point in the schedule to its conclusion.

One of the key uses of the system lies in its resource estimation capabilities. Schedules that approximate optimal resource utilization can be generated by comparing different-sized resource pools against different training requirements (e.g., student load and/or flexibility in training plans). By studying various what-if scenarios, a schedule can be produced that accomplishes all training objectives with a minimal number of resources.

There are many other scheduling challenges within the airline industry, such as flight, crew, maintenance, gate and slot scheduling. Each has unique difficulties that could benefit from the solutions prototyped in ANATS. BehavHeuristics has already designed some of the systems to address these problems. Beyond the airlines, virtually every industry must ultimately deal with the efficient scheduling of its personnel and other resources to accomplish its defined tasks.

5. Conclusions

We have described two applications that demonstrate the value of an approach that combines the strengths of adaptive network software with methods derived from behavioral economics, decision theory, and behavior analysis. This hybrid approach is very powerful for solving resource allocation problems in changing environments, because it adds the well-accepted concept of expected value as a basis for making decisions, and it integrates methods for making use of changes in value in time-dynamic processes. Adaptive network theory provides a method for solving problems that have been conceptualized as choices between situational values through time, without having to make static assumptions that might be erroneous. We have found that the world is rich in problems whose structure matches this solution paradigm, and we look forward to applying our adaptive network techniques to many of them.

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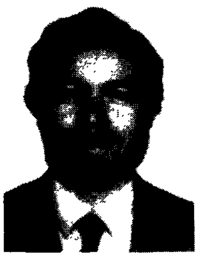

Bill Hutchison's, Ph.D., background combines adaptive systems theory, behavioral decision theory, and computer software systems analysis, both as a university professor and in private industry. Beginning in 1983, he began formal development of an approach to intelligent computer systems that resolves many of the difficulties faced by more traditional symbolic artificial intelligence. This technology, developed in parallel with other researchers around the world, is now known as adaptive or neural networking and is the focus of a professional society with almost 2000 members as well as the basis for Japan's Sixth-Generation Project. Dr. Hutchison is the architect of BehavHeuristics' adaptive network system model which is used in the Airline Marketing Tactician. He has spent several years studying the resource allocation problem in general and airline yield management in particular, since it is an application that is ideally matched to adaptive network techniques. His background understanding of airline revenue management extends back several years to consulting associations with two US national airlines, and has continued in discussions with knowledgeable airline management personnel concerning his technical approach to forecasting and revenue optimization. Dr. Hutchison is President of BehavHeuristics, Inc.

Ken Stephens, Ph.D., has specialized in the field of human-computer interactions, and the design of advanced user interfaces to increase the productivity of management tools and decision aids. The background that led to this interest includes study in the theories of experimental psychology and learning theory, and many years experience in various facets of computer science. As a technical director prior to cofounding BehavHeuristics, he supervised development of many software projects from database and communications applications to artificial intelligence programs. In addition, he served as system manager for large time-shared computer systems. His main interest, however, have been on the side of the user of the software, and in formulating a theoretical model of behavioral interactions between software environments and their users. Dr. Stephens was responsible for the design of the user interface of the Airline Marketing Tactician, which has drawn positive reviews from knowledgeable persons in the airline industry, the press, and other developers in the adaptive networking field. In addition to leading BehavHeuristics' efforts to analyze the information requirements of system users and designing easy-to-use management software tools, he is the Chairman of BehavHeuristics.

Sharon S. Hormby, MBA, has dual strengths in technology and marketing management. She has a technical background in computer science including design and implementation of complex systems and management of diverse groups, hardware, and projects. This foundation is enhanced by an MBA from the Wharton School, followed by experience and advanced training in product management at General Electric Company, USA. Her key area of interest is the marketing of high technology products and services to a global marketplace. With academic and practical expertise in the international arena, Ms. Hormby is an ideal addition to the airline marketing team.

Thomas M. Bell, Ph.D., has diverse specialties in behavioral science and instructional systems design with respect to knowledge engineering for adaptive networks and human factors design. He provided design support for MATIE, an intelligent tutoring system for diagnostic problem solving, and directed the design and construction of ANATS, BehavHeuristics' adaptive network scheduling software for military aircrew training. Dr. Bell continues to provide support in instructional design and training systems, content analysis, and quality assurance. He currently directs customer support and user training for BehavHeuristics' AMT family of revenue management products.