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A BINARY CONFLICT ASCENDING PRICE (BICAP) MECHANISM FOR THE DECENTRALIZED ALLOCATION OF THE RIGHT TO USE RAILROAD TRACKS

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Abstract

The questions posed for study are motivated by controversies over how Sweden might change from a centralized system of railroad management to a decentralized system. The central rail administration, Banverk, will retain ownership and maintenance responsibility of the tracks, but will sell access to the tracks to private firms. The questions are about the mechanism that might accomplish this task. Parties to the controversy have claimed that the technical aspects of networks will, as a matter of principle, preclude the operation of any decentralized method. This paper explores the properties of a mechanism developed as a challenge to that claim. The mechanism is examined in the context of a testbed experimental environment that contains many potential problem causing elements. In the tests performed the mechanism operated to efficiently allocate access to the network and it did so for behavioral reasons that are understandable in terms of theory. The paper closes with suggestions for further study of environments that might present additional challenges to a mechanism.

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1. INTRODUCTION

The Swedish parliament[1] has ordered its central rail administration, Banverket, to make the transition from a centrally allocated system to a market based system for the allocation of its railroads by 1995. In this partial privatization, Banverket will retain ownership and maintenance responsibility for the tracks, and will sell access to the tracks to private firms. The questions posed for initial study here are motivated by the resulting controversy. If the government is to own the tracks, can competition be used to facilitate coordination and use among the many users of the track? Or, is it impossible as a matter of principle for a decentralized competitive process to allocate track time as efficiently as possible, that is, to those who value it most? If such allocations can be achieved through a competitive process, what might be the form of the process?

Proponents of decentralization claim that substantial improvements in efficiency are possible. They point to specific features of the current allocation process that suggest inefficiency in operation and they claim that such problems would be avoided by a properly designed and decentralized market system. Opponents claim that existence of a decentralized mechanism yielding efficient allocation of a rail network has never been demonstrated. Furthermore, as is made clear by the following quote from a key

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[1] In the budgetary bill of 1992 (prop.1991/92:100,suppl.7) the plans for reform were stated. See Nilsson (1991,1993).

consulting report[2], the critics of railway reform claim that decentralized decisions are not possible as a matter of principle:

"These train paths cannot be treated as independent units, since they are not interchangeable, and depend on the specification of all other paths in the integrated timetable. There is therefore no common unit of capacity on a mixed-use railway which can be allocated to owners, priced and traded among a number of buyers and sellers." (p.291)

"However, a simple free auction cannot be used for railway capacity since there are no independent units of capacity to bid for. The viability of every bid to operate a train service depends on the specification of every other train service which has been bid for." (p.293)

The strong positions for and against a market based system are the focus of the research. The primary goal of this research is not to solve the Swedish problem with a single study. Instead, the purpose is to explore questions posed by arguments advanced in the debate. The conclusion of this paper is a demonstration, via experimental methods, that decentralized mechanisms do exist that solve some of the types of technical and economic problems inherent in the railway allocation problem. The demonstration is, firstly, that the mechanism performs as desired under the circumstances tested and, secondly, that it passes a test of design consistency in the sense that it works according to behavioral principles that are consistent with the design.

If the existence of an efficient, decentralized, allocation mechanism can be demonstrated operating in the laboratory for environments with technical economic complications of the rail allocation environment, then the argument that decentralization is impossible due to economic or technical principles has been refuted. In this sense, a demonstration provides a proof of principle or a proof of concept (Ledyard, 1993, Plott, 1994). Proof of principle does not mean that the mechanism will work to solve the Swedish problem, which involves additional complexities such as scale of operation, uncertainties, and politics. However, the demonstration sets the stage for future experiments in which additional problems can be examined and addressed, and the mechanism can be compared with other proposed mechanisms for private allocation of the rail network. Furthermore, design consistency tests create a presumption that the principles of behavior on which the process is built, are reliable and that the properties observed in the testbed can be presumed to be robust against simple parameter changes. Briefly put, the demonstration means that decentralized options for solving the Swedish problem cannot be dismissed immediately as being impossible or impractical, without further study.

Section 2 provides background to the problem of efficient rail scheduling. Notation and concepts used throughout the paper are introduced there. Section 3 discusses the

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[2] This report was prepared by the consulting firm Coopers & Lybrand and was published as an appendix to a larger report by the Committee for Increased Competition Within the Railway Sector: Review of Proposals, January 1993. See: *Okad Konkurrens pa jarnvagen, SOU 1993:13.*

technical problems faced by decentralization advocates by reference to the example introduced in Section 2. The section lists properties of a rail network that critics of decentralization claim will prevent the successful operation of decentralized allocation processes, as well as properties of the existing Swedish policies that advocates of decentralization suggest will be avoided by a decentralized process. Section 4 outlines the testbed environment that contains all of the properties listed in the previous section. The example initiated in Section 2 and continued in Section 3 becomes the testbed environment. Section 4 also contains other aspects of the experimental design and procedures. Section 5 outlines the mechanism to be applied to the environment and Section 6 discusses some properties that will be used to evaluate the performance of the mechanism in the testbed. Section 7 presents the data and an analysis in terms of both the evaluative criteria and models of the behavior of the mechanism. Section 8 presents conclusions.

2. BACKGROUND, NOTATION AND CONCEPTS

Figure 1 shows a map of the rail network in Sweden. Much of the track in outlying areas is single track, which, because of single tracks, cannot support simultaneous two-way traffic. Double track can be thought of as equivalent to two single tracks, and is typically used to provide bi-directional traffic flow. Gothenburg and Malmö are major seaports, and are connected to Stockholm by double track. Much of the rural areas have only single track. As can be seen, the network of rails is complex even though Sweden is a relatively small country, and it follows immediately that size, and complexity due to size, is a problem.

Size is not the only problem and this paper will be focused on problems other than size. Much of the following section will be devoted to a discussion of a rail allocation problem that is trivial from a size perspective but, nevertheless, present a challenge to advocates of decentralization.

Figure 2 shows a very simplified rail scheduling diagram for a hypothetical single track rail line. The vertical line has Stockholm at the bottom, Borlänge at the top, and Uppsala in the middle. Imagine a single track connecting these three locations with a sidetrack located at Uppsala where a train can pull off and stop while another train passes. Time is represented on the horizontal axis. Trains are shown as lines on the diagram. The slope of the line indicates the speed at which the train would travel. Thus the path G on the figure can represent a train that starts early at Stockholm and moves slowly toward Borlänge. Each point on the line G represents the location of the train (the vertical) at each point of time (the horizontal). The curve A is a train that would start later than G and travel faster reaching Borlänge before G would arrive. Curve B is also a train that moves from south to north but the horizontal portion indicates that it pulls to the sidetrack and stops at Uppsala. Curve C is a train that would start in the north and move southward along the tracks. Nine different trains are shown in Figure 2. These are labeled A through H.

The locations on this simple system of railroad tracks can be indexed as the set $\boldsymbol{X}$. A single train can be interpreted as a function from time to a location on a system of tracks. In the notation to be used, a train is a function, r(t), where t is understood to be an element of a well defined set[3], $\boldsymbol{T}$, such as time of day, and r(t) is understood to be a point on a graph representing locations, $\boldsymbol{X}$, on a system of railroad tracks. For example, the train A can be thought of as a function of $r_A(t): \boldsymbol{T} \rightarrow \boldsymbol{X}$. For each time of day $r_A(t)$ gives the location of the train, and the point $(t, r_A(t))$ corresponds to a point on the path of train A in Figure 2. As multiple tracks can be considered to be a collection of single tracks, it would appear sufficient to consider the scheduling problem for single tracks in isolation.

From the figure a notion of feasibility of an allocation can be obtained. If both train A and train C operated, there would be a head-on collision at the location and time of intersection of the two lines. Similarly C and G would involve a collision as would A and G. Because A is faster than G it would run into the rear of G at the time and location of the intersection. Some collisions can be avoided if a sidetrack exists. Thus, trains B and C do not collide because B pulls to the sidetrack at Uppsala and lets train C pass. Notice the line representing train B is horizontal, indicating that the train is not moving. The train waits for train C to pass before continuing on to Borlänge.

Trains and collisions are not the only consideration for feasibility. Track congestion can be a problem, especially if equipment failures occur. Stopping distances require a safety margin between trains. Thus, feasibility can involve constraints that require that either train A or train B can operate but not both. These two trains would leave Stockholm so close together that safety regulations would be violated.

A feasible schedule is a set of trains that involve no collisions and do not violate other side conditions, like safety regulations. Constructing the set of feasible schedules[4], i.e., those with no collisions, is essentially the construction of a "production possibility set" for use of the track. As might be obvious from Figure 2, the set of feasible schedules and, thus, any production possibilities set, is neither smooth nor convex. In order to deal with such problems a somewhat different approach will be used which is based on a recognition that a *binary conflict property* plays a central role in the economics of the problem. Infeasibility of a schedule necessarily involves a conflict between two trains. If many trains collide, then two trains also collide and two is unacceptable. If many trains travel too close, then two travel too close and is unacceptable. Thus, any conflict implies that a pair is in conflict.

Formally, a *Binary Conflicts Environment,* as applied to a rail allocation problem, is defined as a quadruplet $(\boldsymbol{X}, \boldsymbol{I}, \boldsymbol{F}, \boldsymbol{C})$. $\boldsymbol{X}$ is the system of tracks, the set of locations for trains. $\boldsymbol{I}$ is the set of individual agents that would like to have access to the tracks. $\boldsymbol{F}$ is the set of all trains that might operate on $\boldsymbol{X}$, i.e., $\boldsymbol{F}=\{\ r(t): \boldsymbol{T} \Rightarrow \boldsymbol{X}\ \}$, where $\boldsymbol{T}$ is a

[3] Obviously only certain functions can represent trains. Such technical restrictions on the mathematical representations are not imposed because they play no real role in the analysis that follows. The representation should only be considered as notation until otherwise stated.
[4] Which will be a set of sets.

relevant measure of time. In this notation $\boldsymbol{F}$ is infinite but in the analysis that will follow it will be assumed to be finite. $\boldsymbol{C}$ is a set of binary conflicts, a subset of[5] $\boldsymbol{F} \otimes \boldsymbol{F}$, which specifies pairs of trains that are incompatible. Incompatibility means that the two trains would collide if run or that if the two trains run, then some other safety standard would be violated. For example, if $r^1(t) = r^2(t)$ then the two trains 1 and 2 would collide at location r at time t. If all trains are compatible, then $\boldsymbol{C}$ is the empty set.

A *feasible allocation*, $A^* = (\boldsymbol{A}, \boldsymbol{A}_1, ..., \boldsymbol{A}_I)$, is a set of trains, $\boldsymbol{A}$, and a partition scheme, $\boldsymbol{A}_i$, that partitions $\boldsymbol{A}$ among the set of users $\boldsymbol{I}$, such that:

(i) $\boldsymbol{A}_i \cap \boldsymbol{A}_j = \emptyset$ for $i \neq j$

(ii) $\cup_i \boldsymbol{A}_i = \boldsymbol{A}$

(iii) $\boldsymbol{A}$ contains no conflicting pairs, i.e., $\boldsymbol{A} \otimes \boldsymbol{A} \cap \boldsymbol{C} = \emptyset$.

The nonconvexities inherent in binary conflict environments can create difficult computational problems. The use of the graph theoretic formulations facilitates the computation of solutions to some of them. It is easier to check for binary conflicts and reject an allocation if and only if one is detected, than it is to examine all possibilities for which binary conflicts do not occur. In this sense, the concept of a binary conflicts environment is important for the operational and computational feasibility required of processes.

3. TECHNICAL AND ECONOMIC ISSUES IN THE DISCUSSIONS

Historically, scheduling has been seen primarily as a technical problem and not as a economic/political problem. Without the aid of computer technology,[6] scheduling is an incredibly complicated task, and has concentrated on identifying a feasible schedule and then modifying it incrementally when changes are necessary. In Sweden, scheduling has typically consisted of ranking trains in priority and then resolving conflicts as they occur (requiring one train to wait or excluding trains) based on the priority ranking. Schedules are fine tuned by rules developed in administrative committees, and new services are added incrementally into previous schedules as possible.

The system has been criticized for many reasons, many of which can be summarized as saying that access to track is not allocated to the users who value access the highest. The system is defended by those who claim that because of certain technical features nothing else will work. This section contains ten issues that have surfaced in the controversy.

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[5] The notation ⊗ represents a Cartesian product of two sets.

[6] For a discussion of computerized rail scheduling techniques, see the review article of Petersen, Taylor, and Martin (1986). Many models of rail operations seem to fix trains at their maximum possible speed while in motion. A notable exception is Kraay, Harker, and Chen (1989), who study how train speed should be varied to meet an objective function based on travel time and fuel consumption, given the constraints that trains must stop for meets and passes to occur. In general, this literature assumes the viewpoint of a central dispatcher who wishes to maximize some function, and has some sort of administrative powers. The literature does not address issues of decentralized agents with conflicting objectives that are determining the allocation through some competitive process.

The first six are issues raised by those who defend the current system of priorities against those who advocate decentralized and competitive access to the use of tracks. The final four are issues raised by those who criticize the system of priorities as being insensitive to efficiency improving possibilities.

In discussing the issues the railroad system in Figure 2 will be used to illustrate the points. In addition, the values in Table 1 will be used. Table 1 outlines values placed on trains by 10 potential users numbered as agent 0 through agent 9. Each agent has an additive preference for the nine trains labeled A through I. Two trains H and I involve no conflict and will be ignored throughout the discussions in this section.

The issues listed here, and the example from Figure 2 and Table 1, are more than just an illustration. The system from Figure 2 will be the one that is used in actual experiments as a testbed for the mechanism that will be outlined in the next section. The preferences in Table 1 are taken from one of the patterns of preferences that will actually exist in the experimental testbed. The point of this section, and the next, is not only to explain the controversy, but to also show that the controversial elements are actually present in the testbed.

The first six issues listed are those mentioned by critics of the decentralized proposals. They are aspects of the railway allocation problem that lead to skepticism that a decentralized or market based process can be applied successfully. The last four items on the list are issues that are raised by critics of the current system of priorities. These issues lead to skepticism about the system of priorities leading to an efficient allocation. The discussions should make clear that all of the elements are in the testbed.

<u>Non-Track Constraints</u>. How can safety considerations and other non-track constraints be guaranteed if decentralized competitive allocation takes place? Consider again Figure 2 and assume that trains, such as the pair A and B, the pair C and D, and the pair E, and F are too close and, thus, cannot be operated together. If one runs then the other cannot run without violating a safety standard. If we let C be the set of binary conflicts implied by Figure 2, then these three pairs are in the set. (Note that if the set of binary conflicts is symmetric then the order is unimportant). Efficient allocation would require that no such pairs operate and that any process of insuring that non-track constraints be satisfied should not prohibit more than is necessary.

<u>Schedule Interdependency</u>. The network in Figure 2 suggests the many complications that arise from schedule interdependencies. Suppose agent 1 operates early from Stockholm and from a choice of A or B wants to take A. Agent 2 operates from Borlänge early and prefers C from a choice of C or D. However, 2 is persuaded by 1 to choose D which does not conflict with A. However, a choice of D has an impact on agent 3 who operates from Stockholm at a time later than 1, and who wants to choose E from the two options available E and F. If agent 2 runs train D then agent 3 cannot run train E because they are in conflict.

Revelation of Values. How can the private values of independent train operators become exposed and used in a competitive process? A type of "free rider problem" seems to exist. Consider an agent who would like to implement train G. This train is in conflict with all of the trains in the set { A,B,C,D,E,F }. If G is to operate it must somehow preclude all of these, or if any of these trains operate then train G must be precluded. If the set of rights to operate { A,B,C,D,E,F } are held by different operators, then they must either be paid, thereby creating a "holdout problem" for the operator of G who must strike a price with each individually, or if the operator of G has the right to operate, then these different operators must collectively pay the G operator, thereby creating a type of public goods problem among themselves. In both cases the independent operators could have an incentive to misrepresent their true values of operations.

Resource and Market Fragmentation. If a classical market process is to be used, then the number of potential markets would be large. How would markets be defined? It is possible to divide the tracks into mile by time squares and have a market for each. Given the system represented by Figure 2, a natural division would have the track divided into three segments (Stockholm- Uppsala , sidetrack at Uppsala, Uppsala - Borlänge) and time divided into four segments morning, midday, evening, and night. This would create twelve markets. For the example, this number of markets might not be so onerous but for more complex tracks this is going to require a large number of markets, possibly raising transactions costs to both operators and the seller.

Strong Complements. If the "multiple independent market" approach mentioned in the paragraph above is used, then strong complements will be present, and since there exists an inherent discreteness in the commodities, the efficient outcome may not be supportable by competitive equilibrium prices. Suppose only routes G, A, and E from Figure 2 are of value and that the commodity space is as defined by using time of day. For example, assume that the whole track is sold, and as defined by two times of day, morning and midday, which is enough time for train G to travel from Stockholm to Borlänge. This gives only two commodities. Assume that there are only two agents j and k, and that agent k is willing to pay a total of $10 for both morning and midday track access in order to operate G, but otherwise places no value on the tracks. Agent j would pay either $7 for the morning in order to run train A, or would pay $7 for the midday in order to run train E, but does not want to run both trains. Trains A and E just require part of a day for the trip but, by assumption, the market is not sufficiently profitable for j to operate both trains. The optimal allocation is for agent k to own both the morning and the midday track access and for agent j to have neither. Yet, competitive prices for both morning and midday must be above $7 to exclude agent j, but, if the price of both is $7 or above, agent k does not wish to buy. The optimum cannot be supported as a competitive equilibrium.

Competitive Equilibrium Existence. It is clear from the examples that track allocations involve discrete goods regardless of how the commodities might be defined and the number of markets that might be involved. The possibility that competitive equilibria might not exist in the absence of convexities is well established and is demonstrated by the example above. Thus, in the case of rail allocation there is no reason to suppose that competitive equilibria necessarily exist.

Priority and Substitution Between Users or User Types. Suppose any agent is given priority, as is the case with the current system. If G was the most valuable route to any user with priority, then it would be implemented. For example, if agent 0 was given the right of priority for a single train such as G, then, as can be ascertained from Table 1, train G would operate at a value of 1604. But there are many options that have greater value than G. In particular, B, C, and E held by agents 1, 0, and 2, respectively, have a combined value of 3022. Given such a priority system, there is no incentive for the three trains run by different users to be substituted.

Priority and Combining Trains. Suppose that fast trains have priority over slow trains and that agent 0 is operating fast trains but had no priority for a slower train such as G. As can be seen from the Table 1, the value for G to agent 0 is 1604, while the value of the best feasible fast trains to this agent is the set of three trains B, C, and E that total to 1134. The agent has no incentive to combine trains if the result is a slower train because priority, and thus the trains, would be lost.

Priority Gives no Incentive to Wait. If agent 7 has priority with north to south fast trains, then the agent has no incentive to delay and wait. Given the preferences of Table 1, agent 7 would operate train A even though another agent, such as agent 0, must delay and run train D rather than train C. Agent 0 values train C by a difference of 337 over D, while agent 7 values A, which forces agent 0 to delay to train B, in which agent 7 waits, by only a margin of 102. Thus, an allocation in which Agent 7 waits, as opposed to Agent 0, would increase total value by 335. With priorities there is no incentive for this to take place.

Priority Systems Do Not Respond to Changing Circumstances. If the track authority always assigns priorities correctly, then an efficient allocation is often possible and depends on the ability of the priority rule system to span all feasible schedules. However, to assign priorities correctly, the track authority must gather the necessary information from independent operators, or operating divisions, in order to make these decisions. It may not always be in the interests of the operators to truthfully reveal this information. Furthermore, as circumstances change, the information must be gathered again and again. Apparently, the criticism that "access to track is not allocated to the users who value it the most" directly attacks the ability of the track authority to gather this information using the current administrative processes.

4. THE TESTBED ENVIRONMENT AND ASSUMPTIONS

A testbed environment is in a sense a challenge to a mechanism. The philosophy is to include features in the environment that are thought might cause some difficulty but, at the same time, keep the environment sufficiently simple such that, should difficulties be encountered, the causes might be isolated. The elements of the testbed as dictated by the railroad allocation controversy are the physical features (rails and conflicts) and the preferences of agents who want to use the system. The essence of the physical features of the testbed are substantially as outlined in the previous two sections. Agent preferences were induced with monetary incentives.

Experimental Procedures

A total of three experimental sessions were conducted. Subjects were Caltech students recruited through an announcement on the campus computer network. Procedures in each of the three experiments are essentially identical. Each of the three sessions lasted approximately 2-21/2 hours and required ten subjects. Each session consisted of seven periods.

Each subject received common instructions included in Appendix I, as well as an individual incentive table and common supplies (e.g. scratch paper, pocket calculator). Because of space, the individual incentive information tables were not included in Appendix I, but instead are summarized as matrices in Appendix II. Each table consisted of 20 pages. Each page consisted of an individual firm's incentives for the routes (projects) for one period. Only the first 7 pages were actually used.

No mention is made of trains or scheduling in the experimental instructions. The language of the experiment is "project" for train route, and "combination of projects" for train schedule. Language was chosen to make the experiment independent from the specific industrial application, in an attempt to eliminate any effects of preconceived notions subjects may have about railroad operations.

Rail Resources

The set X is the set of tracks represented in Figure 2.

The set F of trains will be the set of nine elements { A,B,C,D,E,F,G,H,I }. Of course this is a small set relative to the number of potential trains that can be imagined. Two factors were considered. The first is whether or not all of the important economic complexities are present. The second was the limitations imposed by existing experimental laboratory technology on the communication of incentives to subjects in an experiment and the capacity of the technology to deal with communication over large sets. It was decided to tackle the questions of scale only after it was established that the mechanism could operate on a small scale. In reality, the scale is not so small since these nine options constitute a very large number of potential sets of operating trains and since the information about the values of these options is not known to a central authority.

The set C, of binary conflicts is represented in graphical form in Figure 3. Recall that C is a binary relation such that each pair in C represent a conflict of some sort or a collision. For example, the line connecting A and B reflect the fact that because of non technical considerations, e.g. safety, trains A and B cannot both operate. From the graph it can be seen that the same is true for pair C and D and for pair E and F. The graph has a line connecting G with each of the letters { A,B,C,D,E,F } representing the fact that G cannot operate without collision with any of these other trains. A comparison of the graph in Figure 3 with the system in Figure 2 will demonstrate that the physical and safety restrictions are fully represented.

Agents and Preferences

The set ***I*** of agents is { 0,1,2,3,4,5,6,7,8,9 }. (In some of the analysis the index is from 1 to 10 and agent 0 is re-labeled as agent 10 so the reader should not become confused. The change in convention was necessitated by some of the software).

Agent preferences for trains in the set ***F*** were induced with monetary incentives that were additive and separable. The value that agent i has for route f is V[f]. Thus, an agent's payment was a sum of independent payments for each train route purchased. For the issues outlined in the above section more complex preferences are unnecessary. All of the issues raised in that section are present.

Given the nine trains A-H of the testbed rail environment, and 10 agents, specification of additive separable incentives[7] involves picking a value for each route and firm, resulting in a matrix of 9x10 values such as Table 1. The testbed environment consisted of a series of periods. Each period a different set of preferences existed. Values in the incentive matrices were randomly drawn from a distribution that was constrained to satisfy several conditions as outlined in Appendix II. The primary purpose of these constraints is to create the routes B,D, and F as inferior substitutes (i.e. delayed version, where delay is always costly) of routes A,C, and E, respectively; to eliminate the possibility of monopoly; and spread out possible allocations over a range of efficiencies. The high value for G is never high enough to make G optimal, thereby creating the potential problems of revelation discussed in the previous section.

Variation of the incentive matrices from period to period provides an opportunity to test the responsiveness of the Binary Conflict Ascending Price (BICAP) mechanism to changes in the marketplace. One criticism of the priority scheme currently used in Sweden is its lack of such responsiveness. Variations in the incentive matrices will result in different optimal allocations, and one can determine if the mechanism outcome follows these changes.

5. THE BINARY CONFLICT ASCENDING PRICE (BICAP) MECHANISM

A mechanism involves three essential elements: a set of feasible outcome allocations, a message space through which agents interact with each other and with the allocation

[7] Clearly more complex preferences of a non additive type could have been used. None of the arguments introduced above depended critically on such preferences so they were not used. Modifications of the mechanism may be needed to deal with certain types of non separable preferences over trains. The preference could also be modified to allow externalities among operators but again such complications are left for future studies.

authority, and an outcome rule which specifies how these messages determine a unique outcome from the feasible set of allocations. In the Binary Conflict Ascending Price mechanism each agent submits bids for trains in a continuous time auction. The highest bid on a train prevails as the potential winner and cancels all lower bids for the train. At every point in time the potential allocation is defined by the set of bids that has no conflict and has the maximum sum of all feasible allocations - those that have no conflicts. The process of bidding continues until some pre specified time has elapsed with no bids taking place. Formally the mechanism as defined by the rules that characterize the process is outlined by the following statements.

A *feasible allocation* A* is as defined in section 2 as a I+1 tuple $(A, A_1, \ldots, A_I)$, consisting of the set of trains, $A \subseteq \boldsymbol{F}$, that will be actually operating and the assignment, A_i, of the rights to operate those trains to the individual operators. Technically the elements of A* satisfy

(i) $A_i \cap A_j = \varnothing$ for i≠j

(ii) $\cup_i A_i = A$

(iii) A contains no conflicting pairs, i.e. $A \otimes A \cap C = \varnothing$.

A *feasible set* $\mathcal{A}(X, I, F, C)$ is the set of all A*. In the case of the railroad allocation problem the feasible allocations are defined relative to the set (X, I, F, C) of section 2 and as applied to the testbed environment as defined in the preceding section.

The *message space* for each individual is the set of pairs, (b,f), where b is a bid in terms of money for the train route f.[8] Where needed, $(b,f)_i$ is the message sent by agent I. For all applications that follow it will be assumed that the message space is finite and, in particular, the values that bids can take are finite, thereby implicitly inducing a property of a minimum possible bid increment.

Payoff relative minimum bid increments are equal to the minimum units in which payoffs can be measured. That is, if the minimum unit in which payoffs can be measured is one cent, then the minimum bid increment is one cent.

Definitions:

B(f) = the highest bid price for each f ∈ F, measured at some particular stage of the mechanism. That is $B(f) = \max_i (b,f)_i$ for a given stage of the process.

$\boldsymbol{B}$ = the set (vector) of all highest bid prices,

H(f) = for each f, H(f) ∈ I = the i that holds the high bid for f, i.e. $(b,f)_i = (B,f)$.

$\mathcal{P}^*[\boldsymbol{B}]$ = a potential allocation = an allocation that will actually be carried out if the auction ends given bids the vector of bids $\boldsymbol{B}$.

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[8]The message space could be generalized to include sets of trains or even ordered sets of trains. A set would be interpreted as a request that all bids be accepted or none be accepted. Such generalizations will not be pursued in this paper.

Throughout the auction, (X,I,F,C), $\boldsymbol{B}$, H, and $\mathcal{P}^*[\boldsymbol{B}]$ are all common knowledge.

Bid Submission and Termination Rules The auction proceeds as follows:

a. At the beginning of the auction, B(f) is set to 0 for all f.

b. An agent (say i) may send a bid message $(b,f)_i$, stating a willingness to pay b for the train f. If b > B(f), then B(f) is set to b and H(f) is set to i, and $\mathcal{P}^*[\boldsymbol{B}]$ is recomputed. Otherwise, the bid is rejected and B(f), H(f) and $\mathcal{P}^*[\boldsymbol{B}]$ remain unchanged.

c. If no bid message is made for some time period T, then the auction ends, the allocation $\mathcal{P}^*[\boldsymbol{B}]$ is implemented, and agents with high bids who receive allocations must pay their bids.

Determination of $\mathcal{P}^*[\boldsymbol{B}]$ is by the following "track value" optimization problem: $\mathcal{P}^*[\boldsymbol{B}]$ corresponds to a feasible allocation which maximizes the sum of stated willingness to pay B(f), where the sum is taken over the f that are allocated in A*. That is, $\mathcal{P}^*[\boldsymbol{B}] = [A, A_1, A_2,..,A_I] \in \mathcal{A}$: maximizes $\Sigma_{f \in A}\, B(f)$. In the event of a tie the status quo is always chosen.

In summary, the mechanism works as a set of simultaneous ascending auctions. Each auction is for a different train, f, and so there could be as many auctions as there are possible trains. A bid is submitted in real time and with each bid the mechanism determines if the new bid is higher than the old bid for the train on which the new bid was submitted. Only the highest bids are kept as information by the mechanism. After the high bid changes on any train the mechanism then determines the set of trains that maximize the total value of the track sale given the existing bids. This set of bids is announced by the mechanism as the potential allocation, which would actually be carried out if there are no more bids during some pre specified period of time.

Any mechanism must have operational features. The mechanism must be implemented in a form that works when used by human agents. Each subject/agent was stationed at a personal computer that was attached to other agents through a token ring network. Figure 4 is a representation of the screen as seen by a subject. On the actual screen, different project lines were in different colors to aid in reading the table. The status column indicates the potential allocation. If a bidder had a high bid for one or more projects, those bids were tagged on the screen, as is project "C" in Figure 4. Bids are entered by pressing the key corresponding to the project, and then entering a value. The bid value and project may be edited, or the bid may be deleted. A special key (F1) must be pressed to actually send the bid into the mechanism, at which point it is checked against the high bid. If the new bid beats the high bid, it is sent to the other screens and becomes binding (if accepted in the final allocation) until replaced by a higher bid.

When entering bids into the experimental software, subjects had difficulty with typographical errors. It was easy for subjects to create typographical errors by forgetting to hit a key which deleted previous input. This tended to cause false large bids to be entered into the system, such that a subject would lose $10-$50 if forced to honor the bid. When such an error occurred, the experimenter reset the experimental software. The subjects were instructed that the period would start over and that they should continue using the same incentive value sheet. The possibility exists that subjects created false typographical errors to delay the mechanism, but there are no obvious profit opportunities from using such a delay strategy since incentives are the same when the period is restarted. For the purpose of analysis, only the error free run of each period is considered valid data.

The Binary Conflict Ascending Price (BICAP) mechanism is actually somewhat similar to the Adaptive User Selection Mechanism (AUSM) of Banks, Ledyard and Porter (1982) but with some important differences. Appendix III addresses these differences and contains a sketch of related literature.

6. BEHAVIORAL THEORIES, ASSUMPTIONS, AND PERFORMANCE

In this section, some behavioral models of the BICAP mechanism will be reviewed. Performance of the system will be evaluated primarily in terms of its capacity to produce an efficient allocation. The behavioral modeling will be used as a check for design consistency. The question is whether or not the mechanism is operating according to the principles that were the underpinning of the design. Since there is no fully worked out theory about the behavior of such complex mechanisms, especially when operating in complex environments, an approach less ambitious than a general and rigorously tested behavioral theory must be used. The questions that the models will help answer are, "Does it work and does it work for the right reasons?" If it works, but for the wrong reasons, then one would be very cautious about whether or not it might work in more complex environments, or even in environments in which it had not been tested.

The primary evaluative tool will be the *efficiency* of the final allocation. The system will operate at 100% efficiency if the sum of the private values of operators in the final allocation is the maximum possible over the feasible possibilities. This measure is motivated by the classical consumer surplus arguments and related cost-benefit analysis. Notice that under the conditions of the environment this is not a simple task. The values of agents are known only to themselves and they are never asked to communicate these values to anyone. Thus, the process must behave *as if* it knew the values and *as if* it could solve the related constrained maximization problem, even though the values are never communicated as such.

The modeling effort developed in the following paragraphs departs somewhat from the modern view that behavior is captured by a fully developed theory of games and, instead, is based on the concept of "stationary points" that were used in the early development of mechanism theory. Parts of game theoretic principles are retained, but the heart of the behavioral models will rest on the limited actions that are available to an agent at any stage of the mechanism. In essence, an individual's options are to choose to bid and the amount, or to choose not to bid. The behavior hypothesis is that such choices are conditioned on the state of the system, the last choices, including the choices of others and himself/herself, and the value of the trains.

Classify bids $(b^*,f^*)_i$ which agent i might make according to their effect on agent i's potential profits - that is, the profit agent i would make if the auction ended after the bid $(b^*,f^*)_i$.

pivotal bid = a bid that increases agent i's potential profit should the mechanism terminate immediately after the bid is submitted. That is the bid is below i's train value and high enough to change the potential allocation of the mechanism.

strong neutral bid = a bid that leaves agent i's potential profit (and allocation) the same, and the bid is low enough for its future acceptance to possibly improve future potential profit, i.e. $b^* < V_i[f]$. That is, the bid is below i's train value but not enough to change the set or potential allocations.

dominated neutral bid = a bid that leaves agent i's potential profit (and allocation) remains the same, but $b^* > V_i[f]$.

dominated bid = a bid that would reduce profit for agent i should the mechanism terminate immediately after the bid is submitted.

null bid = a bid that is below the high bid for a train route and is thus equivalent to a bid of zero.

The definition of an equilibrium, or a stationary point to be introduced next, has some of the features of the classical Nash equilibrium but it falls far short of incorporating the full range of strategic possibilities and considerations. The behavior model will have individuals looking only one period ahead in which only a limited set of strategies are available. That is, the agents strategies are functions only of the current state of the mechanism. That is, consider only strategies that depend on the environment $(\boldsymbol{X}, \boldsymbol{I}, \boldsymbol{F}, \boldsymbol{C})$, the highest bid vector $\boldsymbol{B}$, and the agent's allocation $A_i[\boldsymbol{B}]$ in $\mathcal{P}^*(\boldsymbol{B})$ and train redemption values $V_i[f]$ that result from the allocation of the trains. Principles of game theory have the level of information on which strategies could be conditioned to be much larger, and would include the complete history of previous moves as well as beliefs about the train value vectors of other agents. Nevertheless, the analysis presented below will be confined to the limited set of strategies for purposes of definitions and modeling. In order to emphasize the fact that the behavioral models have the special feature of agents that look only one period ahead, the equilibrium is called a Nash-1 stationary equilibrium.

Definition. A Nash-1 Stationary Equilibrium (NE1) for the BICAP mechanism is a feasible allocation A* and a set of highest bids $\boldsymbol{B}$, indexed by f, supporting this allocation that have the Nash property that no pivotal bids exist for any agent.

The idea of a stationary point is much different from the idea of an equilibrium point in a game because the property of stationarity at a point is completely divorced from the dynamics or logic that might have brought the system to the point. As a consequence, it is clear that in the testbed environment NE1 stationary points exist and it is also clear that the pattern of bidding that allocates the trains to those that value them the most can be supported as a NE1. Consider the allocation and bids resulting from every agent bidding his/her value V[f] for each train f. Such behavior might not be sensible, but if it happens then the system is "stuck" at a NE1, because no agent can make a profit increasing bid given his/her previous bids and the bids of others. The first price rule and the fact that bids must be increasing assure the stationarity property. Perhaps a more interesting example in the additive, separable individual values environment, is the case in which the agent with the second highest value has bid his/her value and the individual with the highest value is bidding only the minimum necessary increment above the bid of the second highest value. This is again an efficient allocation and no individual has an incentive to bid. The system is at a stationary point.

An additional equilibrium concept will be useful. It is based on the concept of a strong Nash equilibrium of a game in which no coalition has available a strategy from the coordination of the strategies of its members that makes all members better off. Of course, in the context of the discussion here the concept is related to stationary points.

Definition. A Strong Nash-1 Stationary Equilibrium (strong NE1) is a NE1 in which no collection of agents can tender a set of bids that improve the profits of all members of the collection should the mechanism terminate immediately after the bids are tendered.

The literature on mechanism design contains the suggestion of a dynamic behavioral process that will cause the process to terminate at an NE1.[9] The proposed behavioral principle is that agents follow a type of "gradient method" of exercising choice, which involves keeping the mechanism going if they detect the existence of pivotal bids. This does not mean that they necessarily choose to make a pivotal bid as they would according to Nash/Cournot models of behavior, but the individual does not allow the process to stop. If individual choices are characterized by such a principle then the final resting place of BICAP will be a NE1 as defined above. The principle is not necessarily that agents choose an optimum over the "short term" strategies that present themselves, but does choose to keep the process going if profitable opportunities exist. The following paragraphs will make the ideas clear.

Definition A dynamic process is called a *discrete pivotal process* if

(i) Agents never submit dominated bids.
(ii) Train redemption values are finite for all agents.
(iii) There is a minimum bid increment, finite, non-zero, and payoff relative.

[9] The process is the B process invented and studied by Hurwich, Radner and Reiter. While the B process is developed as part of an exchange process and is, therefore, different in many ways from a behavioral hypothesis developed in the context of BICAP, the basic behavioral structures are very similar. See L. Hurwich, R. Radner and S. Reiter, (1975a, 1975b).

(iv) No agent allows the auction to end whenever he or she has the ability to make a pivotal bid.

Remark 1. If agents decision behavior in the BICAP mechanism is a pivotal process, then the outcome will be NE1 and furthermore, any NE1 can be supported as the terminal point of some pivotal process.

In order to understand the reasoning that supports the remark, notice that under assumptions (i)-(iii) the auction must eventually stop. Then, when the auction does stop, condition (iv) implies that the outcome is NE1. Conditions (ii) and (iii) of the discrete pivotal process guarantee that for k, trains with redemption values bounded by v, there can be, at most, kv bids while satisfying condition (i). Only non-null bids allow the auction to continue. Therefore, the auction will stop at some set of bids. When the auction ends, (iv) implies the absence of pivotal bids for all agents. Clearly (iv) implies NE1. Suppose the auction has arrived at an NE1 and consider the pivotal process in which individuals take only actions that are pivotal. Under these conditions the mechanism will terminate.

From the above remark we know that a pivotal process will converge to a NE1 and we know that the efficient allocation can be supported by a NE1 if the process happens to converge to it. But, many NE1 may exist so simple convergence to an allocation supported by an NE1 is not necessarily satisfactory performance. The following definitions provide concepts that can help better characterize principles of behavior that will lead to efficient outcomes.

The idea is to extend the model beyond the intuition provided by the Nash response assumption, which has individuals only taking actions that result in a direct benefit. The behavioral principle to be added to the model asserts that individuals will not let the process stop as long as they can make bids that have a potential for improvement, depending upon the actions taken by others. The role of this new principle is similar to the role played by "out of equilibrium" play in the literature on refinement concepts in games. Of course, in the mechanism model, agents are not assumed to have a complete analysis of all contingent actions. The following principle will make the idea precise.

The Exhaustive Offer Hypothesis. No individual will allow the mechanism to terminate as long as he or she has the ability to make a strong neutral bid.

Definition. A dynamic process is called a discrete *strong neutral bid process* if

(i) Agents never submit dominated bids.
(ii) Train redemption values are finite for all agents.
(iii) There is a minimum bid increment, finite, non-zero, and payoff relative.
(iv) Individual bidding behavior is consistent with the Exhaustive Offer Hypothesis.

A strong neutral process is a pivotal process since pivotal bids are strong neutral. Clearly, a strong neutral process will converge to the efficient allocation. Rather than allowing the market to close when an agent cannot make a pivotal bid, the agent will behave according to the Exhaustive Offer Hypothesis and submit a strong neutral bid, if one exists, precommitting himself to a higher level of potential payment on some unallocated train. In part, this could be negotiation or signaling, but the neutral bids also form the basis of a game of chicken in precommitments. As the clock ticks down, agents must decide whether they are willing to increase their bid by the minimum bid amount in order to continue the auction, or if they wish to risk relying on some other agent to do this. In this way, the "local" game will encourage some revelation of redemption values on all unallocated routes. The revelation of values then guides the process to the efficient allocation under the condition of separability that is present in the testbed.

7. RESULTS

The experiments confirm, that , in fact, a decentralized mechanism can solve some of the technical aspects of the rail scheduling problem and yield efficient allocations. Not only are the results efficient, but design consistency appears strong. Outcomes correspond to one-stage Nash-1 stationary equilbria. Evidence exists that the process of convergence is essentially as captured by the pivotal process introduced in the previous section. In addition, inefficient NE1 seem to be avoided because of a high degree of revelation in the bid prices. These results tend to refute the argument that efficient decentralized rail allocation is impossible as a matter of principle.

Table 2 summarizes the experimental parameters and results, simultaneously. Only the highest and 2nd highest incentive values are thought to be important for determining prices, allocation, and strategic behavior. There are 7 different periods (parameter sets) which were repeated in identical sequence in 3 different experiments.

The table is read as follows. The first row contains for the first period (of all three experiments) the high redemption value for each of the nine individual routes, the identification number of the agent that held the high value, and the optimum system schedule which is the maximum valued feasible schedule. Reading across the row, the optimal schedule is {A,D,F,H,I}; and the maximum redemption value for route A is 1699 held by participant number 3, etc.,. Row 2 contains the second highest redemption values. Row 3 shows that the actual schedule that resulted in period 1 of experiment 1 ({A,D,F,H,I} - which was optimal), and it shows, for example, that the maximum bid for route A was 1300 tendered by participant 3. Rows 4 and 5 show the period 1 data for experiments 2 and 3 respectively. Row 6 starts the enumeration of the same data for period 2. The table continues through period 7.

The first result suggests that the mechanism is successful in producing efficient allocations for the rail allocation problem. Efficiencies are calculated from the table, as the ratio of the total of redemption values for agents at the outcome allocation divided by the maximum possible total value of redemption values. The maximum possible total is attained at the optimal allocation. As was discussed in the previous section, this is a standard measure.

RESULT 1. The outcomes produced by the mechanism are near 100% efficient.

SUPPORT. The table directly supports three statements concerning efficiency. (i) Inefficient outcomes are rare. In 18 out of 21 experimental trials, the mechanism resulted in the optimal allocation. Only 3 of the 21 trials, only period 2-experiment 3, period 3-experiment 2, and period 5-experiment 3 resulted in allocations that were not optimal. Thus, for trains A-G the efficiency is 100% in 86% of the experimental trials. (ii) For the 3 inefficient trials in periods 2, 3, and 5, efficiency for trains A through G is at 0.82,0.65, and 0.93 respectively. This yields an average efficiency of 97% for trains A-G for the experiment. (iii) Trains H and I are always allocated in the optimal manner.•

Given that the mechanism is efficient, the question of design consistency is now addressed. It is not sufficient that the outcomes are efficient, but rather they should be efficient for theoretically understandable reasons. This increases the guarantee that the mechanism will behave similarly in other environments which are untested but theoretically similar.

To begin this examination, Table 3 represents a measure of " distance " of outcomes from NE1 outcomes in terms of the potential profitability of pivotal responses. The entries in the table are the maximum potentially profitable pivotal response available to any agent. In a sense the entries are the maximum opportunity cost of stopping (assuming that the process would go only one step more). For each agent, a search was made for the most potentially profitable pivotal bid at the final bid prices for each period. A maximum was then taken over all the agents for that period, and the amount of this potentially foregone profit, along with the agent i.d. number with the corresponding pivotal bid opportunity were tabulated and entered in Table 3. Entries of zero correspond to NEl outcomes, since a zero entry is only possible if there are no remaining pivotal bidding opportunities at the close of each trial. Positive entries represent possibilities for profit, and are stated in Francs. (Francs conversion rates varied, worth $0.005-$0.02, or so).

Typically, in experiments there is an unknown variable subjective cost for getting agents to take any action. That is, if only $0.10 is to be made by pressing the keys, it is possible that the agent will not take any action. Taking these costs into consideration suggests a classification of outcomes from Table 3 into strict NEl and "thick indifference" NEl type outcomes. Consideration of both as degrees of NEl behavior yields Result 2.

RESULT 2. Outcomes tend to be NE1.

SUPPORT. Consider the entries in Table 4 that are a classification of the outcomes taken from Table 3. A little over one third of the periods result in strict NE1. Approximately 71% have deviations less than 50Fr ($0.25-$0.50). This leaves only 29% of the periods resulting in outcomes that were not NEl or "near" NEl in the sense that the maximum opportunity cost of a move was low.•

The property is strengthened by the fact that the outcomes that are near NE1 tend to be *strong* NE1. Given the bids expressed in the mechanism at the final outcome, no coalition of more than one individual could construct a joint bid unavailable to members acting alone, that would produce benefits for some members of the coalition and hurt none of the others.

RESULT 3. Outcomes tend to be *strong* NE1.

SUPPORT. All *strong* NE1 outcomes are outcomes that are coalition-proof in the sense that a coalition of members has no profitable opportunities available to it at the final prices and allocations that the individual members could not carry out unilaterally. This result was obtained by brute force, i.e., a computer algorithm was used to do an exhaustive search over all coalitions for profit opportunities, given the final prices and allocations in each trial. No additional opportunities for profitable bids, outside those available to individual agents, were found.•

An efficient outcome does not require NE1 behavior, just as NE1 behavior does not guarantee efficiency due to the existence of multiple equilibria. However, if the conjectures behind the design of the mechanism presented in the preceding section are correct, one would expect there to be a correlation between NE1 and efficiency. An examination of the inefficient outcomes yields the following result:

RESULT 4. Inefficient NE1 do not occur.

SUPPORT. In the environments studied, inefficient outcomes coincide with failure to converge to a NE1. Period 2-experiment 3, period 3-experiment 2, and period 5-experiment 3 resulted in inefficient outcomes. In Table 3, these three trials account for the three largest deviations from a NE1 outcome.•

COROLLARY. If outcomes are inefficient then they are not NE1.

The Corollary above, together with Result 2, present natural questions. Why does the process result in NE1 outcomes and why among those does it seek only the efficient outcome? Is this a lucky accident or is it related to the game theoretic structure of the problem? The answer is suggested by the Nash equilibrium convergence property of the discrete pivotal process stated as Remark 2 in Section 6. The next result indicates that is the case.

In order to facilitate the result, Table 5 was compiled. Every non-null individual bid was recorded by a computer during the experiments. Classification of these bids into the pivotal, neutral, and dominated categories is done and recorded in the table.

RESULT 5. Convergence to NE1 is governed by the *discrete pivotal process*.

SUPPORT. If the process is operative then convergence will be to a NE 1 by virtue of Remark 2. Only two assumptions of the process involve behavior. One of the assumptions, listed as (iv), is that individuals will choose in accord with the Exhaustive Offer Hypothesis and then will not let the process stop if pivotal bids exist. The tendency for this property to be satisfied is established by Result 2. The second property is that individuals not tender dominated bids. The data in Table 5 reveal that dominated bids account for 0-6% of the bidding activity. Thus, the tendency of bidding behavior is to tender non dominated bids as required by the process. With the tendency for both of the properties of the process to be satisfied one can conclude that it is operative and thus characterizes equilibration.•

The fact that the assumptions for the class of discrete pivotal processes seem to be satisfied suggests searching the bidding data to see if the type of behavioral dynamics in operation can be isolated more precisely. Result 6 shows that the strong neutral bid processes are good candidates. The case is made by eliminating from consideration those dynamics, like "local" or "one stage" Nash/Cournot reaction functions, that suggest that no choice will be made unless it changes the state in a favorable way. Strong neutral bids are those (non dominated bids) that place the bidder as the high bidder for a train that is not part of the potential allocation even after the bid is tendered. Thus, it does not change the state and thus is not explained by the dynamics of one stage Nash/Cournot reactions. The concept of strong neutral bids adds behavior that is absent from the more game theoretic principles of behavior. The data from Table 5 will be used to show that strong neutral bids are frequently made. The data from Table 6 will be used to show that the dynamics exhibit no tendency to stop at a NE1 the first time such a state is reached.

RESULT 6. From among many possible discrete pivotal dynamic processes, the class of strong neutral processes receives support as an explanation of the convergence path.

SUPPORT. First, strong neutral bids exist as a substantial feature of bidding behavior. On average, strong neutral bids consist of approximately one third of all bidding behavior. Note from the Table 5 that in some periods there are more strong neutral bids than pivotal bids, and in others, vice versa. Thus, even though with the same period parameters, different experiments can have substantially different ratios of pivotal bids to neutral bids, a tendency exists for a substantial portion of bids to be strong neutral. Second, a tendency exists for the dynamics to not stop at NE1 when they are attained. Thus, the dynamics tend to not be the discrete pivotal processes that limit behavior to NE1 reaction functions. Table 6 examines the frequency with which bids place the mechanism at an NE1 intermediate outcome. No attempt is made to distinguish between NE1 outcomes which support the same allocation but which are slightly different in bid price and those which produce different allocations. According to Table 6, either the mechanism never reaches an NE1 outcome, or it passes through multiple NE1 outcomes. From Tables 3 and 6 , only in two of the twenty-one cases, namely period 3-experiment 3, and period 6-experiment 2 does the mechanism stop at the first NE1 outcome reached. Since, the class of discrete pivotal processes where strong neutral bids are not used must stop at the first NE1 outcome encountered, those dynamic processes can be discarded from consideration. Thus, the presence of multiple NE1 intermediate outcomes and the use of strong neutral bids at intermediate NE1 outcomes suggests a refinement like the strong neutral process.•

The fact of efficiency when taken with Results 5 and 6 creates an interesting picture of the dynamics. The mechanism wanders over the allocations until the optimal set of trains is "discovered". The bidding then proceeds to advance until an allocation of the set of trains and a set of bids is attained that supports the optimal as a NE1. The process of the "discovery" of the optimum must be associated with a process of preference revelation and coordination. We have no rigorous theory about how this might take place but the intuition rests on the submission of strong neutral bids which reveal the social opportunity cost of the allocation. The basic intuition is that individual bidding behavior is consistent with the Exhaustive Offer Hypothesis. Strong neutral bids will be made as a type of "negotiation" process driven by the possibility that the auction will terminate unless a bid is made. By making bids on unallocated trains an agent is contributing to the "public good" of defeating the current allocation. The strong neutral bid process holds that a person will reveal rather than let the market close. When the possibility for strong neutral bids is exhausted, then all excluded agents have revealed the maximum any would ever be willing to pay for the excluded trains. Since the potential allocation is of higher value than any allocation possible from the excluded trains, the final allocation must necessarily be efficient if the excluded agents are fully revealing their willingness to pay.

If the NE1 property of the dynamics of the discrete pivotal process guarantees that the high value bidder has the final standing bid for allocated trains; and, if the high value bidder has the final standing bid for excluded trains, then whatever trains are allocated will be allocated to those who value them the most. The only question is how the proper set of trains might be chosen. If, in addition, the excluded agents bid as high as their redemption value, then the operation of the BICAP mechanism assures that the proper allocation will be chosen and that an efficient allocation will be the final result. Thus, several measurements of value revelation are suggested by this logic. For excluded trains, does the high value bidder have the final standing bid? How high is this bid, either in terms of a percentage of the agent's redemption value or as a distance from it?

A complication in the parameters makes a clean analysis difficult. Often an agent will have high redemption values on a pair of trains which are in conflict. In this case, it may not be to that agent's advantage to have the high bid for both trains, since he would, in effect, be bidding against himself. An opportunity cost exists for the agent that lowers the agent's value on the excluded train by the amount of potential profit on the allocated train for which he has the standing high bid and which would be foregone if the allocation switched to the other train. Thus, the data can be divided into the "clean cases" for posing the questions and the "unclean cases." The conjecture that follows summarizes the weight of our assessments.

CONJECTURE. Social opportunity costs of allocation are revealed through the operation of the BICAP mechanism.

SUPPORT. The clean cases are selected pairs in selected periods in which the conflicts happened to not exist. Different agents have the high value for trains A and B in period 7, for trains C and D in period 4, trains E and F (also) in period 4, and for train G in periods { 1,2,3,5,6 }. In all other periods the same agent will have high values for a pair of conflicting trains. In period 7, train B is excluded from the allocation, and in period 4 trains D and F are excluded while G is excluded in all periods. Aggregation over the periods and trains above provides 24 excluded train "clean cases" for analysis of the conjecture. In these cases the high value individual tends to hold the high bid and also reveal the value to the mechanism. The results are: (i) The high value agent has the high closing bid in 18/24 or 75% of the 24 excluded train cases; (ii) On average the excluded agent bid 93.8% of the high redemption value for the 24 excluded train cases.[10] Thus, the social opportunity cost is revealed in these cases.

The "unclean cases" are more difficult. Revelation behavior is different when the holder of the high redemption value for one train that is included in the potential allocation also holds the high redemption value on another train that is excluded from the potential allocation. If all unclean cases are aggregated (all cases in which the high value agent has the high value for a pair of conflicting items), the high value agent has the final bid on the excluded item in the pair a total of 33 out of 60 cases. Thus, in 27 of 60 unclean cases the high bidders on the excluded items are not the agent with the highest redemption value. In this sense, the social opportunity cost information is not reveled to the mechanism. However, the revelation is as one might expect from a design consistency point of view. The second high value agent has the final bid on the excluded item in an additional 18 out of 60 cases. Bid revelation by one of the top two value agents then yields a total of 51 out of 60 cases. This suggests that while agents may not bid as high as the highest redemption value on excluded routes, the second highest redemption value holder is being revealed.

The natural question now is whether the redemption values are being revealed. For this a measure is developed.
For each train, set

$$d_2(f) = \max(0, \text{2nd highest redemption value for } f - B(f))$$

If the final bid is above the 2nd highest redemption value, then $d_2(f)=0$. d_2 is thus a measure of the amount by which the bid is less than the second highest redemption value.

Table 7 compares bid prices with redemption values, in such a way as to pool data across all periods. On average, when optimal allocations occur, revelation of values is near the second highest redemption value. This occurs to within an average of 10Fr on allocated routes and 28Fr on unallocated routes. Depending upon the individual this amounts to something on the order of a nickel to a quarter on an item that is worth several dollars.•

[10]The overbid by agent 10 in period 4, experiment 2, train D was counted as a bid for the full amount of the redemption value, 594, and not the amount of 920 which was bid. Using the amount of 920 would have raised this figure still further.

The pattern of results provide much evidence of design consistency. The reasons for the efficient allocations are for theoretically understandable reasons. Agents do not limit their behavior to reaction functions that only make themselves better off. They take actions that make no changes in their own well-being but depending upon the actions taken by others might make themselves better off. This dynamic leads away from inefficient allocations that otherwise might exist as equilibria. The nature of BICAP is such that it pits competitors against each other such that values become revealed to the mechanism and then it uses that information to move the system in a dynamic in the direction of optimal allocations. The analysis also suggests that the nature of potential inefficiencies might be related to agents with "conflicts" and the resulting "market power." Having a degree of "power" they might not bid against themselves and as a result prevent some degree of information revelation. This lack of efficient operations is clearly a parameter issue and not an issue related to the principles upon which the mechanism design rests. Nevertheless, it is important to note that while from the point of view of design consistency this issue surfaces, it was not generally a problem in the operations of the mechanism since the mechanism operated at near 100% efficiency.

9. CONCLUSIONS

This paper began with questions motivated by the proposal to privatize the railroads in Sweden. Critics of the proposal have claimed that as a matter of principle a decentralized decision process cannot be used as an allocation tool. Advocates of the program have claimed that certain problems created by a system of priorities that exist in the current allocation process could be solved by a decentralized process. The question posed was whether or not it is possible to create a process that will successfully allocate resources under conditions that critics say will render the task impossible, which at the same time will avoid problems that would exist if a system of priorities was in place?

The answer is that is it is possible. Such processes exist. A testbed environment, which was developed in the paper, contained many of the elements that decentralization critics claim will prevent the operation of a decentralized allocation or market process. In this environment the Binary Conflict Ascending Price (BICAP) mechanism operated at near 100% efficiency. Furthermore, analysis of the behavior of the mechanism reveals that the reasons for the efficient operations was not simply a fluke or an accident of choice of experimental procedures. The details of behavior were substantially in conformance with behavioral models of the process. Thus, proof of concept has been established in the sense that the process is observed operating efficiently. Furthermore, a principle of design consistency has been satisfied as well since the outcomes are occurring for the right reasons.

Clearly the issues raised by the deregulation effort in Sweden do not end with this paper. More complex environments must be pursued and the BICAP might become modified in order to accommodate the problems that they present. Firstly, there are issues of scale. The restriction of trains to only a set of nine avoided problems that may surface with presentation of data to participating agents. The reduced scale also avoided confrontation with certain computational problems. While these two problems must be solved, the experiments here suggest that the problems are only technical. If speed of computation can be attained and if the screen displays are manageable then under the additively separable preferences and a sufficiently competitive network, the BICAP mechanism should work efficiently at a large scale.[11] Nothing in the testbed environment suggested that strategic or coordination or any other economic consideration, would be a source of problems.

More complex environments must be studied now and might be more important than scale considerations. There are problems that might surface with different types of preferences. Preferences in the testbed were additively separable. More complex preferences involving non additive sets might make the pivotal process less applicable and thus take the research into areas in which the behavior might not be so clearly understood as it was in this first testbed. In addition to the problem of non additivity, a possibility exists that network externalities between specific operators might be present. The passenger load of one train might depend heavily on the particular operator of a different train. Or, even more complex would be cases in which the preferences of operators for other trains in the network might depend on the particular operator of the trains. The theoretical literature contains suggestion about how BICAP mechanism might be modified to deal with such problems but the research is yet to be done.

This study as provided a first step along a possibly long road of necessary research. A decentralized mechanism can be designed to facilitate the efficient access to a complex network like a railroad. Such processes cannot simply be dismissed as impractical. The BICAP mechanism introduced here and the testbed environments are an open invitation to theorists that might want to try their hand at improved designs.

[11] Depending upon the pattern of train conflicts, computing time could rise exponentially in the number of trains. This is because the optimization problem is NP-complete. If this effect exhausts computing resources, then some changes to the optimization portion of the mechanism would probably be required.

APPENDIX I EXPERIMENTAL INSTRUCTIONS. BICAP. 7/7/93. 1ST7 TESTBED

Introduction

This is an experiment in the economics of market decision making. The instructions are simple, and if you follow them carefully and make good decisions you might earn money which will be paid to you in cash.

In this experiment, we are going to conduct a computerized market over a sequence of trading periods. The items to be sold are called projects, and are designated by letters of the alphabet (project A, project B, project C, etc...). You may try to purchase any number of projects as you wish. The value to you of any particular project is detailed on an attached set of redemption value sheets. Notice that these sheets are labeled period.1, period.2, etc... Notice that the redemption values vary from period to period. During the experiment, pay careful attention to make sure you are using the correct sheet in evaluating which project(s) you wish to purchase. [note: the information on the redemption sheets is your own private information. do not reveal it to anyone.] At the end of each period, project(s) you have purchased are redeemed by the experimenter for the amounts indicated on these sheets.

Your profits in a period, then are determined by the difference in the redemption amount you receive for the projects you purchased and the amount you paid for them.

i.e. **your profit = (total project redemption value) - (total purchase price)**

Each project can be sold to one and only one buyer during each period. The projects are sold via an auction, carried out using the computer terminals. You will have an opprotunity to bid on each project as many times as you wish. To bid, follow the instructions at the bottom of the screen. Bids are not binding until the SEND key is hit. Bids which are lower than the current bid on the screen are ignored. Once your bid for a project is sent into the system, and becomes the current bid, you are obligated to honor it until someone else bids higher on the same project, at which point it is deleted from the system.

There is an additional complication. Not all combinations of projects are possible. For example, it could be that if X is sold, that Y or Z cannot be sold. Incompatible groups of projects are detailed on an attached sheet. The computer will use the bidding information to determine which group of projects to sell to maximize the amount of money collected from buyers. The set of high bids which would actually be accepted by the computer at any particular time is displayed on the computer screen and updated along with any new bids.

At the end of each period, the computer notifies each buyer of any successful bids. Unsuccessful bids are not displayed. At this time, buyers should fill out their BUYER RECORD SHEET and calculate any profits (or losses) from the period.

Currency:

The currency used in these markets is "francs." At the end of the experiment francs will be

converted to dollars at the rate of: ________________ francs equals one dollar. [the exchange rate is also private information. do not reveal it to other participants.]

None of the following pairs are feasible, nor is any combination containing one or more of these pairs:

A,B
A,C
A,G

B,A
B,D
B,G

C,A
C,D
C,G

D,B
D,C
D,E
D,G

E,D
E,F
E,G

G,A
G,B
G,C
G,D
G,E
G,F

H: nothing conflicts with H. H is allways feasible.

I: nothing conflicts with I. I is allways feasible.

Examples:

{A,D,F} is feasible since neither A,D , A,F or D,F are listed above.

{B,D,F} is not feasible since B,D is listed above as being impossible.

ID NUMBER: ________ PERIOD#	LIST PROJECTS PURCHASED	TOTAL PURCHASE PRICE	TOTAL REDEMPTION VALUE	PROFIT OR LOSS(-)

Appendix II: Experimental Data

The data sets for this experiment, if printed out, would easily exceed 50 pages. Only summary information is presented here, yet this information should be sufficient for most analysis. A full data set on diskette is available by request.

The information is broken down as follows:

II.A : Parameter summary

II .B: Final allocation and prices by period

Second by second bidding information is available from the authors on diskette, but is not presented here.

Rule	Interpretation
A>B; C>D; E>F for every firm.	Firms always can make more money running A,C or E than B,D, or F. Delaying the train imposes an additional cost.
max(G) < max(B+C+E,A+D+F), with the max computed over all firms (i.e. this is only one restriction, not a restriction for each firm – indeed it may be violated for particular firms but not in the whole)	G is never optimal. However, G is often high enough to be an obstacle to firms trying to obtain one of the others (recall that G conflicts with all of A through F). This presents the possibility that a coordination problem may cause G to win when it is not optimal. note: the first two rules force the optimal allocation to be either A+D+F+H+I, B+C+E+H+I, or A+E+H+I. B+C+F+H+I is never optimal.
A firm may have the maximum value (among all firms) for up to one pair of {A,B}, {C,D} or {E,F}	This is to prevent monopoly. We are only interested in studying competitive behavior.
There is at least a separation of 500 between A+D+F and B+C+E.	From an efficiency viewpoint, there is no reason to be concerned if GAUSM yields only a slightly sub optimal allocation. We wish to test GAUSM in an environment where efficiency is substantially different over different allocations.
Firms having a maximum value (among all firms) for H or I may not have a maximum value for A through F.	This is to spread earnings out over subjects, so that none is so unlucky as to leave the experiment with zero earnings. Recall that routes H and I are always allocated, because they do not conflict with anything.

Train Redemption Values $V_j[f]$ for each period.
These same redemption value tables were used in all the experiments.

period 1

agent id#	A	B	C	D	E	F	G
0	332	232	878	708	746	426	2619
1	946	521	321	241	739	265	2491
2	302	198	307	270	1013	645	1329
3	1699	645	307	206	306	217	509
4	1282	454	1634	1447	341	134	2543
5	801	354	933	465	936	561	2339
6	389	242	387	117	583	348	423
7	320	132	1405	974	528	360	594
8	708	332	309	188	1635	1421	2005
9	372	277	341	138	395	284	1549

period 2

agent id#	A	B	C	D	E	F	G
0	368	133	683	346	320	108	1604
1	1124	980	319	269	340	291	93
2	303	219	335	168	1359	641	373
3	305	171	371	149	524	177	466
4	403	325	463	237	475	382	124
5	692	487	320	267	1027	515	1625
6	405	315	370	194	375	284	570
7	413	311	417	343	430	377	531
8	558	340	354	270	577	224	304
9	362	154	320	96	312	206	1710

period 3

agent id#	A	B	C	D	E	F	G
0	425	365	360	116	500	310	598
1	319	241	337	263	463	194	1843
2	528	382	350	117	306	206	1570
3	1858	615	840	662	384	264	412
4	456	376	1227	964	315	105	206
5	660	405	342	217	328	169	1336
6	413	227	314	248	368	257	382
7	448	290	371	274	943	774	1387
8	312	267	1025	657	482	341	247
9	300	109	451	244	309	257	1731

period 4

agent id#	A	B	C	D	E	F	G
0	1020	410	788	594	356	187	48
1	883	553	1193	381	537	310	392
2	516	334	768	385	309	106	1533
3	362	147	446	151	455	249	1401
4	496	348	303	128	1300	430	918
5	334	258	312	228	300	174	1386
6	516	222	386	139	1067	812	2057
7	366	157	309	245	652	290	607
8	319	158	597	499	306	247	1135
9	1371	1105	615	439	410	277	130

period 5

agent id#	A	B	C	D	E	F	G
0	680	501	347	121	318	283	1589
1	645	302	302	121	340	299	606
2	341	189	699	518	363	153	1636
3	365	151	599	193	873	557	1039
4	650	246	505	255	576	300	1395
5	2108	700	384	263	321	175	1616
6	436	349	726	235	580	356	1999
7	568	438	1162	873	369	246	34
8	301	103	465	194	570	281	1295
9	648	527	760	634	315	267	1470

period 6

agent id#	A	B	C	D	E	F	G
0	438	342	353	176	1005	603	514
1	565	398	419	151	405	141	114
2	788	459	675	334	514	360	67
3	300	219	462	179	389	305	214
4	305	111	671	327	342	218	143
5	374	294	669	272	785	471	864
6	527	360	385	218	500	245	1340
7	309	174	347	124	690	243	956
8	408	340	325	231	342	227	645
9	353	210	1341	749	645	397	724

period 7

agent id#	A	B	C	D	E	F	G
0	1444	581	308	174	452	270	401
1	480	288	337	224	838	554	54
2	1685	550	648	292	509	418	41
3	635	558	301	127	473	283	710
4	305	220	1071	931	486	266	1260
5	971	394	538	256	335	218	698
6	740	614	415	319	519	301	25
7	835	447	315	127	361	229	331
8	540	341	307	144	517	211	174
9	325	198	316	107	557	169	1133

II.B: High bids by period.

Format:

4960.	120.	12.	800-5.	350-3.	700-3.	302-9.	400-3.	1060-8.	1400-6.	350-2	575-4	0-0
time	d-time	period	bidsA	B	C	D	E	F	G	H	I	J

time — time in sec. since beginning of program (only differences are significant)

d-time – how long period lasted, in seconds.

period – period # in experiment. whenever a subject made a typographical error, it was necessary to reset the period. see the conversion table with each file to see which periods are free of typos and which periods go with which data sets.

bidsA — amount of high bid, followed by bidder ID number of high bidder.
Note: ID"10" here = ID"0" in parameter sets.

Note: The data here includes summaries for periods in which the subject made typographical errors. A table is included which maps experimental periods to parameter sets.

Data for 7/7/93:

Experimental Periods	Parameter Set Period
1	practice
2,3,4	1
5	2
6,7	3
8,9	4
10,11,12,13	5
14,15,16	6
17,18	7

time	d-time	period	bids A	B	C	D	E	F	G	H	I	J
133	96	1	0-0	0-0	300-4	0-0	300-4	0-0	500-3	0-0	0-0	0-0
1009	224	2	1650-3	451-1	251-1	3004-1	405-1	210-10	1600-10	400-9	600-10	213-6
1398	92	3	1001-4	500-3	50-6	0-0	200-1	0-0	5606-1	200-9	100-10	0-0
2338	923	4	1300-3	601-1	1401-4	1295-4	731-1	800-8	2601-10	890-5	1250-5	0-0
3203	727	5	1090-1	486-1	610-10	340-7	1030-2	514-5	1610-9	320-5	240-6	100-1
3379	42	6	3705-3	10-1	300-8	10-1	10-1	0-0	0-0	225-2	150-6	0-0
3944	554	7	1050-3	600-3	1100-4	811-4	500-7	341-7	1840-1	700-2	790-8	0-0
4340	330	8	99-10	6604-1	670-10	594-10	967-6	430-4	1450-6	500-3	400-2	0-0
4564	198	9	1000-10	726-9	790-1	594-10	1050-4	500-6	1450-6	400-3	400-2	0-0
4675	46	10	500-5	90-2	720-9	300-5	300-3	0-0	500-4	200-2	2855-7	0-0
4830	150	11	800-5	275-9	650-3	410-7	500-3	2222-7	900-4	250-2	420-6	0-0
4960	120	12	800-5	350-3	700-3	302-9	400-3	1060-8	1400-6	350-2	575-4	0-0
5624	659	13	1320-5	525-9	932-7	654-7	850-3	360-3	1589-10	550-4	800-4	0-0
5774	76	14	550-2	300-2	1505-9	120-1	500-5	120-1	800-6	150-3	210-8	0-0
5957	173	15	600-2	400-2	666-9	300-2	6306-7	305-3	1340-6	156-3	222-1	0-0
6234	272	16	701-5	425-2	676-9	310-4	791-10	400-5	1340-6	353-1	450-6	0-0
6419	67	17	910-5	400-2	500-2	300-5	101-8	100-1	0-0	100-1	2727-6	0-0
6810	387	18	1450-2	560-1	610-1	350-4	730-1	410-1	710-1	165-10	396-10	0-0

Data for 7/10/93 – 7pm

Experimental Period	Parameter Set Period
1,2,3	equipment testing, subject practice
4,5,6,7	1
8,9,10	2
11,12	3
13,14,15	4
16,17,18,19	5
20	6
21,22	7

time	d-time	period	bids A	B	C	D	E	F	G	H	I	J
109	5	1	0-0	0-0	0-0	0-0	0-0	0-0	0-0	0-0	0-0	0-0
499	29	2	0-0	0-0	0-0	0-0	0-0	0-0	0-0	0-0	0-0	0-0
1954	255	3	5000-3	4400-2	3350-1	1000-4	501-6	520-5	4400-7	9045-1	7000-7	1000-6
2154	111	4	900-4	240-6	800-7	100-3	1000-8	130-4	5008-9	70-5	400-5	99-8
2314	133	5	1120-4	1100-9	850-7	500-7	1000-8	999-8	2100-1	200-5	600-10	0-0
2449	128	6	950-3	500-1	800-7	3005-4	1100-8	1001-8	2500-10	700-9	1100-10	0-0
2875	412	7	1300-3	520-1	1300-7	974-4	1112-8	900-8	2600-10	888-5	1250-5	0-0
3158	166	8	750-1	250-6	340-8	270-7	360-3	202-4	6012-10	161-5	88-9	0-0
3378	207	9	1000-1	250-8	3503-4	330-10	705-5	300-7	1620-9	177-5	200-6	2-5
3847	448	10	1000-1	500-1	660-10	330-10	1000-2	505-5	1660-9	320-5	190-6	0-0
3988	65	11	1002-3	100-4	0-0	100-7	0-0	0-0	1010-8	100-2	10-8	0-0
4743	750	12	675-3	381-5	1025-4	656-8	600-7	400-7	1830-1	786-2	790-8	0-0
4886	52	13	100-10	20-8	0-0	0-0	0-0	0-0	100-6	90-1	8004-2	0-0
5007	113	14	3203-6	101-8	300-1	101-8	370-4	101-8	500-3	155-8	358-2	0-0
5499	485	15	901-10	600-9	730-1	920-10	1299-4	805-6	2040-6	300-3	458-2	0-0
5795	219	16	400-1	2002-1	634-7	120-8	400-3	301-6	1336-2	77-5	350-4	0-0
5852	49	17	400-1	0-0	0-0	0-0	0-0	0-0	0-0	4211-8	0-0	0-0
5964	107	18	420-7	189-2	612-7	137-7	363-2	1502-1	100-3	470-6	600-4	0-0
6604	634	19	1101-5	527-9	800-7	634-7	750-3	360-3	1999-6	555-4	800-4	0-0
7262	595	20	700-2	409-2	700-9	334-2	800-10	360-2	1300-6	355-1	400-6	0-0
7419	104	21	900-2	1002-4	500-4	450-8	300-7	400-2	400-4	120-4	125-1	0-0
7761	340	22	1485-2	551-10	600-4	400-4	570-1	370-1	700-3	221-10	391-10	0-0

Data for 7/10/93 – 10pm

Experimental Period	Parameter Set Period
1,2	testing practice
3,4,5,6	1
7,8	2
9,10,11	3
12	4
13	5
14,15,16,17,18	6
19,20,21,22	7
23,25	8

time	d-time	period	bids A	B	C	D	E	F	G	H	I	J
3904	177	2	6-7	9999-7	9999-7	9999-7	9999-7	9999-7	9000-6	700-5	1200-3	9999-2
4108	117	3	800-3	400-1	300-6	400-5	1000-8	1000-8	2001-8	1000-5	800-5	700-10
4192	75	4	2002-3	6002-8	1000-4	0-0	2002-6	0-0	2000-1	1000-5	700-5	0-0
4286	69	5	200-3	0-0	2508-4	0-0	2300-6	0-0	2030-10	500-5	500-5	0-0
4902	602	6	1500-3	520-1	1000-4	1000-4	1100-8	1000-8	2615-10	900-5	1250-5	0-0
5256	231	7	1000-1	275-4	460-4	300-10	2655-8	500-2	1500-10	207-5	200-6	0-0
5992	729	8	1100-1	400-5	682-10	345-10	1059-2	300-4	1610-9	333-5	200-6	0-0
6159	88	9	500-3	100-4	700-4	500-3	340-6	0-0	100-9	1002-10	300-8	0-0
6241	77	10	500-3	0-0	700-4	500-3	400-7	0-0	1200-1	500-6	1250-5	0-0
6664	421	11	1000-3	364-10	1050-4	675-4	550-7	350-7	1560-2	786-2	770-8	0-0
7065	319	12	1150-9	550-9	800-1	500-10	1100-4	255-9	1900-6	260-3	458-2	0-0
7495	380	13	1500-5	520-9	1135-7	520-9	700-3	360-3	1995-6	575-4	760-4	0-0
7633	81	14	400-10	200-8	400-9	100-9	3005-7	50-9	800-6	100-1	300-6	0-0
7742	103	15	350-8	210-3	400-9	100-9	1206-.10	200-2	1000-6	135-1	320-8	0-0
7818	71	16	300-8	200-8	5030-9	50-9	650-10	50-9	0-0	310-1	310-8	0-0
7917	49	17	400-6	0-0	4503-9	0-0	0-0	0-0	0-0	0-0	0-0	0-0
8337	417	18	700-2	400-2	750-9	400-9	780-10	400-5	1000-6	353-1	400-6	0-0
8495	73	19	700-7	200-3	500-4	50-10	1002-1	0-0	710-9	1-5	0-0	0-0
8627	128	20	800-10	4254-3	600-4	450-4	560-1	250-6	900-9	125-2	125-2	0-0
8959	324	21	1389-10	555-3	640-2	440-4	700-1	650-1	1250-9	200-10	399-10	0-0
9170	209	22	1485-2	510-10	648-2	450-4	625-1	420-1	1133-9	170-10	400-10	0-0
9422	178	23	530-2	450-5	675-4	320-9	801-5	200-6	1750-7	6107-10	650-9	0-0
9619	194	24	700-8	555-5	675-4	400-8	1000-8	400-8	1600-10	9049-10	850-9	0-0
10266	634	25	900-8	567-5	670-4	400-8	1050-8	500-8	1842-2	1203-10	1510-9	0-0

APPENDIX III

In recent years, several different computer assisted markets or other computer assisted allocation mechanisms have been developed, possibly as a response to both a perceived increased demand for decentralized allocation of complicated systems and an increasing supply of networked computing equipment necessary to carry out complex bargaining procedures involving many agents. The Table in this appendix summarizes these efforts. Many of the mechanisms listed in the table could be suitably modified for rail allocation. Rather than compare and contrast the results from each study, the purpose of this appendix will be to compare the BICAP mechanism developed here with the AUSM mechanism of Banks, et.al. [1982]. To begin, a short review of the AUSM mechanism is presented. Then, the similarities and differences between the two will be explained.

The AUSM mechanism was developed in response to space station resource planning problems. On the space station there are N goods in finite supply, and agents require definite packages of these goods. Often the goods are strong complements and not substitutes, e.g. an astronaut needs oxygen, heat, water and volume, and without the required amounts of each of these goods cannot be safely placed on the station. The question posed was how to allocate goods packaged to agents' specifications in such a way as to maximize efficiency.

Banks, et.al. message space allows bids to take the form (**d** , V) where **d** is a demand vector specifying (possibly zero) demands of each of the N goods and V is a willingness to pay for this vector of resources in terms of a numeraire good. At each stage of the mechanism, there is a potential allocation consisting of a set of bids which would be accepted if no more bidding were to take place.

When a new bid is entered, it is compared with the potential allocation. If there is sufficient unallocated supply for the new bid to be satisfied, the new bid is included in the potential allocation. If there is not sufficient unallocated supply, the new bid is compared with the bids in the potential allocation, and those bids which maximize allocation value are retained as the new potential allocation. This means that either the new bid is accepted, and older, less valuable bids are discarded, or the new bid is discarded.

There are two different versions of AUSM, depending on what is done with the discarded bids. In AUSM with QUEUE, discarded bids are sent to a bulletin board where agents coordinate and possibly recombine and resubmit their bids. Without the queue, no such coordination between agents is allowed.

In comparison to BICAP, these mechanisms sound very similar. Both are iterative, and report back to agents potential allocations which would take place should no more bids be submitted. In both cases, the potential allocations correspond to the bid revenue maximizing allocations, given the current bids retained by the mechanism.

Mechanism	Environment	Iteration Rule	Acceptable Bids	Bid Rejection / Removal	Allocation Rule	Payment Rule
Binary Conflict Ascending Price (BICAP)[a]	1 Seller Many Buyers	iterate until soft close	bid must improve upon previous bid for that object	higher bid on same object removes old bid.	objects allocated to maximize sum of closing bids	1st price
Adaptive User Selection Mechanism (AUSM)[b]	1 Seller Many Buyers	iterate until soft close	bid must improve value of the allocation	higher bid on same object removes old bid. change in potential allocation may remove bids.	objects allocated to maximize sum of closing bids	1st price
Sealed Bid Combinatorial Auction[c]	1 Seller Many Buyers.	one-shot sealed bids	bids with packaging constraints	does not apply	objects allocated to maximize sum of closing bids	dual pricing. price = value of additional unit.
Iterated Vickrey-Groves[d]	1 Seller. Many Buyers.	iterate until soft close	bids with packaging constraints	no cancellation possible (?)	objects allocated to maximize sum of closing bids	2nd price, from Vickrey /Groves formula.

[a] First defined in this paper.

[b] Jeffrey S. Banks, John O. Ledyard, and David P. Porter, "Allocating uncertain and unresponsive resources: an experimental approach," Rand Journal of Economics. Vol. 20, No.1 , Spring 1989

[c] S.J. Rassenti, V.L. Smith, and R.L. Bulfin, "A Combinatorial Auction Mechanism for Airport Time Slot Allocation" Bell Journal of Economics. Autumn 1982.

[d] Banks, et.al. 1989.

Mechanism	Environment	Iteration Rule	Acceptable Bids	Bid Rejection / Removal	Allocation Rule	Payment Rule
Rail Tantonnement[e]	One Seller, Many Buyers.	iterate until soft close.	train routes demanded at announced prices for track	prices adjust to reflect excess demand or supply and bidding starts over with old bids eliminated	demands granted when process equilibrates	market clearing price for each track segment
Gas Auction Net[f]	Many Sellers. Many Buyers.	iterative until soft close	suppliers /demanders send in limit order curves.	does not apply	objects allocated to maximize reported surplus	market clearing price for each market
Pipeline Tatonnement[g]	Many Sellers. Many Buyers.	iterate until soft close.	quantity demanded at announced price.	prices adjusts to reflect excess demand or supply and bidding starts over with old bids eliminated	demands granted when process equilibrates	market clearing price for each market
Cassini Resource Exchange[h]	Many Sellers. Many Buyers.	continuous	offers to trade resources	bid cancellation possible	chains of trades executed upon request	1st price

[e] P. Harker, S. Hong . "Pricing of Track Time in Railroad Operations: An Internal Market Approach". Working Paper, Fishman-Davidson Center for the Study of the Service Sector, The Wharton School, University of Pennsylvania.1992

[f] Stephen J. Rassenti, Stanley S. Reynolds, and Vernon L. Smith, "Cotenancy and competition in an experimental auction market for natural gas pipeline networks." Economic Theory, Jan. 1994.

[g] Charles R. Plott, "Research on Pricing in a Gas Transportation Network" Office of Economic Policy Technical Report No. 88-2. Federal Energy Regulatory Commission. Washington, DC. July, 1988.

[h] John Ledyard, David Porter and A. Rangel (1994) forthcoming

However, because AUSM discards bids which are not part of the current allocation and because BICAP does not, the mechanisms are not the same. In the BICAP bids once tendered are commitments until they are replaced by a better bid. This is true in BICAP whether or not the train is part of the potential allocation. However, in AUSM if a bid is not part of the currently accepted set it can be removed or canceled. Thus the strategic features of the two mechanisms differ.

Table 1: Operator Values for Trains in an Experimental Rail Environment

agent #	A	B	C	D	E	F	G	H	I
0	368	133	683	346	320	108	1604	127	127
1	1124	980	319	269	340	291	93	127	127
2	303	219	335	168	1359	641	373	127	127
3	305	171	371	149	524	177	466	10	2
4	403	325	463	237	475	382	124	68	173
5	692	487	320	267	1027	515	1625	430	7
6	405	315	370	194	375	284	570	0	1259
7	413	311	417	343	430	377	531	222	103
8	558	340	354	270	577	224	304	24	28
9	362	154	320	96	312	206	1710	319	168

Table 2: Summary of Experimental Parameters and Results.

period	high feasible package	A	B	C	D	E	F	G	H	I
1 - high redemption values	ADFHI	1699-3	645-3	1634-4	1447-4	1635-8	1421-8	2619-10	1432-5	1318-5
1 - 2nd highest redemption values	BCEHI	1282-4	521-1	1405-7	974-7	1013-2	645-2	2543-4	888-9	1231-10
1 - data from experiment 1	ADFHI	1300-3	601-1	1401-4	1295-4	731-1	800-8	2601-10	890-5	1250-5
1 - data from experiment 2	ADFHI	1300-3	520-1	1300-7	974-4	1112-8	900-8	2600-10	888-5	1250-5
1 - data from experiment 3	ADFHI	1500-3	520-1	1000-4	1000-4	1100-8	1000-8	2615-10	900-5	1250-5
2 - high redemption values	BCEHI	1124-1	980-1	683-10	346-10	1359-2	641-2	1710-9	430-5	259-6
2- 2nd highest redemption values	BCEHI	692-5	487-5	463-4	343--7	1027-5	515-5	1625-5	319-9	173-4
2 - data from experiment 1	BCEHI	1090-1	486-1	610-10	340-7	1030-2	514-5	1610-9	320-5	240-6
2 - data from experiment 2	BCEHI	1000-1	500-1	660-10	330-10	1000-2	505-5	1660-9	320-5	190-6
2 - data from experiment 3	AEHI	1100-1	400-5	682-10	345-10	1059-2	300-4	1610-9	333-5	200-6
3 - high redemption values	ADFHI	1858-3	615-3	1227-4	964-4	943-7	774-7	1843-1	886-2	849-8
3 - 2nd highest redemption values	BCEHI	660-5	405-5	1025-8	662-3	500-10	341-8	1731-9	757-6	759-5
3 - data from experiment 1	ADFHI	1050-3	600-3	1100-4	811-4	500-7	341-7	1840-1	700-2	790-8
3 - data from experiment 2	BCEHI	675-3	381-5	1025-4	656-8	600-7	400-7	1830-1	786-2	790-8
3 - data from experiment 3	ADFHI	1000-3	364-10	1050-4	675-4	550-7	350-7	1560-2	786-2	770-8

period	high feasible package	A	B	C	D	E	F	G	H	I
4 - high redemption values	BCEHI	1371-9	1105-9	1193-1	594-10	1300-4	812-6	2057-6	1123-3	1258-2
4 - 2nd highest redemption values	BCEHI	1020-10	553-1	788-10	499-8	1067-6	430-4	1533-2	254-8	368-5
4 - data from experiment 1	BCEHI	1000-10	726-9	790-1	594-10	1050-4	500-6	1450-6	400-3	400-2

4 - data from experiment 2	BCEHI	901-10	600-9	730-1	920-10	1299-4	805-6	2040-6	300-3	458-2
4 - data from experiment 3	BCEHI	1150-9	550-9	800-1	500-10	1100-4	255-9	1900-6	260-3	458-2
5 - high redemption values	ADFHI	2108-5	700-5	1162-7	873-7	873-3	557-3	1999-6	755-4	1102-4
5 - 2nd highest redemption values	BCEHI	680-10	527-9	760-9	634-9	580-6	356-6	1636-2	554-6	758-9
5 - data from experiment 1	ADFHI	1320-5	525-9	932-7	654-7	850-3	360-3	1589-10	550-4	800-4
5 - data from experiment 2	ADFHI	1101-5	527-9	800-7	634-7	750-3	360-3	1999-6	555-4	800-4
5 - data from experiment 3	ADFHI	1500-5	520-9	1135-7	520-9	700-3	360-3	1995-6	575-4	760-4
6 - high redemption values	BCEHI	788-2	459-2	1341-9	749-9	1005-10	603-10	1340-6	358-1	676-6
6 - 2nd highest redemption values	BCEHI	565-1	398-1	675-2	334-2	785-5	471-5	956-7	353-6	394-1
6 - data from experiment 1	BCEHI	701-5	425-2	676-9	310-4	791-10	400-5	1340-6	353-1	450-6
6 - data from experiment 2	BCEHI	700-2	409-2	700-9	334-2	800-10	360-2	1300-6	355-1	400-6
6 - data from experiment 3	BCEHI	700-2	400-2	750-9	400-9	780-10	400-5	1000-6	353-1	400-6
7 - high redemption values	ADFHI	1685-2	614-6	1071-4	931-4	838-1	554-1	1260-4	1483-10	1465-10
7 - 2nd highest redemption values	ADFHI	1444-10	581-10	648-2	319-6	557-9	418-2	1133-9	164-8	392-3
7 - data from experiment 1	ADFHI	1450-2	560-1	610-1	350-4	730-1	410-1	710-1	165-10	396-10
7 - data from experiment 2	ADFHI	1485-2	551-10	600-4	400-4	570-1	370-1	700-3	221-10	391-10
7 - data from experiment 3	ADFHI	1485-2	510-10	648-2	450-4	625-1	420-1	1133-9	170-10	400-10

Table 3: Most potentially profitable, available pivotal bids at end of period.

period	experiment 1		experiment 2		experiment 3	
	possible profit	who	possible profit	who	possible profit	who
1	0		0		0	
2	0		26	5	538	1
3	56	6	913	3	0	
4	16	6	57	0	10	6
5	30	6	105	7	352	7
6	0		0		4	5
7	7	5	47	5	0	

Table 4: Classification of final allocations as Nash equilibria.

Equilibrium Classification	#cases
strict Nash equil (d=0)	8
N.E. if subjects have thick indifference. (1<d<50)	7
borderline cases (d=56,57)	2
not Nash equil (d>100)	4

Table 5: Classification of individual bids.

period	experiment	bid event counts		
		dominated	neutral	pivotal
1	1	6	121	83
	2	2	20	60
	3	1	28	45
2	1	12	101	91
	2	1	44	63
	3	0	42	90
3	1	4	104	111
	2	3	81	142
	3	0	19	73
4	1	2	12	25
	2	4	54	74
	3	1	27	62
5	1	3	46	93
	2	3	66	93
	3	2	36	70
6	1	4	15	74
	2	6	34	129
	3	0	21	66
7	1	1	44	94
	2	6	37	75
	3	1	17	24
totals		62	969	1637

Table 6: NE1 outcomes during each period.

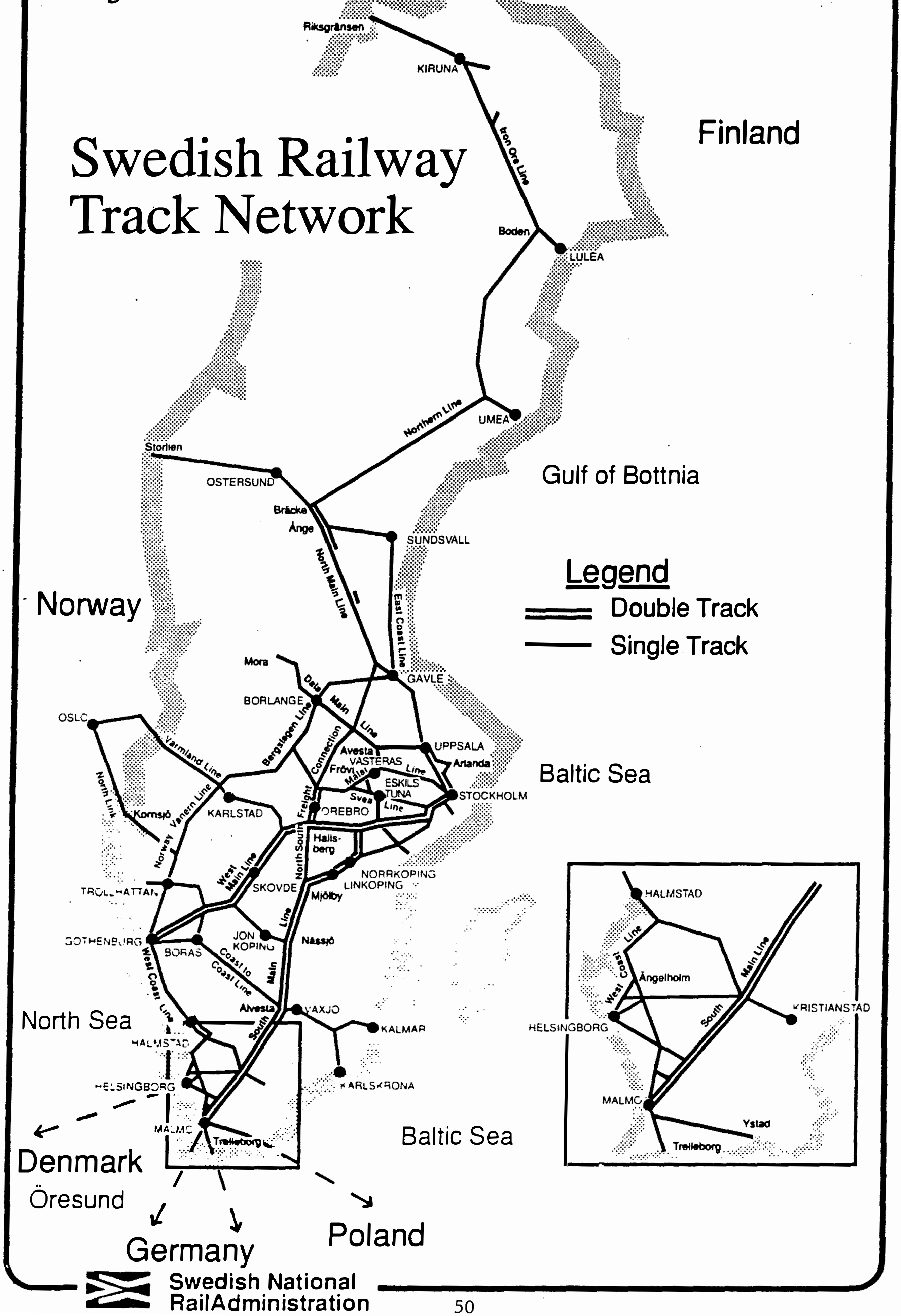
period	experiment	bids producing NE1 outcomes	
		strict (d=0)	within 50Fr
1	1	17	17
	2	2	9
	3	8	9
2	1	6	19
	2	0	4
	3	0	0
3	1	0	0
	2	0	0
	3	1	3
4	1	0	10
	2	0	0
	3	0	2
5	1	0	13
	2	0	0
	3	0	0
6	1	4	10
	2	1	7
	3	0	4
7	1	0	4
	2	0	1
	3	4	8

Table 7: Comparison of bid prices and the 2nd highest route redemption values.

Optimal Schedule	Allocated Schedule	#trials		d_2(A)	d_2(B)	d_2(C)	d_2(D)	d_2(E)	d_2(F)	d_2(G)	d_2(H)	d_2(I)
ADFHI	ADFHI	11	avg	0	15.8	44.6	10.4*	25.6*	0.7*	97.6	5.6	0.1
			max	0	71	405	114*	282*	8*	433	57	1
BCEHI	BCEHI	8	avg	17.4	0.5	7.3*	5.0	6.1	54.9	12.3	0	0
			max	119	3	58*	24	27	175	83	0	0
BCEHI	AEHI	1 (per#2-exp#3)	---	0	87	0	0	0	215	15	0	0
ADFHI	BCEHI	1 (per#3-exp#2)	---	0	24	0	6	0	0	0	0	0

Note: * --- this deviation value is entirely due to one experimental trial.

Figure 1


Swedish Railway Track Network
Legend
Double Track
Single Track
Finland
Norway
Gulf of Bottnia
Baltic Sea
North Sea
Denmark
Öresund
Germany
Poland
Riksgränsen
KIRUNA
Iron Ore Line
Boden
LULEA
Northern Line
UMEA
Storlien
OSTERSUND
Bräcke
Ånge
SUNDSVALL
North Main Line
East Coast Line
Mora
Dala Main Line
BORLANGE
Bergslagen Line
GAVLE
OSLO
Varmland Line
Connection
Freight
Avesta
VASTERAS
Mälar Line
UPPSALA
Arlanda
STOCKHOLM
Fröv
ESKILSTUNA
Svea Line
OREBRO
North Link
Kornsjö
Norway Vanern Line
KARLSTAD
Halls-berg
NORRKOPING
LINKOPING
Mjölby
West Main Line
SKOVDE
TROLLHATTAN
North South Line
GOTHENBURG
BORAS
JONKOPING
Nässjö
Coast to Coast Line
West Coast Line
Alvesta
VAXJO
KALMAR
South Main Line
HALMSTAD
HELSINGBORG
KARLSKRONA
MALMO
Trelleborg
Baltic Sea
Ängelholm
KRISTIANSTAD
Ystad
Swedish National RailAdministration

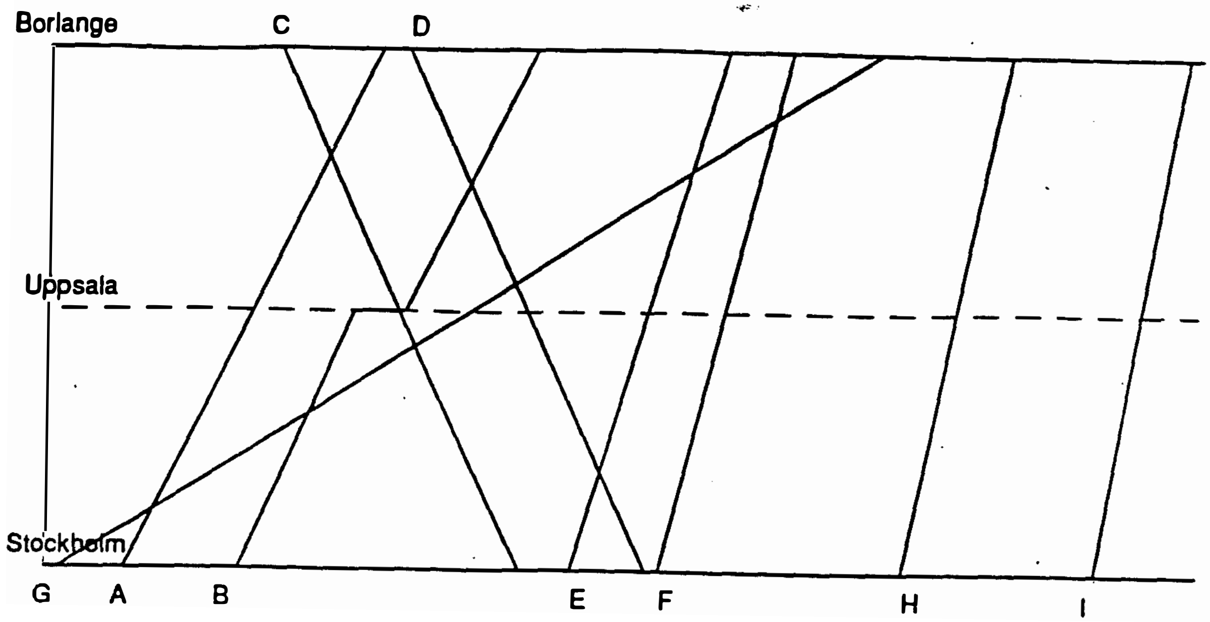


Fig. 2: Scheduling Diagram for routes in Experimental Rail system time ---->

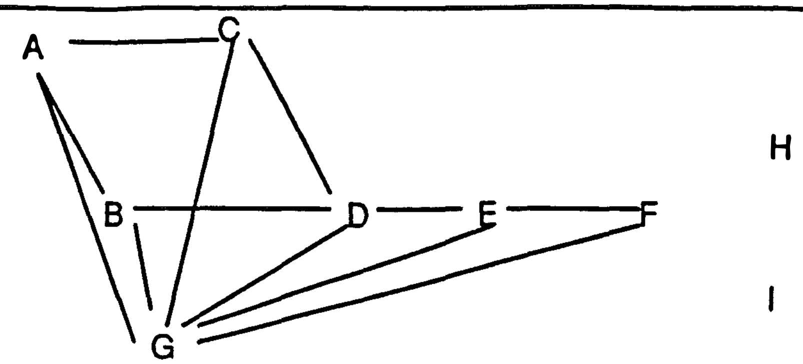


Fig 3 - Binary Conflict Graph for Testbed Environment id number: 7

Project	Current High Bid	Bidder ID#	Status	
A	225	3	ACCEPTED	
B	438	3		
C	80	7		<-- yours
D	500	8	ACCEPTED	
E	300	9		
F	290	2	ACCEPTED	
G	600	5		
H	50	1	ACCEPTED	
I	75	4	ACCEPTED	

To enter a bid for a project, press its corresponding key A-I.

Figure 4 -- Sample Screen

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