EQUAL TREATMENT UNDER THE LAW: THE EFFECT OF SOCIAL POLICY OPTIMIZATION ON CRIMINAL SUBPOPULATIONS

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ABSTRACT

Preliminary simulation analysis investigating the effects on recidivism, incarceration lengths, and CJS costs of alternate plea bargaining scenarios shows that, depending on how one chooses to weight sectors of the criminal population, different socially optimum policies result. However, not only will the optimum policy change for a given weighting scheme, but the effects on each subpopulation vis-a-vis recidivism rates and sentence lengths will differ as well. Our results show that CJS policy analysts should weight criminal subpopulation according to the subpopulation's representation in the entire criminal population when considering policy alternatives.

Introduction

The issue of performance measurement for the Criminal Justice System (CJS) has long been an issue for policy analysts, e.g., [11], [12], [16], [17], [18]. In the pursuit of the best statistic for measuring the efficacy of the CJS, models of the system or of the criminal phenomena itself are frequently used as tools for descriptive, predictive and prescriptive purposes [6]. To date, however, no one has determined if the usage of particular performance measures can introduce bias against classes of offenders. That is, can performance measures arise which, when used as policy making criteria, bias the operation of the CJS against classes of offenders without any component of the system knowingly prejudicing itself against a class of offenders. It is the purpose of this analysis to show, using a discrete event simulation model, that such bias can be introduced by inproperly defining aggregate measures of performance. Specifically, we develop career criminal-related statistics of the CJS cost and recidivism, and we show that weighted averages of these measures for each criminal subpopulation results in unbiased operation when the weights are proportional to the size of each subpopulation relative to the whole. We refer to the operation of the CJS in an unbiased fashion as the Equal Treatment Scenario.

The organization of this paper is as follows. First, we examine the methodological issues which are required for this analysis. The simulation model is discussed at length so that the reader is appraised of the vehicle of the analysis. Then, career criminal statistics are developed for guaging the performance of the CJS, and the experimental design is described in as much detail as is necessary for analyzing the

Equal Treatment Scenario. Finally, we discuss the results of these experiments in light of the bias issue, showing how bias can cause an analyst to select an otherwise less desirable policy over a better (to be defined) alternative. We also show how bias alters the treatment of offenders and we conjecture that biases in sentencing may be a result of the improper definition of a measure of performance.

Methodology

Simulation methods have been used to address many issues related to the operation of the Criminal Justice System. From the analysis of court delays, to the improvement of police dispatching, to the forecasting of work loads and recidivism rates, simulation models have touched on many topics related to the efficient operation of the CJS. Since several references are currently available which review these models [5], [6], [8], we shall not attempt a comparison of these methods here. The purpose of this section is to describe the specific model used in this analysis and to examine those performance measurement and experimental design issues which enable our exploration of the equal treatment scenario.

Model Structure

Our model of the CJS tracks each arrested offender from the time of his first arrest, through the court and corrections subsystems, and for the offender who is arrested more than once, until he either dies or his career in crime otherwise ends. However, it should be made clear that this model does not emphasize the events of the criminal career. Rather, the CJS itself is represented as a stochastic network with offenders percolating through the system.

The model has been implemented using the Generalized Network Simulator (GNS). GNS was chosen because it allows the simultaneous consideration of queueing, resource allocation and costing phenomena without the development of new computer code [9], [14]. Unlike other network representations, GNS requires that the nodes represent activities and that the arcs portray precedence relationships between the nodes. GNS differs from many network flow models in that the nodes for these other models represent either the initiating or terminating events of the activity represented along the arc. In either case, entities travel through the network along the arcs. If multiple arcs leave a particular node, GNS allows the user to choose the method of arc selection: it may be probabilistic or it may be a special user-designed rule.

The structure of the modeled CJS is displayed in Figure 1 using the diagraming techniques described by Tonegawa [14]. The solid arcs represent paths along which offenders travel through the network, and the dashed lines represent paths used by dummy entities for simulating the pre-trial detention of offenders. Each rectangle in the diagram represents an activity of non-negative duration, whereas rectangles butted against circles are referred to as queue boxes. Delays are simulated using these queue boxes in one of two manners. In some instances, queue boxes are used to postpone the movement of offenders through the network. This occurs notably with the recidivism processors (Box 19, 47, 48) where no real queue develops. The second use of the queue box occurs whenever one or more CJS resources (servers) must be available to process (service) an offender. (Table 1 shows the resources assumed for each CJS processor. Note that each box may require more than one resource type to process an offender, in which case one unit of each must be available for each offender served.) Other GNS diagraming conventions require the use of circles to describe the stochastic network. Large circles represent events (milestones) instead of activities in the network, whereas the smaller circles merely simplify the diagram. Half circles, on the other hand, represent sinks in the model where offenders are permanently removed from the simulation.

The generation of all offenders in the network occurs at the rectangle labeled Virgin Arrest Forecaster (Box 1). Deutsch's forecasting models are used to forecast the number of arrests per month [13]. Then Box 1 introduces each offender into the network, where each offender's route is determined randomly based upon the characteristics of the offender and of his offense. Certain interdependencies which have also been modeled to affect an offender's route through the network will be discussed in more detail later.

Because of the career criminal perspective of this model, several attributes must be maintained for each offender. These are an offender's sex, current age, and the age (or time) of his death, as well as the crime committed. Only the seven index crimes are considered: homicide, robbery, aggrevated assault, burglary, grand larceny, auto theft, and forcible rape. In addition, the length of the criminal career is assumed to be exponential (see [13] for more details). Other offender attributes are also maintained because of the objectives of our analysis. These attributes are statistics collected on each offender's criminal career:

1. The number of arrests,
2. The types of crimes committed,
3. The CJS cost attributable to the offender.

The importance of these statistics will be clarified in the next section

Much of the data used to implement this model has been taken from the CJS of Sacramento County, California; however, when such was not available for one reason or the other, statistics from other systems or from the nation's averages have been assumed. Regardless of the source of this data, care has been taken to ensure the normative behavior of the simulation model. The reader interested in further examining this data or the model's validation should consult Richards and Deutsch [13] for the details.

Performance Measurement

Measuring the performance of the entire Criminal Justice System typically centers around both the level of crime and the cost of operating the CJS. Although it is futile in the aggregate to differentiate between the costs of each subsystem (e.g., courts or police), it does make sence to examine the sources of crime. Thus, crimes committed by first offenders should be tabulated separately from those of recidivists since it can be argued that different forces are at work in each instance. The CJS's role in curtailing crime has been identified as being either through deterrence, rehabilitation, and incapacitation. Although the rehabilitative effects have been discounted as being negligible [18], the deterrence of first offenders and the deterrence and incapacitation of recidivists have recently been the subject of several analyses of the CJS [1], [2], [4], [10]. However, for this model, it shall be assumed that the deterrent effects of the CJS are also negligible, leaving only incapacitation to affect the crime rate. Because of these assumptions, it is obvious that only recidivism rates need to be considered in evaluating the CJS's impact on the crime rate.

In reporting the performance of the CJS with respect to cost and recidivism criteria, several approaches may be taken. The approach taken here is to view these measures in the career criminal sense. That is, recidivism shall be measured as the average number of arrests which occur during the lifetimes of offenders whose criminal careers end during the planning horizon. (Our experience with this measure shows that, after a suitable initialization period, the time series of this statistic is stationary and, therefore, it can be represented by the average over the planning period.) In a similar manner, the average cost of processing offenders through the CJS can be represented as the average cost of processing an offender over his entire criminal career. This so-called career criminal cost is computed assuming that all fixed costs and set-up costs are zero. The only mechanism used to impute the cost of operating the CJS to each offender is through his usage of resources, and these costs were given in Table 1. The actual career criminal cost for the i^{th} offender, $(CCC)_i$, is updated by the cost, C_k, of each resource k required for processing him at activity e by the relation

$$(CCC)_i = (CCC)_i + \sum_k C_k T_{ei} R_{ek}, \qquad (1)$$

where T_{ei} is the processing time of offender i at activity e, and R_{ek} is one if resource k is required to process offenders at activity e or it is zero otherwise. The average career criminal cost is simply the average over all offenders who desist during the planning horizon. (The time series of career criminal cost was also investigated. Like the recidivism measure, it too is stationary after the initialization period.)

These career criminal performance measures seem ideally suited to evaluating policy alternatives. Principal objectives of any systems analysis of the CJS is to appraise over the long term the rate of entry of citizens to the criminal population (as observed by the arrest of first offenders), the rate at which the criminal population commits crime, and the cost to society of suppressing the criminal element. Since our model assumes the rate of entry to the criminal population is invariant between scenarios, our concern is with the recidivism and cost statistics. The stability of the career criminal measures makes them more useful relative to such aggregate measures as the annual cost of operating the CJS or the total number of arrests of repeat offenders during each year. Annual cross-sectional statistics will in general be non-stationary if the recidivism rate is non-zero; it will be more informative to compare the average career criminal values rather than the gradients of the annual measures. In addition, the career criminal measures also have the advantage of being related to a specific cohort of offenders. Thus, one would not expect the biases which frequently arise in cross-sectional statistics to occur. (See Wolfgang, et al. [19] for a further discussion of the benefits of cohort studies.)

Although the career criminal statistics have several advantages, one disadvantage in analyzing policy scenarios arises from the strong negative correlation which exists between cost and recidivism (results show a correlation coefficient on the order of -.85). Optimally, one would like to simultaneously minimize both measures, but since reducing recidivism increases the cost of incapacitation, this is not possible. To avoid suboptimization by minimizing only one of these measures, a combined career criminal statistic is proposed which explicitly includes both the cost and the recidivism aspects of career criminality. The use of weighted measures is not uncommon in the field of optimization, especially under these circumstances. The new statistic is a linear function which converts the average number of arrests per criminal career into an expected social cost (in dollars) that society endures beyond the normal CJS costs when an offender commits a crime. Define the social cost of a single crime as γ. The expected cost to society of a criminal career under experimental policy ν is defined by

$$E_\nu(\gamma) = \gamma \, \overline{\beta}_\nu + \overline{C}_\nu \, , \qquad (2)$$

where $\overline{\beta}_\nu$ is the average number of arrests during a criminal career that is observed under policy ν, and $\overline{C}_\nu$ is the average career criminal cost for policy ν. With the selection of an appropriate γ, a social optimum may be found by choosing ν such that

$$E^* = \underset{\nu}{\text{minimum}} \, \{E_\nu(\gamma)\}. \qquad (3)$$

Minimizing $E_\nu(\gamma)$ over all policy options ν, however, reduces the appeal of career criminal statistics to policy makers. Not that optimizing an aggregate measure of social cost is faulty, but the particular statistic in (3) fails to allow for the ranking of categories of offenders under the paradigm of social optimization. To correct this inadequacy, redefine the social optimum as the policy which minimizes the weighted sum of the average career criminal social costs of each offender class j. That is, let

$$E^{*} = \underset{\nu}{\text{minimum}} \left\{ \sum_{k=1}^{J} P_j \, E_{\nu}^{j}(\gamma) \right\} \quad (4)$$

be the social optimum cost corresponding to the optimum policy ν^{*}, where P_j is the relative importance given to offender category j. For convenience, we require that

$$\sum_{j=1}^{J} P_j = 1. \quad (5)$$

Note that $E_{\nu}^{j}(\gamma)$, the career criminal social cost for offender category j, is defined by (2). Also note that γ is a constant over all j. We will specify a particular value for γ later in our discussions.

Experimental Scenarios

For our evaluation of CJS performance measures, a complete understanding of the policy scenarios examined and of the experimental design invoked is necessary for this particular effort. If our intent was to show that one measure is better than another, then full details of scenarios and experimental design would be essential; however, because our purpose is to illustrate the consequences of particular weights P_j in equation (4), then the details of each run are not essential now.

But, it should be understood that these scenarios deal with plea bargaining and, as such, they impact the rate and duration of incapacitation dynamically. The factors which are examined deal with the dynamic relationship of the length of the pre-trial delay and of case-specific variables to the disposition of offenders during plea negotiations [13]. The impact of these scenarios on incapacitation, although not measured directly, is inversely related to the expected number of crimes committed by career criminals, $\overline{\beta}_\nu$. Because the exact relationship is confounded (the recidivism delay is a function of disposition and age and the probability of re-arrest is both a function of the offense committed and the sex of the offender), the expected sentence length, S_ν, is defined by

$$S_\nu = f_\nu\left(\frac{1}{\overline{\beta}_\nu}\right), \tag{6}$$

where f_ν is some unknown function. Thus, only by conjecture can we "measure" the incapacitation effect of each policy.

To evaluate the impact of alternate P-weights, let it be sufficient to say that each of the policy runs affects recidivism and CJS cost measures and, by deduction, the incapacitation measure as well. For each policy run, then, the following statistics are collected: average career criminal cost and recidivism for each offender category. For this particular demonstration, the only distinguishing trait for offenders is assumed to be the criminal's sex. Thus, we divide the offender population into male and female offenders and evaluate changes in P_1 and P_2 (the weights for men and women, respectively) against the resulting optimal policy and the surrogate measure for incapacitation.

Simulation Results

The results of ten experimental runs using our model, are shown in Table 2. The statistics represent the average recidivism and career criminal costs for both male and female offenders whose careers in crime desisted during a 35-year planning horizon. The career criminal social cost has also been reported for both offender categories on all runs as specified by equation (2). The value assumed for the social cost of each arrest is γ = \$10,000. Beside each statistic in Table 2, its normalized equivalent is enclosed within parentheses. That is, define $\Xi_{\ell,\nu}$ as the ℓ^{th} statistic in Table 2 for run ν. The normalized value of $\Xi_{\ell,\nu}$ requires the linear transformation

$$\Xi'_{\ell,\nu} = \frac{\Xi_{\ell,\nu} - E_{\ell}\left(\Xi_{\ell,\nu}\right)}{\left[V_{\ell}\left(\Xi_{\ell,\nu}\right)\right]^{\frac{1}{2}}} , \qquad (7)$$

where E_{ℓ} and V_{ℓ} are the expectation and variance operators defined for the ℓ^{th} statistic as

$$E_{\ell}\left(\Xi_{\ell,\nu}\right) = \frac{1}{10} \sum_{\nu=1}^{10} \Xi_{\ell,\nu} \qquad (8)$$

and

$$V_{\ell}\left(\Xi_{\ell,\nu}\right) = E_{\ell}\left(\Xi^{2}_{\ell,\nu}\right) - E_{\ell}\left(\Xi_{\ell,\nu}\right)^{2} . \qquad (9)$$

Therefore, if $\Xi'_{\ell,\nu} < 0$, the statistic $\Xi_{\ell,\nu} < E_{\ell}\left(\Xi_{\ell,\nu}\right)$; likewise, if $\Xi'_{\ell,\nu} > 0$, then $\Xi_{\ell,\nu} > E_{\ell}\left(\Xi_{\ell,\nu}\right)$.

It is interesting to note from Table 2 that recidivism is almost two arrests for a male offender and almost 1.5 for a female offender. These averages underestimate the national average of about four arrests [7; 48], partly for empirical reasons and partly because approximately 20 percent of all offenders died in the model before their criminal careers ended stochastically. These deaths are a direct result of the exponential assumption on the remaining lifetime of an arrested offender, and the career criminal social cost should be scaled upwards accordingly; however, for our analysis we choose not to scale $\bar{\beta}_\nu$ because our conclusions are insensitive to such modifications.

If the ten runs are ranked on the basis of career criminal social cost for men, the ordering would appear as in Table 3. Note that this ranking portrays a weighting scheme corresponding to equation (5) of $P_1 = 1$ and $P_2 = 0$. The resulting list of policies places run $\nu = 10$ at the top, which is associated with above-average recidivism for both men and women (see Table 2). In fact, the ranking shows that policies ranked one to six, all have $\Xi'_{1,\nu} > 0$, while for policies ranked seven to ten $\Xi'_{1,\nu} < 0$. Thus, relatively high levels of recidivism tend to minimize career criminal social cost. Although this particular result may change depending on the true value of $\bar{\beta}$, the fact still holds that a policy's importance in a social optimum sense is affected by the measurement of recidivism. However, the choice of a CJS policy essentially prescribes a rate of recidivism which society is willing to withstand and, by conjecture, the expected length of prison sentences. Therefore, the choice of the recidivism measure and, in a more general sense, the priority weights, P_i, of equation (4) not only prescribe which policy is best, but they also define which policy changes are necessary and, consequently, the new rates of recidivism and incarceration.

To further illustrate this point, we have ranked these ten policies using weighting schemes other than $P_1 = 1$ and $P_2 = 0$. Two alternatives which might be chosen by an analyst are to weight each offender category in proportion to its representation in the entire offender population and, secondly, to weight each offender category equally. For our case of male and female offenders, we have computed E'_ν and E''_ν using these new weight distributions. As can be seen from their ranking in Table 4, only the order of policies 5, 7 and 8 changes from the $P_1 = 1.0$ to the $P_1 = .872$ case (viz, from E_ν to E'_ν). This restructuring of the ordered list, however, could change the final decision, not to mention the rate of recidivism. For example, if the decision became a simple choice between policies 5 and 8, the E_ν statistic would prefer policy 5 over 8, since $\text{Rank}(E_5) = 5$ while $\text{Rank}(E_8) = 6$. However, if E'_ν were chosen as the deciding factor, then policy 8 would be preferred to policy 5 with the gap between the ranked policies having been increased from 1 to 3. That is, if E'_ν is the decision criteria, two policies separate policy 8 from policy 5, whereas none separated these policies under E_ν.

Not only is the desirability of policies affected by the choice of E_ν over E'_ν, but the impact on recidivism is also considerable. For the above example, if policy 8 is selected over policy 5, recidivism increases for both sexes. The rate of increase varies for each sex. For men, 4.0 percent more re-arrests are made under policy 8, whereas women are re-arrested 1.5 percent more under policy 8 than under policy 5.

If, on the other hand, policies 2 and 5 were the only candidates for implementation, policy 2 would be preferred under either E_ν or E'_ν statistics and policy 5 would be preferred under the E''_ν statistic. Once again, differential recidivism rates exist for men and for women, except that now one rate increases while the other declines. For the transition from policy 2 to policy 5, the recidivism rate for men decreases 1.2%, while the rate for women increases by 1.1%.

Recalling our conjecture in equation (6), we can presume that under certain circumstances differential sentencing takes place. That is, it is now clear that each policy impacts each segment of the criminal population differently. One effect is different sentencing rates and/or durations for each sector of the population; another effect precipitated by differential sentencing is the observed differences in the rates of recidivism for each sector. This idea of unequal treatment by the CJS should not be unexpected, since at the outset it was stated that the policies ν are concerned with the disposition of plea bargaining defendents when case-specific information is available to the prosecutor. Since each offender may be classified on the basis of his sex, it is not inconceivable that the analysis of case-specific factors prior to disposing of defendents would tend to "pre-dispose" certain categories of offenders (under a more general offender classification scheme) whose case-specific variables usually fall within certain dispositional categories. This is not to say that the CJS knowingly discriminates against any sector of the criminal population, but statistically some offender categories may, on the average, receive harsher dispositions than other categories.

Because differential treatment must be predicated on the merits of a defendent's case and not on an apriori classification scheme, when CJS policy analysts compare feasible scenarios, bias against particular offender categories must not be introduced. To minimize the introduction of an arbitrary bias in the handling of cases, the selection of policy should be based, at least in part, upon a performance measure like E'_ν where the trade-offs between career criminal cost and recidivism are explicit and where each offender category's contribution to the measure is according to its percentage representation in the entire criminal population. Any other measure of performance for a CJS where deterrence is ineffectual would tend to bias the apparatus of the CJS against certain offender categories, since the normative response would require an equally weighted average over all offenders. In other words, the normative response would require a weighting scheme for E^* such that P_i is equal to the proportion of all offenders who are a member of category i. We have already observed that differing the weights, P_i, can alter the choices between policy alternatives and precipitate a situation in which very different outcomes would result for the average offender of each category.

Conclusions

Our analysis of a representative CJS using a discrete event simulation has shown the utility of evaluating policy as it impacts categories of offenders. By simulating offenders individually, we were able to examine the effect of each policy on career criminal cost and on recidivism for each category and inferences concerning the expected sentences of each were drawn. By assuming that a deterrent effect does not exist, we were able to show that an aggregate measure of performance which combines recidivism and cost statistics can be misused unless each offender, regardless of his classification, has an equal affect on the measure of performance. To use another scheme for measuring the contribution of offenders to the aggregate measure (for example, by weighting each offender category equally rather than each offender) may produce a different optimal policy than the unbiased case, and also may result in the differential treatment of offenders who belong to specific offender classifications. In other words, the system would be operating with a bias against certain offenders even though each individual component of the CJS would be operating in an unbiased fashion using decision criteria or operating procedures suggested by the optimum policy.

Although it may seem that our results in Tables 2-4 are due to random error rather than to differential treatment, the tabulation in Table 3 of the estimated number of crimes saved in going from policy ν to policy 10 (which minimizes E_ν) shows that the difference in the number of crimes resulting from two differnt scenarios is significant for male offenders. In addition, for $n \doteq 15000$, the Central Limit Theorem tells us that the variance for both the recidivism and the career criminal cost statistics for men is small [15]. Similarly, the variance for female offenders is also small because the number of women whose criminal careers ended during the planning horizon is on the order of 2200 for each run.

The question that should arise after reading this analysis is: what is the benefit of incorporating criminal subpopulations into a model of the CJS if ultimately it is necessary that the optimization measure be based upon the average characteristics of all offenders? In part, the answer is based on precedence. Several models of performance are currently being used to evaluate the CJS and these models do not assume a homogeneous offender population. Because the empirical data has been available, simulation models like JUSSIM [3] and COURTSIM [11] have all used crime as a discriminating factor for criminal populations and a great deal of work has evolved which examines the transition of offenders from one category (crime) to another [19]. What is used here, however, is not only a model wherein offenders commit different crimes, but a more fundamental grouping is based on the demographic characteristics of offenders. Thus, not only does this information directly impact the CJS, but it also offers a means wherein crime control policies can be examined which are directed specifically at crime-prone subpopulations.

ACKNOWLEDGEMENTS

This work was performed, in part, under grants numbered 75NI-99-0091 and 78-NI-AX-0003, from the National Institute of Law Enforcement and Criminal Justice. Points of view or opinions stated in this document are those of the authors and do not necessarily represent the official position or policies of the U.S. Department of Justice.

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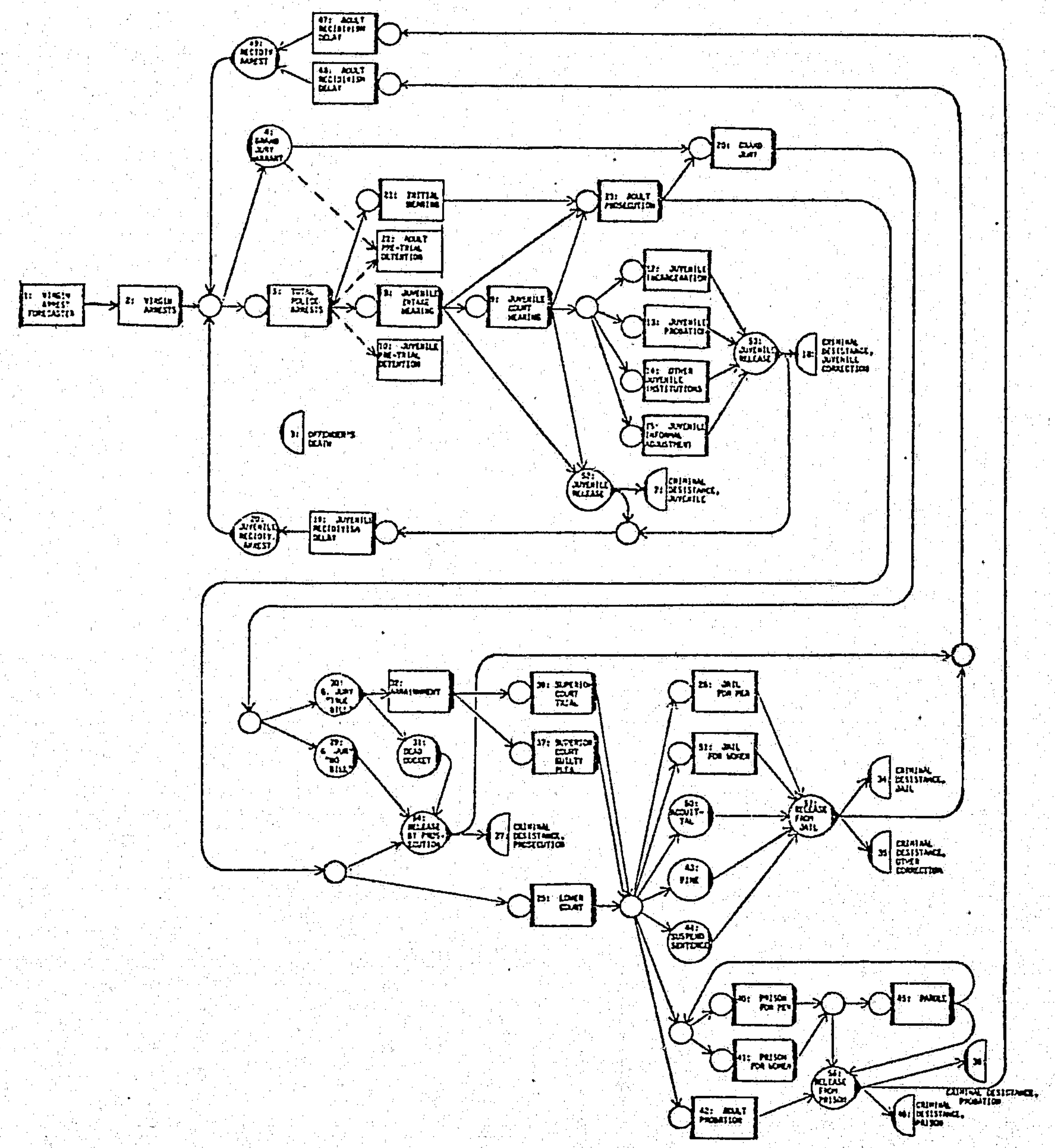

Figure 1. A GNS Model of the Criminal Justice System

Table 1. CJS Model Resources

Resource Number	Resource Type	Daily Cost Per Offender	Queue Box Numbers
1	Prosecution	$ 425	23, 28, 37, 39
2	Police	4010	5
3	Superior Court	1550	37, 39
4	Other Courts	336	8, 9, 21, 25
5	Grand Jury	474	28
6	Junvenile Corrections	103	12, 13, 14, 15
7	Adult Incarceration	20	26, 40, 41, 51
8	Parole and Probation	10	42, 45
9	Pre-Trial Detention	145	10, 22
10	Indigent Defense	544	25, 39

Table 2. Simulation Performance Measures

Experimental Run	Average Male Recidivism (No. Offenses)	Average Male Career Criminal Cost	Average Social Cost Per Male Career Criminal*	Average Female Recidivism (No. Offenses)	Average Female Career Criminal Cost	Expected Social Cost Per Female Career Criminal*
1	1.906 (-0.76)	$49,619 (1.67)	$68,679 (2.02)	1.456 (-1.18)	$36,691 (1.67)	$51,251 (1.70)
2	1.979 (0.41)	46,560 (-0.48)	66,350 (-0.45)	1.492 (-0.09)	32,803 (-0.11)	47,723 (-0.14)
3	2.018 (1.05)	45,800 (-1.01)	65,980 (-0.84)	1.528 (1.00)	32,490 (-0.25)	47,770 (-0.12)
4	1.857 (-1.55)	48,910 (1.17)	67,480 (0.75)	1.472 (-0.70)	34,711 (0.76)	49,431 (0.75)
5	1.956 (0.05)	46,914 (-0.23)	66,474 (-0.32)	1.509 (0.42)	32,321 (-0.33)	47,411 (-0.30)
6	1.919 (-0.55)	48,406 (0.82)	66,596 (0.87)	1.467 (-0.85)	34,919 (0.86)	49,589 (0.83)
7	2.004 (0.82)	46,256 (-0.68)	66,296 (-0.51)	1.521 (0.79)	33,020 (-0.01)	48,230 (0.12)
8	2.038 (1.37)	46,294 (-0.67)	66,674 (-0.11)	1.533 (1.15)	29,587 (-1.57)	44,917 (-1.60)
9	1.858 (-1.53)	48,525 (0.90)	67,105 (0.35)	1.438 (-1.73)	34,504 (0.67)	48,884 (0.47)
10	1.995 (0.68)	45,154 (-1.47)	65,104 (-1.77)	1.534 (1.10)	29,374 (-1.67)	44,714 (-1.71)

*Career criminal cost computation assumes γ = $10,000 as the social cost of each arrest.

Table 3. Ranking Policy Alternatives on the Basis of Career Criminal Social Cost ($P_1 = 1$, $P_2 = 0$)

Rank	ν	E_ν	Crimes Saved #
1	10	\$65,104	0
2	3	65,980	-345
3	7	66,296	-135
4	2	66,350	240
5	5	66,474	585
6	8	66,674	-645
7	9	67,105	2055
8	4	67,480	2070
9	6	67,596	1140
10	1	68,679	1335

Crimes Saved $\equiv (\overline{\beta^*} - \overline{\beta}_\nu) \times 15000$, where approximately 15000 male criminal careers ended during the planning horizon for each policy ν.

Table 4. Ranking Policy Alternatives on the Basis of Career Criminal Social Cost - Variable Weighting Schemes

ν	E_ν	Rank(E_ν)	E'_ν	Rank(E'_ν)	E''_ν	Rank(E''_ν)
1	$68679	10	$66448	10	$59965	10
2	66350	4	63966	4	57036	5
3	65980	2	63649	2	56875	3
4	67480	8	65170	8	58455	8
5	67474	5	64033	6	56942	4
6	67596	9	65291	9	58592	9
7	66296	3	63984	5	57263	6
8	66674	6	63889	3	55795	2
9	67105	7	64773	7	57994	7
10	65104	1	62494	1	54909	1

Note: E_ν subsumes $p_1 = 1$ and $p_2 = 0$; E'_ν subsumes p_j is equal to the proportion of the entire offender population which belongs to category j, $p_1 = .872$ and $p_2 = .128$; E''_ν subsumes $p_1 = p_2 = .5$.

END