CRIMINAL JUSTICE SIMULATION:

TRADE-OFFS BETWEEN PERFORMANCE MEASUREMENT AND OTHER MODEL DESIGN CRITERIA

by

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ABSTRACT

The theory of performance measurement (see Deutsch [1976]) tells us that the performance measure and the measurement strategy and process define the accuracy, reliability and even the appropriateness of any estimate of behavior. The history of modeling the Criminal Justice System (CJS) exhibits a variety of strategies and processes of performance meacurement: probabilistic models, nonlinear programming models, simulation and other models all recur. Without exception, each model form and its concomitant methodology prescribe and/or restrict the measurement strategy and process, and often leave the usefulness of a model in a heap next to a list of necessary assumptions. In many cases, the form of a model also limits the type of performance measure that is appropriate, but flexibility to choose the performance measure and, consequently, the form of the model can provide the modeler relief from an otherwise fruitless experience.

This paper examines several models used in the past and assumptions and compromises that were necessary to make them work. Next, an unpublished individual offender simulation model is presented. The variety of performance measures that can be generated with this model and the model's attributes are described in order to complete the analysis of the historical development of CJS models. In the next section, the kernel of performance measurement theory is explored within a model-building environment. The role of the process, measure and strategy, is examined

further; the orientation and goals of measurement are discussed as well. It is shown that the choice of a performance measure for a model often imposes restrictions on the form of the model. Consequently, by evaluating the limitations of the measure and of the proposed model, the model builder can ascertain which performance measure and model form best suits his needs. The benefit of considering such trade-offs is a more eclectic approach to modeling, to performance measurement using models, and, ultimately, to the evaluation of CJS performance.

In the final section, two simulation approaches to CJS modeling are examined. Depending on how offenders are portrayed, whether as individual entities or aggregate flows, these two model forms can be used to generate many measures of system performance, some exactly and some not exactly. The implementation in simulation models of many of the most common measures--and of some not as common--is discussed and each measure's attributes are recorded for both model types. It is shown that the individual offender simulation requires fewer assumptions for a greater number of these measures than does the flow model.

I. INTRODUCTION

The consistent application of a uniform performance measurement philosophy has been identified as a fundamental element of measuring and evaluating the behavior of the Criminal Justice System (CJS). Deutsch [1976] proposed that such a philosophy and technology be developed, and he formulated a strategy for developing what he called "empirical truths" regarding CJS behavior; such facts are only uncovered through the repeated application of uniform principles and methodologies of performance measurement, and they are an absolutely essential element of any effort to explore alternatives to present policy.

Prior to Deutsch's presentation, both empiricists and model-builders alike had been applying their own philosophies and methodologies to the measurement of CJS performance. Many analysts, in fact, have formulated models worthy of policy analysis and which would be quite useful if only the empirical truths necessary to validate their research paradigms were available. The purpose of this paper, nonetheless, is not to provide insight into the construction of a uniform measurement philosophy for developing empirical truths. Rather, the models which ultimately may be used for policy studies—but which now must contribute to the development of such truths—are themselves of considerable interest.

It is the intention of this paper, therefore, to show that many simplifications of CJS behavior found necessary for representing it in a mathematical model may be overcome via the theory of performance measurement. By more fully understanding the attributes of the performance measure and the strategy and process by which an estimate is obtained, it is expected that modeling assumptions can generally be made less restrictive, that the models themselves can become more useful, and that the choice of a mathematical model to explore empirical phenomena in the CJS can be made more judicially and less by compromise. Such optimism is based upon the premise that the definition of a measure of performance often limits the model builder in the type of model that may be constructed and, consequently, in the methodologies of model construction, validation, analysis, and hypothesis testing. Thus, it is through the re-definition of a measure or the substitution of a surrogate for the original that enables a modeler to trade-off the characteristics of the model with those of the performance measure. The limitations of the model and of the measure of system performance are, then, in some sense additive, and the objective of the modeler is to minimize them. Thus, the heightened awareness of the nexus between performance measurement and system modeling should help the Criminal Justice community to establish a more eclectic philosophy and technology of measurement, modeling, and evaluation.

Other than the conclusions, the balance of this paper is divided into four sections. The first provides an introduction to several important developments in Criminal Justice System (CJS) modeling. The reader generally familiar with this literature may wish to omit that section, as it provides historical insight into the methodology and limitations of several principal models. In the next section, the historical perspective is maintained in order to examine an unpublished simulation model. This model has been used elsewhere to examine the effect of the pre-trial delay

on several system-level performance measures (see Richards and Deutsch [1979]), but only the attributes of the basic model and the types of performance measures used with that model are considered here, in keeping with the spirit of the history of CJS modeling presented earlier.

The third section examines the theory of performance measurement and draws the connection between it and the many theories of system modeling. In this section the orientation and goals of measurement are defined, and the measurement process and strategy are illustrated in a model-building context. While several brief examples of the trade-offs between performance measurement and model design criteria are described in the third section, in the fourth section a detailed example is considered. The example illustrates the differences between CJS simulation models a) which track each offender separately and collect statistics on the entire simulated population, and b) which aggregate offenders in the model into what are often referred to as offender flows. These flow models have several modeling advantages over the individual offender models, but they are defficient in their performance measures. This straightforward example illustrates that many problems of performance measurement may be readily overcome by redefining the measure of interest. For other models not simulations the choice of model will often not be as easy. An approach to simplify the trade-offs for the more complex models is demonstrated.

II. A HISTORY OF CJS MODELING

Before examining the connections between performance measurement and model design criteria, a brief history of CJS modeling from the performance measurement perspective is in order.

The mathematical models most often found are either analytical or similar. The analytical models are all aggregate representations of criminal behavior. To obtain solutions for these models, the scope of each is generally limited to addressing one or two specific hypotheses, and little interaction among policy variables ever exists. In general, the analytical models can be characterized by: a high level of aggregation, a homogeneous criminal population (i.e., differentiation of offenders is assumed not to be important), steady-state behavior, time invariant parameters, and lacking in CJS cost and resource components. The simulation models, on the other hand, have emphasized the operations of the CJS as opposed to the characteristics of the offender population. Thus, they deal directly with the issues of CJS policy-making. Whereas the performance measures of the analytical models have been the crime rate (first offenders and recidivists), the performance measures of the simulation models have been varied, using one or more of the following criteria: annual CJS operating cost, total CJS cost attributable to the average criminal career, CJS resource availability, delays in processing offenders, and recidivism. The greater variety of performance measures of the simulation models is an indication of the greater flexibility of that methodology in modeling complex phenomena.

The simulation models, as will be seen, can be categorized by the manner in which the offenders are modeled. Some models simulate each offender individually. That is, the input to the model is a forecast of the number of offenders who are arrested, and this forecast is converted into that many separate entities which are tracked through the model. The other approach, most often used in CJS simluations, does not convert the input into separate entities; rather, these models maintain the aggregate nature of the forecasts by simulating flows of offenders through the CJS. These two different mechanisms of simulating offenders have considerable impact on the simulation's scope and limitations. These shall become obvious later in this analysis.

Both the analytical and the simulation model forms first reached national prominence in 1967 upon the publication of the <u>Task Force Report: Science and Technology</u> by the President's Commission on Law Enforcement and the Administration of Justice. Therein, Christensen [1967] developed a digital simulation model of the Washington, D.C. judicial system. One of Christensen's models forecast the number of first offenders who are arrested per year; his other model approximated the number of convictions that would be expected during the average recidivist's criminal career. Although they were simplistic, these descriptive models sparked the imaginations of other analytical model builders who have developed policy-oriented models as well.

The first attempt to simulate the operations of the CJS was by Navarro, Taylor and Cohen [1967]. Their model, called COURTSIM, makes use of the General Purpose System Simulation (GPSS) language to trace on a day-to-day basis the paths along which offenders progress through the

Washington, D.C. judicial system. An individual offender orientation is taken for this simluation; offenders are generated in the model one-at-a-time, each with its own attributes, and their progress through the courts is determined by these attributes, in CJS parameters, and by probability distributions. Processing begins at the moment of an offender's arrest, but continues only until the presiding magistrate delivers his sentence. A limited number of case-specific attributes, such as the date of the indictment and the offender's bail status, accompany each simulated case. The COURTSIM study is particularly noteworthy for its treatment of court delays; besides including the unavoidable delays associated with processing an offender, capacity and resource scheduling constraints were also introduced for each court processor. More recent court models, essentially applications of the same methodology, are discussed by Chaiken, et al. [1975].

COURTSIM is an open-loop model, since only the epoch during which an offender is under the direct purview of the CJS is examined. Another important open-loop model was first published by Blumstein and Larson [1969]. The so-called JUSSIM I model was used to forecast system costs, workloads, and resource requirements. Unlike the COURTSIM model, JUSSIM does not deal with individual offenders; such a model is said to simulate offender flows rather than individual offenders. Queueing phenomena cannot be examined using this characterization of offenders. Following their arrest, offenders are routed through the model by branching ratios that specify the proportion who will follow a specific arc at each decision point in the system. The identifier used to differentiate between offender categories in JUSSIM's first application was the most serious crime

for which the offender was charged; however, any set of descriptors could be used. The JUSSIM model is driven by a forecasting function of the total arrest rate. By following the flow of offenders through the model, analysts can predict the workload on each component of the CJS from which it is a simple matter to compute the resources required from the workload forecast. The cost per resource unit and the total CJS cost follow directly, assuming all CJS costs are variable (see Blumstein and Nagin [1977] for a discussion of this assumption). Other assumptions of JUSSIM I are that delays in processing offenders through the CJS are negligible, and that branching ratios do not change with system loads.

Blumstein and Larson extended the JUSSIM concept to include the re-arrest of recidivists. JUSSIM II, as it is now called, is a feedback model wherein offenders are tracked from the month of their first arrest until they finally leave the Criminal Justice System for the last time. JUSSIM II necessarily included measures of criminal recidivism (the feedback process) in order to determine if and when offenders are re-arrested. The input to this model, the number of first offenders, is added to the number of recidivists to give the total number of arrestees. The input may be either an age-specific cohort or the entire first-offender population. If offenders are incarcerated, JUSSIM II approximates the delay until the inmates are released by determining the fraction to be released each month, assuming a negative exponential delay distribution. Following their release, the number of arrestees who are re-arrested is computed assuming this branching probability to be a function of an offender's age; the delay until the re-arrest is negative exponential. The model computes the number of offenders arrested for each of seven crime categories (the

UCR index offenses, see Deutsch [1976]) by computing the number of first-offenders for each crime type, assuming each offender is arrested for the most serious crime committed, and adding to it the number re-arrested for each crime category. The latter measure of performance is computed using a crime-switch matrix to determine the number of persons arrested for each crime given their previous offenses. The crime-switch matrix is, in this case, a matrix of branching probabilities. (Crime-switch behavior is assumed to be Markovian; Wolfgang, Figlio and Sellin [1972] tested their model and found it to be acceptable using their birth cohort.)

Since JUSSIM II analysis of CJS costs attributable to the average criminal career is dependent upon the cost estimates derived using JUSSIM I, many of the limitations of the open-loop model also apply to the feedback model. However, this model is one of the more popular planning tools; several implementations now exist (see Chaiken, et al. [1975] and Richards and Deutsch [1978]).

In 1972, an individual offender queueing model of the entire CJS was designed which incorporates a model of recidivism similar to that demonstrated in JUSSIM II. The model is called DOTSIM, and acronym for Dynamic Offender Tracking Simulation (6). DOTSIM, like COURTSIM, follows each simluated offender through the Criminal Justice System; however, like JUSSIM II the input to DOTSIM is the number of first-offender arrests by crime type. DOTSIM has the capability of delaying offenders whenever the demand for a particular CJS resource exceeds its supply. This competition over scarce resources allows the performance of the CJS to be examined under policy scenarios which induce resource imbalances and, consequently, abnormal queueing behavior in the system. Such causal hypotheses are the

next step in refining the modeling paradigm begun by the COURTSIM model and followed by the JUSSIM family of simulators. (The latter includes CANJUS, the Canadian version, and Mathematica's PHILJIM among others. See Chaiken, et al. [1975] and Richards and Deutsch [1978].) The random processing of offenders through DOTSIM lends greater resolution to the intricacies of offender-specific policy formulation; the effects of each policy scenario can be determined by measuring the change in the crime rate, resource requirements and system costs relative to a baseline policy. The costs embedded in the model include those which are directly attributable to an offender and the indirect costs of equipment and facilities.

The limitations of DOTSIM depend almost entirely upon the attributes of the implementation and not upon the model's individual offender orientation or its CJS resource, delay, or cost components. The initial formulation prevented the testing of hypotheses which examine differential recidivism tendencies of alternate correctional programs or which examine the performance of the CJS as measured by such career criminal statistics as arrest histories, conviction histories, incapacitation effects, and career criminal cost. A limitation of a model like DOTSIM is the amount of data required to accurately simulate the CJS with the amount of detail required by this approach; according to Chaiken, et al. [1975], the extra empirical data and the cost of running such a model have been the major reasons for there not being any empirical implementations of DOTSIM. However, several data bases like PROMIS (Prosecutor's Management Information System; see U. S. Department of Justice [1977]) or OBTS (Offender-Based Transaction Statistics; see California Department of Justice [1976]) now make much of the required data routinely available—thus removing the empirical restrictions. The cost of operating the simulation may be reduct reduced by scaling down the model so that the number of offenders simulated is actually smaller than for the system being simulated. Such a device will be demonstrated later in this paper.

Another feedback simulation model of CJS operations was developed by Pittman [1973] to evaluate alternative correctional policies. His model is a Markov chain representation similar to the model of crime-switching behavior used in JUSSIM II; however, unlike the crime-switch model whose states correspond to the seven index crimes, Pittman's offenders may be in any of the following four states: in prison because of conviction, in prison because of a technical violation of parole, on parole, and not under CJS supervision. Possessing the transition and the cost matrices, Pittman simulates the model to estimate future system loads and the crime mix given the number of first offenders who are arrested and convicted. In addition, the expected number of times the offender is re-arrested, the average sentence length, the expected criminal profile, and the expected career criminal cost of an offender can all be computed analytically under steady-state conditions. Thus, Pittman's model is as much analytical as it is similar.

Pittman's model is used to analyze the effects on the average offender's statistical profile of changes in the transition matrix and, hence, of changes in the policies which affect the flows of offenders. Unfortunately, the association of the transition probabilities with changes in actual policy is not always obvious and therefore threatens such a model's usefulness. On the other hand, this model can provide optimal solutions to problems which, when modeled using another methodology, might

otherwise prove to be intractable. By examining the cost matrix of state transitions, for example, this model can be used to develop a least-cost solution for reducing crime and thereby overcome one of the major deficiencies with other analytical models. Of course, the criticisms of Blumstein and Larson's model apply here as well. The invariance of the transition probabilities could be a problem in forecasting system load, while aggregating the costs can also create problems if the future cost distribution were to change. In addition, to expand the scope of the model to include, say, the police and court subsystems of the CJS, the data requirements are increased considerably not to mention that it complicates the computation of the performance measures. Thus, to raise Pittman's model up to the scope of a system-level model would require considerably more data and model analysis in order to draw conclusions about the performance of the entire CJS.

Since DOTSIM in 1972 and Pittman's model in 1973, other CJS simulation models have not appeared in the literature. The analytical models which have since been developed all tend to possess more of the Criminal Justice System's structure than did Christensen's early efforts. The first purely analytical model following the Presidential Commission's report is the work of Bellin, Blumstein and Glass [1973], who developed a feedback model of the CJS. Although the model contained only two components of the CJS, a combined police/court component and a prison component, their objective was to model the entire criminal career. Thus, the feedback in the model is the flow of recidivists back into the police subsystem following their release from prison. Offenders released from the police/court component are re-arrested with probability α_1 following τ_1 elapsed years, while offenders who are released from corrections are re-arrested after τ_2 years with probability α_2. The delays τ_1 and τ_2 were both assumed to be the expected values of negative exponential distributions. The input to the Belkin, Blumstein and Glass model was the number of first-offense arrests. The model was used to analyze offender recidivism assuming $\alpha_1 = \alpha_2$ (i.e., rehabilitative or special deterrence effects do not exist). By varying the model's parameters, they fit the total number of arrests predicted by the model to the FBI's statistics for the decade beginning in 1960. This parametric analysis resulted in the estimates $\alpha = .86$ and $\tau_1 = 1.2$ years. Further analysis showed that the number of offenses by first-offenders had increased over time, while recidivism had declined over the same period. (They assumed $\tau_2 = 1$.)

To be sure, Belkin, Blumstein and Glass's model reached a much greater level of sophistication than those of Christensen. They demonstrated that recidivism can be modeled and they later showed that reducing the rate of recidivism is a much more effective method of reducing the total level of crime than is reducing the virgin arrest rate. Unfortunately, this model does not tell the CJS planner how to reduce recidivism, nor does it give any hint as to which alternatives are the least costly. These important problems of policy interpretability, it will be seen, arise in each of the analytical models surveyed. Only the simulation models possess a truly structural relationship to the CJS and, as a consequence, an obvious means of effecting solutions in the actual system that are obtainable in the model.

The first analytical model to possess explicit policy variables was developed by Avi-Itzhak and Shinnar [1973] and later refined by Shinnar and Shinnar [1975]. These authors modeled the criminal career of an offender and incorporated the incapacitation effect of the CJS into the model formulation. Two policy variables were included, the length of incarceration and the effectiveness of both the police and the prosecution. The processes being modeled were assumed to be in steady state. They further assumed that an offender commits λ offenses per year according to a Poisson distribution, that q and S are the policy variables representing the joint probability that an offender is both arrested and convicted and the actual time served in prison, respectively, and that J is the conditional probability that an offender is incarcerated following conviction. Thus, if the CJS does not affect the behavior of the offender through deterrence, incapacitation or rehabilitation, the expected number of crimes committed by an offender is $E(x) = \lambda T$, where T is the length of a criminal career. However, to include the incapacitative effect of the CJS, $\eta = 1/(1+\lambda qJS)$ defines the proportion of an offender's criminal career that he is active (not incarcerated), and $E(x) = \lambda\eta T$.

The Avi-Itzhak model is a powerful tool because it relates the expected number of offenses per offender, $E(x)$, to the policy variables q and S. As with other models of this type, the model is highly aggregate and does not differentiate between the treatment of classes of offenders. The parameters q, J, and S must be estimated separately for each offender category in order to test differential treatment hypotheses. The lack of a cost function and a resource component precludes both the minimization of total CJS and career criminal costs, and the maximization of the incremental reduction in crime per incremental increase in cost.

An extension of the Avi-Itzhak and Shinnar model incorporates the deterrence hypothesis into the earlier formulation and conceives the new model in an optimization framework. Blumstein and Nagin's model [1977] is a nonlinear program which minimizes the level of crime, given a capacity constraint on the number of offenders who can be imprisoned at any one time. Although such a constraint appears to hold nationally, local or regional capacity may not be so static. Blumstein and Nagin's expression for the aggregate crime rate is $C = \lambda\eta P$, where P, the fraction of the population that is criminal, is a logistic function of the disutility of imprisonment, and the product $\lambda\eta$ is the effective crime rate per offender. The average number of persons incarcerated, $I = qJCS$, must be less that the prison capacity constraint U. Since both C and I are nonlinear, use of this model requires searching over the acceptable ranges of both Q and S, so that C is minimized subject to $I \leq U$.

A problem particularly evident with this model, however, is its inability to determine an optimal dynamic policy. Neither this nor the other analytical models facilitate the exploration of transient behavior between a current and a proposed policy. Such a dynamic model would be of particular interest to CJS policy analysts even though system delays, missing in the Blumstein and Nagin model, would confound the results for the incapacitation effect if these delays were to increase with an increase in q. In addition, the possibility of an infeasible level of incarceration as the result of a policy change makes the examination of the dynamic response a critical shortcoming of this and the other analytical models surveyed here. In the next section, a simulation model designed to take into account the dynamics of CJS policy is introduced. Offenders are modeled as individuals and, hence, the model can be used

to analyze performance measures like those used in the COURTSIM and DOTSIM models.

III. A DYNAMIC CJS SIMULATOR OF INDIVIDUAL OFFENDERS

To complete the history of CJS modeling, a final simulation model is examined which can be used to explore dynamic hypotheses concerning the behavior and performance of the System and individual offenders who make a career of crime. Unlike the DOTSIM model, this simulator is not proprietary; its more recent development makes the model to be described the more likely to be of interest now to CJS modelers and analysts. The dynamic simulator combines the queueing, resource allocation, cost, and recidivism capabilities ascribed to the DOTSIM model, but the detail in the recidivism component, the extra array of performance measures, and the ability to categorize offenders by other variables in addition to the crime committed all help to differentiate this model from its predecessors.

This simulator has been constructed using the Generalized Network Simulator, GNS. Historically, GNS evolved from the General Evaluation and Review Technique Simulator (GERTS) series of network models (see Hogg, et al. [1972] and Tonegawa [1973]). Combining into one simulator the queueing, resource allocation, and costing capabilities that were available in the Q, R, and C versions of GERTS III, GNS is a sophisticated tool for use by planners of a variety of systems including criminal justice. 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. GNS, on the other hand, requires that the nodes represent activities and that the arcs

portray precedence relationships between the nodes. Offenders 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. Technically speaking, the nodes of the GNS network are referred to as either nodes or boxes, the former representing an event with a duration of zero and the latter representing an activity with a positive duration. A certain type of box, called a queue box, also allows the model builder to specify the maximum number of servers available which, when all servers are busy creates a queue of entities waiting to be served. Only one server is required to process each entity, but an unlimited number of resources of not more than 30 types (at this time) may also be required to process each entity. An unlimited number of servers can be associated with each queue box, but resources may be shared between two or more queue boxes.

GNS has several costing options which may be implemented at a user's discretion. First, there may be costs associated with the entire project (model): a one-time set-up cost and an overhead cost per time period. Second, there may be costs associated with each queue box: a one-time set-up cost and a cost of operating a box each time period. Finally, since each queue box may also require resources to process an entity, each resource may have a cost per unit time of use that is also attributed to the appropriate box. Hence, the costing and the resource allocation capabilities are comprehensive.

The GNS model of the Criminal Justice System is displayed in Figure 1 using the notation established by Tonegawa [1973]. It is a feedback model, similar to that developed by Belkin, Blumstein and Glass; however, each

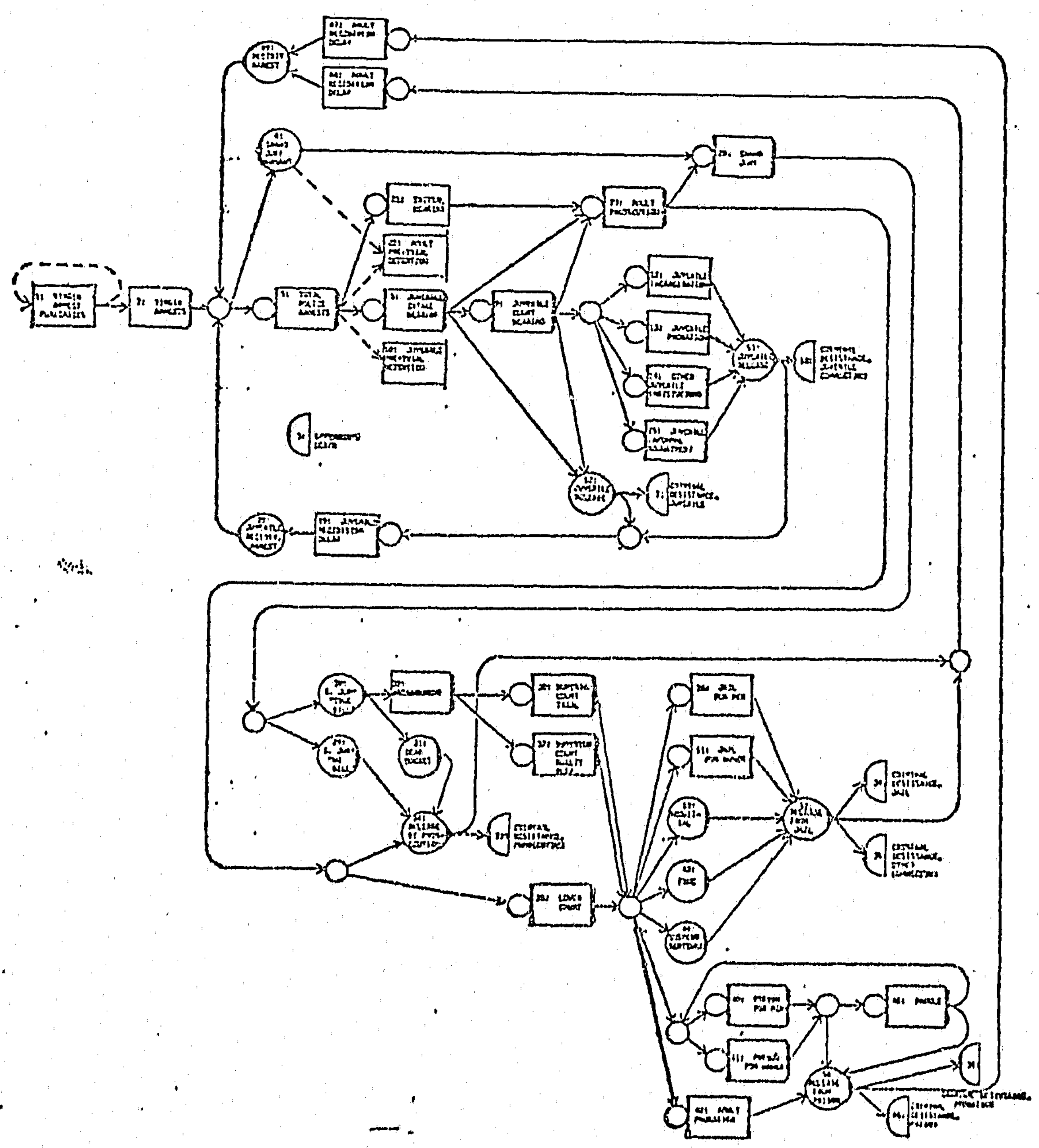

Figure 1. A GNS Model of the Criminal Justice System

offender is modeled separately in a manner similar to DOTSIM. By simulating each offender as he progresses through the CJS, the delays in the system can be simulated. In addition, the emphasis on the offender and the special capabilities of GNS enable the analysis of the effects that limited resources have on the system. Since the resources are frequently shared between two or more queue boxes, each offender must also compete for the resources that are available. Hence, the observed queueing behavior may be confounded by limited resources. This is another contribution of this model to CJS analysis; the ability to model the effect of scarce resources in this manner has not, to our knowledge, been attempted heretofore.

Each queue box, represented by a rectangle with a circle intersecting the box's inputs, has associated with it exponentially distributed service times specified for each of the FBI's seven index offenses. CJS resources are also specified; each server in the model corresponds to one unit of at least one type of resource. Thus, for each offender processed at a queue box, at least one resource unit is being consumed and its cost added to the cost of the system.

Another special event is the sink node. This node is differentiated from the other nodes by its half-moon shape. The function of these nodes is to remove offenders from the simulation lists. For this particular model, this happens only if an offender dies (Node 3) or if he is never re-arrested (Nodes 7, 18, 27, 34, 35, 36 and 46). Thus, an offender's criminal career begins upon his first being arrested by the police, and it ends when he reaches a sink node. The lengths of criminal careers, and the age at death are both generated from probability distributions, and are stored along with the other attributes of each offender: current age, demographic category, career criminal cost, total number of arrests, and types and ordinal arrangement of offenses committed.

Two measures of performance which have not been in CJS simulation modeling before are the number of times an offender is arrested during his criminal career and the career criminal cost. The manner in which an offender's career criminal cost is determined is very similar to that used by Pittman; all set-up costs are assumed zero. The fixed costs of operating the CJS per time period and of operating each queue box are also assumed zero. The only mechanism used to impute the cost of operating the CJS to each offender is through the usage of resources. The actual career criminal cost for the i^{th} offender, $(CCC)_i$, is updated by the amount of each resource k required for processing him at activity e by the relation

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

where C_k is the cost of resource k per offender per time, 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 and it is zero otherwise.

In a sample run, it was assumed that ten different resource types are sufficient to describe the resource scarcity and queueing interaction. See Table 1. Three types of career criminal statistics are shown in Figures 2-4 for both male and female offenders. (See Richards and Deutsch [1978] for details not presented here.) Figures 2 and 3 show five time series beginning after 20 years of initializing the model. These results show that the average rates of recidivism per offender and the career

Table 1. GNS Model Resources

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

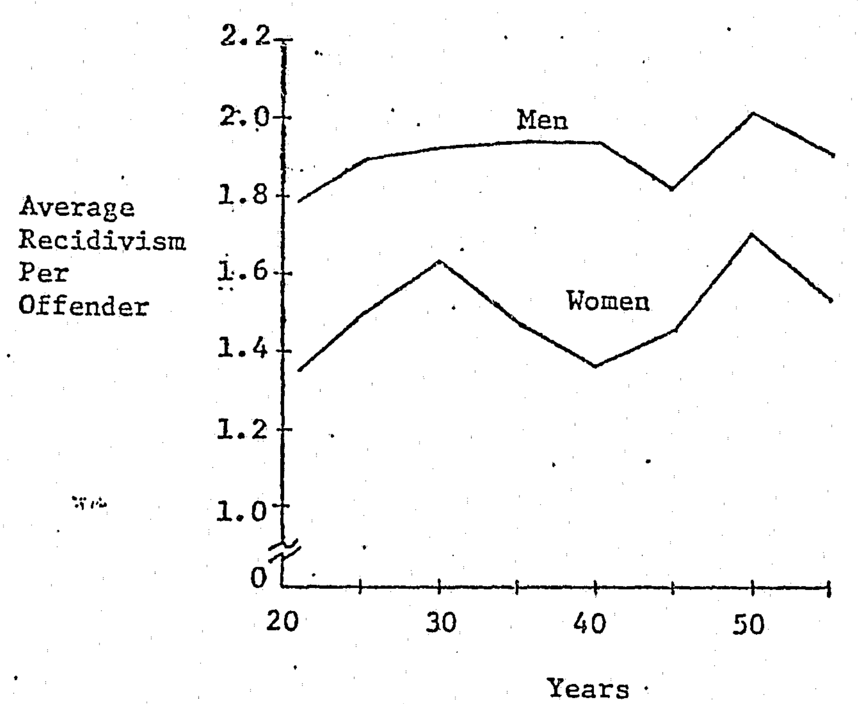

Figure 2. Time Series of the Number of Arrests Per Offender for the Basic Plea Bargaining Model

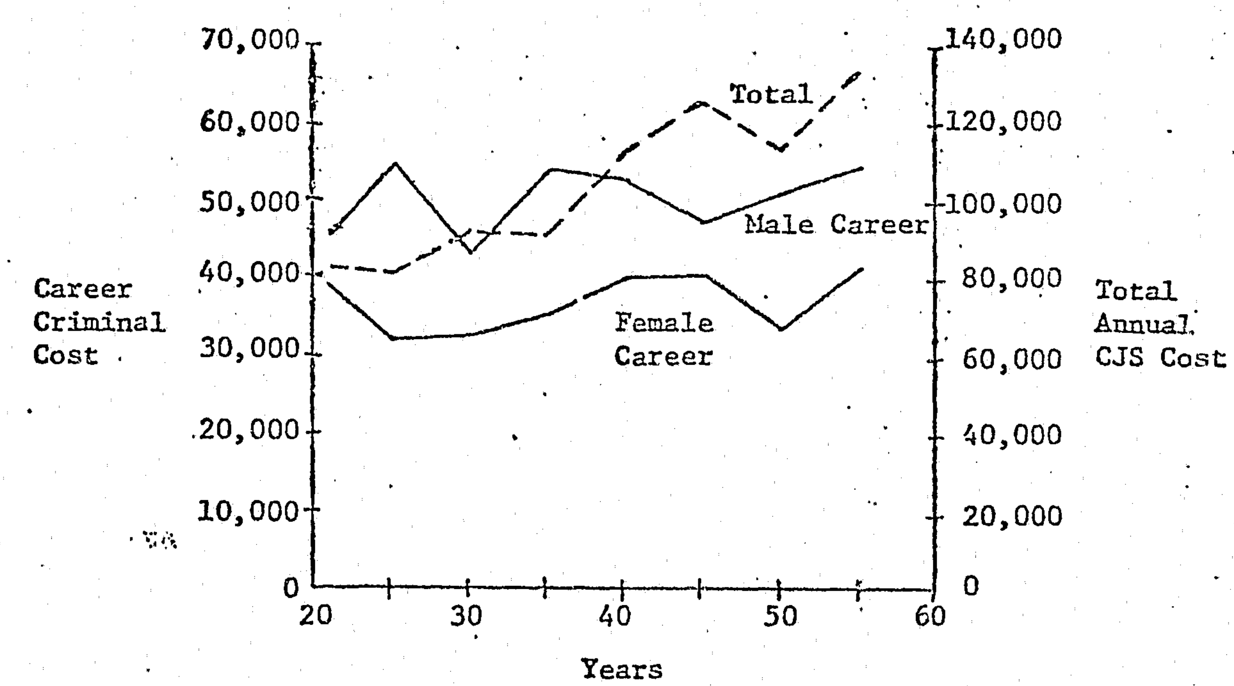

Figure 3. Time Series of Career Criminal and Total Annual CJS Costs for the Basic Plea Bargaining Model

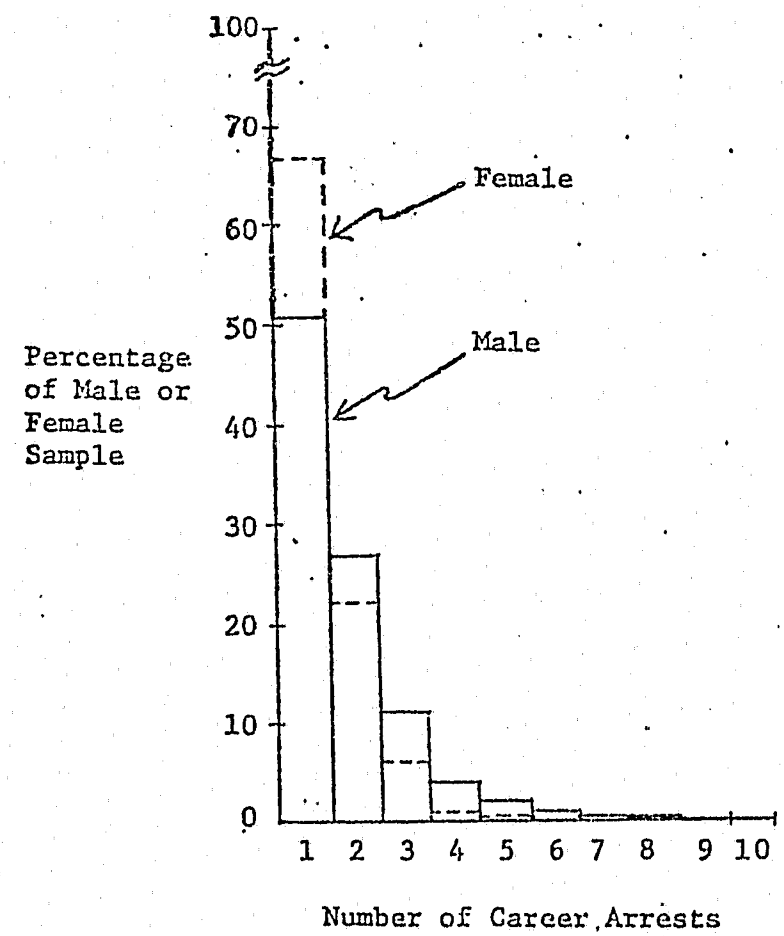

Figure 4. Distributions of Career Arrests for Male and Female Offenders

criminal costs as defined are stationary and, hence, may be represented by their mean values (even though the total arrest rate is increasing as demonstrated by the total CJS cost time series). The distributions of the number of arrests per criminal career appear to be negative exponential distributions, whereas the distribution of career criminal cost appears to be gamma. Thus, this simulation model can be used to analyze career criminal behavior, in addition to the resource allocation and delay processes in the CJS, by relying on the expected value and the shape parameter of the observations of these time series. However, since time series data are also collected for the career criminal, the queue, and resource consumption statistics, dynamic analysis of the CJS is easily pursued.

IV. PERFORMANCE MEASUREMENT THEORY AS MODEL DESIGN CRITERIA

Having studied the measures of performance, the strengths and the weaknesses of many state-of-the-art models of the Criminal Justice System, we now re-examine the theory of performance measurement in order to assign it a proper role in a CJS modeling paradigm. The objective of such an analysis is to obviate certain choices open to model builders and persons wishing to use already available models, and to present these options in such a way that these technology users may better meet the objectives mandated by the problems at hand. What follows, then, will aid both the modeling community and the host of empiricists aiming to establish those empirical truths discussed by Deutsch through the use of such models. By offering a performance measurement structure to the problem of model design, the future of CJS modeling is expected to yield a more eclectic, goal-oriented philosophy of modeling which is fundamentally in consonance with the notion of a uniform philosophy of performance measurement, and it is expected to produce modelers and analysts who are alert to the alternatives available to them. Although it would be pretentious to assume that some of the considerations which follow are not already understood by much of the intended audience, subtleties arising out of the aforementioned perspective can assist the most astute reader.

According to Deutsch [1976], good performance measurement depends upon appropriate measurement goals backed-up by good performance measures, strategy and processes. The goals of CJS performance measurement might

be summarized as providing robust measures of system performance, using a uniform philosophy and appropriate technologies to describe:

1. The <u>impact</u> of the CJS on criminal behavior and society at large,
2. How well the CJS meets the <u>objectives</u> outlined for it,
3. The <u>processes</u> by which it attempts to achieve its goals and objectives,
4. The <u>resources</u> it finds necessary to expend to operate, and
5. Its <u>response</u> to its environment.

These five areas of responsibility of the performance measurement community have been referred to by Deutsch and Richards [1979] as the several orientations of performance measurement, and they fairly-well map out the entire CJS measurement domain.

To see how well the models reviewed earlier span these five dimensions, the orientations in which several measures of performance appear strongest are marked in Table 2. A similar approach may be taken in evaluating the usefulness of a particular model or a series of models whose purpose it is to examine the spectrum of CJS activity. By grouping the measures into categories based upon measurement's objectives, as is done in Table 2, an analyst can see where within each set of objectives a deficiency in the measurement strategy lies. For example, take the objective of cost measurement. A complete strategy for measuring cost would not rely strictly on CJS cost as defined since only three orientations apply. In fact, it may not be of any value to evaluate social costs since they also cover the same dimensions; instead, a more complete strategy would also include the annual change in cost in order to estimate

Table 2. Performance Measure Orientations

Measures	Impact	Objective	Process	Resource	Response
Crimes/Arrests:					
Crime Rate	X	X			
Arrest Rate		X			X
Recidivism Rate	X	X	X		
CJS Effects:					
General Deterrence	X	X			
Special Deterrence and Rehabilitation	X	X	X		X
Incapacitation	X	X	X		X
Costs:					
CJS Costs		X	X	X	
Social Costs		X	X	X	
Career Criminal Costs	X	X	X	X	X
Annual CJS Cost Change		X	X	X	X
Resources:					
Facilities			X	X	
Personnel			X	X	
Career Criminal Usage	X		X	X	
Delays:					
Procedural Delays		X	X		
Delays from Resource Shortages		X	X	X	
Total Delays Over Career	X	X	X		
Due Process:					
Bias	X	X	X		
Procedural Guarantees		X	X		

(Orientations[1])

[1]An "X" in a column means that the measure in whose row it appears has the orientation of that column.

the response dimension of CJS cost. For hypothesis testing and performance optimization, an objective function would be quantified from those measures whose objective dimension scores highly.

Other elements of the measurement strategy relate to the type of model considered, and hence, the methodology used in constructing it. Although it is impossible to judge whether the definition of a model presupposes that a particular methodology will be used, whether knowledge of a particular modeling paradigm predetermines the type of model that results from a model-building session, or whether the form of a model simultaneously accompanies the selection of a methodology of model building, the etiology of such relationships is immaterial, here. However, of considerable importance is that the measurement strategy not be constrained to either one model or method a priori; an eclectic modeling approach is prescribed, in which the objectives of measurement dictate the measure, the strategy for modeling the system and collecting the estimates of the measure, and the process of using the model to obtain the necessary data. The methodology for modeling and for analyzing a model, then, comprises part of the strategy and process of performance measurement which is dictated by the measurement goals. The measure, according to its importance in the performance measurement paradigm, is therefore equally important as the model and accompanying methodologies, but--to be sure--this is not new to experienced analysts.

What is important to model builders and users, however, is the following mandate: when formulating a measurement strategy in which the limitations of a particular model and methodology seem to outweigh the advantage arising from their use, re-exploring the nexus between the attributes of the performance measure and the attributes of the model can show how changing the attributes of both will favorably effect the outcome of measurement toward meeting its objectives. Consider, for example, the list of performance measures and characteristics of those models, surveyed earlier, given in Table 3. When viewed in this admittedly perfunctory manner, the trade-offs between model attributes and methodologies, and the performance measures obtainable are readily seen. This allows an analyst to better choose between competing strategies and processes, models and methodologies. Since such trade-offs should be obvious to most without this tabulation, the question remains: How can this simplistic approach to analyzing design trade-offs benefit the experienced analyst? A detailed example of the design trade-offs in model and measure attributes of simulation models, and the importance of performance measurement theory in evaluating such decisions follows. This example also helps to distinguish the individual offenders and the offender flow models by their abilities to meet the objectives of performance measurement.

Table 3. Attributes of Models of the CJS

Model (Year)	Model Type[1]	Model Purpose[2]	Performance Measures[3]: Total CJS Cost	Career Criminal Cost	Crime Rate	Recidivism	Deterrence	Delay	Resources	Model Characteristics[3]: Costs	Deterrence	Recidivism	Recidivism by Disposition	Incapacitation	Queues and/or Delays	Resources	Offender Demographics	Crime-Switch Behavior
Christensen (1967)	A	D			X	X		X			X			X				
COURTSIM (1967)	BO	E	X					X	X	X					X	X		
JUSSIM I (1969)	BF	E	X						X	X						X		
JUSSIM II (1969)	BF	E	X	X	X	X			X	X		X	X	X	X	X	X	X
DOTSIM (1972)	BO	E	X					X	X	X		X		X	X	X		X
Pittman (1973)	BF	E	X	X				X		X		X	X	X			X	
Belkin, Blumstein and Glass (1973)	A	C			X	X	X	X			X	X						
Avi-Itzhak and Shinnar (1973)	A	E			X	X						X		X				
Blumstein and Nagin (1977)	A	E			X	X	X		X		X	X		X		X		
Richards and Deutsch (1978)	BO	E	X	X	X	X		X	X	X		X	X	X	X	X	X	X

[1]Model types are: Analytical (A); Simulation--Individual Offender Orientation(BO); Simulation--Offender Flow Orientation (BF).

[2]Primary model purpose is: Descriptive (C), Predictive (D), Prescriptive (E).

[3]An "X" in a column means that the particular performance measure or model characteristic is present in the model.

V. SIMULATION MODEL DESIGN TRADE-OFFS

In this section, performance measurement and other model design criteria are critiqued for two approaches for simulating the Criminal Justice System. The individual offender and the aggregate flow models have been quite popular tools for exploring system behavior; Table 3 in the preceding section shows which models surveyed in this paper fall into the two categories. The objective of this exercise is to show by way of a detailed example how elements of performance measurement are at least equally important to the more typical model design considerations. The misconception that the issue of performance measurement will resolve itself after the model has been specified is one that needs to be dispelled. It is both the model builder's and the user's responsibility to ensure that the compatibility between the problem and the measures of performance be guaranteed as much as possible by designing the CJS model according to the objectives of performance measurement.

In the analysis that follows, rather than compare two specialized implementations of each model form, we examine two hypothetical feedback models like the JUSSIM II flow model and the GNS individual offender model discussed earlier. The usual criteria for choosing between two such model forms depends upon:

1. The cost of the simulation in manhours, computer time, and in elapsed time;
2. The assumptions that the analyst is willing to make about the

model that are necessary for its construction and analysis. These criteria, of course, presume that the measure of performance is fixed, but this is not normally the case. As shown in the previous section, measures of performance can be categorized by measurement objectives and the five dimensions of measure orientation. It is conceivable and even likely that another measure can be substituted for one which imposes unreasonable constraints on the model structure or its analysis.

Thus, not only must the two guidelines above be examined when choosing between competing simulation models, but the measures of performance—which in many ways dictate the model form, see Table 3 for examples—must be scrutinized simultaneously with the criteria resulting from those guidelines. The linkages between measure and model, and model and methodology are too strong to ignore in the design of or selection between competing measurement strategies and processes.

To illustrate these results, we choose to examine the attributes of potential measures of performance that may be inplemented in the hypothetical aggragate flow and individual offender models. Table 4 presents the attributes of each measure of performance, i.e., of those already discussed with regard to Table 2, as it would be implemented in these models. Most of the characteristics are defined by Deutsch and Richards [1979], while the others are self-explanatory. The purpose of such a tabulation is to pinpoint the strengths and weaknesses of each model relative to the performance measures available. The table shows that the flow model cannot accomodate career criminal statistics. In addition, the flow model must rely on surrogate measures--a surrogate measure is one that substitutes for another--for incapacitation, resource usage, and de-

Table 4. Characteristics of Performance Measures As Implemented in Two Simulation Models

Measures	Univariate	Multivariate	Simple	Composite	Exact	Approximate	Direct	Surrogate	Objective	Subjective	Qualitative	Quantitative	Absolute	Relative
	Measure Characteristics[1]													
Crimes/Arrests:														
Crime Rate	FO	FO		FO		FO	FO			FO		FO	FO	FO
Arrest Rate	FO	FO		FO	FO		FO		FO			FO	FO	FO
Recidivism Rate	FO	FO	FO		FO		FO		FO			FO		FO
CJS Effects:														
General Deterrence	FO	FO		FO	FO		FO			FO		FO		FO
Special Deterrence and Rehabilitation	FO	FO		FO	FO		FO			FO		FO		FO
Incapacitation	FO	FO	FO		FO		O	F	O	F		FO	O	F
Costs:														
CJS Costs	FO	FO		FO	O	F	FO		O	F		FO	FO	FO
Social Costs	FO	FO		FO		FO	FO			FO		FO	FO	FO
Career Criminal Costs	O	O		O	O		O		O			O	O	O
Annual CJS Cost Change	FO	FO		FO	O	F	FO		O	F		FO		FO
Resource Usage:														
Facilities		FO	F	O	O	F	O	F	O	F		FO	FO	FO
Personnel		FO	F	O	O	F	O	F	O	F		FO	FO	FO
Career Criminal Usage	O	O		O	O		O		O			O	O	O
Delays:														
Procedural Delays	FO	FO	FO		O	FO		F	O	F		FO	FO	FO
Delays from Shortages	FO	FO		FO		FO	O	F		FO		FO	FO	FO
Total Delays over Career	O	O		O	O		O		O			O	O	O
Due Process:														
Bias		FO		FO		FO	FO			FO	FO	FO		FO
Procedural Guarantees		FO		FO		FO		FO		FO	FO	FO	FO	FO

[1] An "F" in a column indicates that the measure of that row would have this characteristic when the measure is implemented in a flow model. Similarly, an "O" is the designation for measures implemented in individual offender models.

lay measures; approximations are also required for cost and delay measures that are not necessary for the individual offender model.

The foregoing analysis demonstrates that the measures of performance can play an important role in choosing between CJS models. Rather than analyzing two existing models, a modeler should also conduct such an analysis of model forms (or modeling paradigms) before beginning to construct the model itself. If properly executed, he should not be limited by the restrictions on the performance measures as severely as if he had been satisfied to compromise the measurement process by defining it around a particular model. The conclusion, then, is that careful analysis of performance measures to be incorporated in a model should be undertaken as a necessary step of model selection or design to guarantee that the measurement process, as embodied by the model and the methodology needed to evaluate its performance, approach the objective reflected in the measurement strategy.

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