

## **A NUMERICAL SENSITIVITY ANALYSIS OF PROCESS DELAY IN THE INCARCERATION OF JUVENILE OFFENDERS**

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### **ABSTRACT**

The analysis unit of the New York State Division for Youth is responsible for providing admission forecasts to allow the Division to anticipate changes in demands for facility space. Arrests of the most serious offenders had shown a 38% growth between 1987 and 1988, yet the annual admission rate declined 19%. In an effort to understand the reasons and account for this difference, a STELLA model of the offender processing system was created and simulated using historical exogenous time series inputs. Utilizing linear processing ratios and simple causal assumptions, the model reproduced the historical admission rates without any changes in processing trends. The results indicate that the admission rate was proportional to the arrest rate, given the long lag time involved in the conviction process. Further, the growth in cases backlogged due to an increase in processing time during 1987 did not imply that a small increase in processing resources would cause a surge of admissions.

### **PROBLEM STATEMENT**

When the New York State Legislature created the Juvenile Offender Law of 1978, they enacted the most punitive penal sanctions on juveniles in the United States. Those serious juvenile offenders between the ages of 13 and 15 charged with specific offenses may be tried in adult criminal court as Juvenile Offenders (JO) and face lengthy terms of incarceration. The trend in JO arrests has shown a significant increase during 1988, with the annual arrest rate increasing 38% over the previous year (from 1,119 to 1,548). All other things being equal, one would expect that the number of JO admissions to the state's juvenile facilities would show a similar growth pattern (after an appropriate lag period).

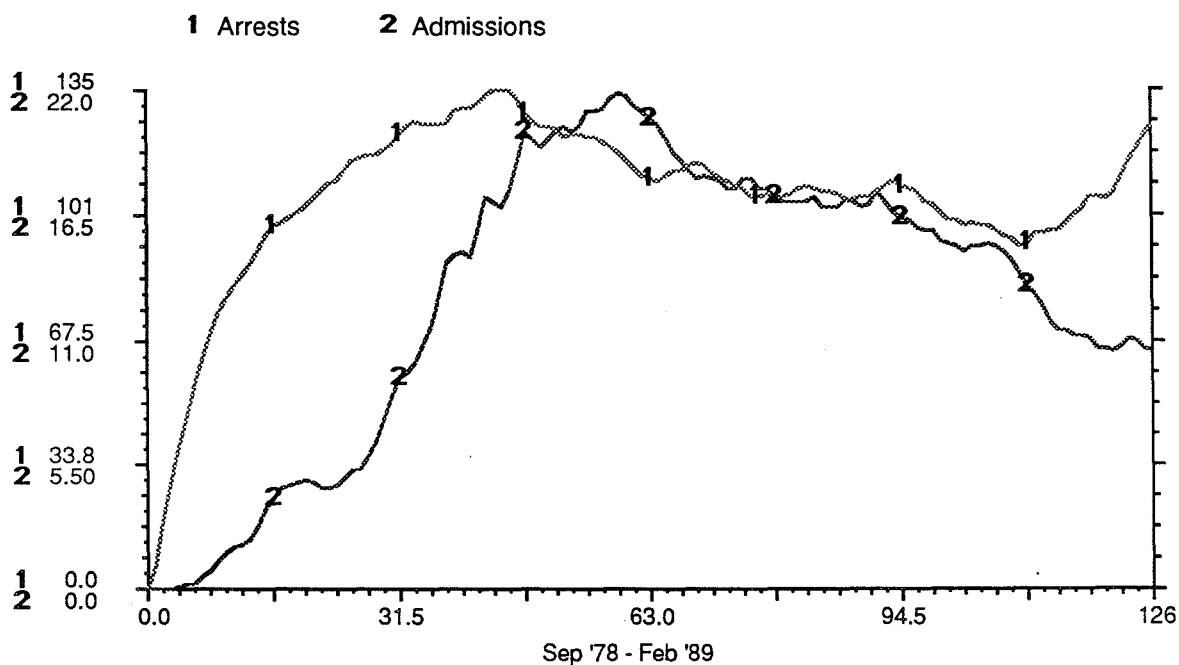


FIGURE 1  
SMOOTHED TRENDS IN  
JO ARRESTS VS ADMISSIONS PER MONTH

However, admissions do not display a similar growth pattern, and in fact declined 19% between 1987 and 1988 (from 141 to 114). The admission rate had not grown as rapidly as arrests, even after 18 months. This anomaly becomes apparent by comparing the monthly arrest and admission rates smoothed over a 12 month period as shown in Figure 1\*.

This creates something of a problem for the State's Division For Youth (DFY) researchers and their ability to accurately provide planners with population forecasts. If the lack of an increase in admissions is due to a greater proportion of cases being screened out of the system (via failure to prosecute, increased dismissals, lowered conviction fractions or lowered DFY sentencing fractions), then future JO admission rates will remain lower than anticipated. If the lack of growth in admissions is due to increased processing time (at any point in the process), then the backlog of cases pending disposition will have increased and the admission rate can be expected to demonstrate a proportionate rise making current projections too conservative (i.e., lag time greater than anticipated).

\* The admission rate contains one data "outlier" - for June 1982. The rate for this month exceeds twice that for any other month and is the result of a court order requiring that convicted offenders held in New York City be admitted within 7 days. This one month surge is not relevant for the problem discussed so the average admission rate for 1982 is used in its place.

## METHODOLOGY

An exogenously driven STELLA model was created in order to test which of these two hypotheses could account for the lack of numerical sensitivity in admission rates. The initial JO processing model is shown in Figure 2. Arrests are either dropped or prosecuted. Defendants either plead guilty or are tried. Those tried are either convicted or acquitted. Before admissions are added to the model, this structure will be tested for validity by comparing the simulated convictions to actual convictions as best as can be determined. All court processing must be estimated because of missing dispositions and expected recent data "censoring" (i.e., cases not yet disposed). The "time\_input" variable is the simulated months (Sept '78 - Feb '89 = 126 months).

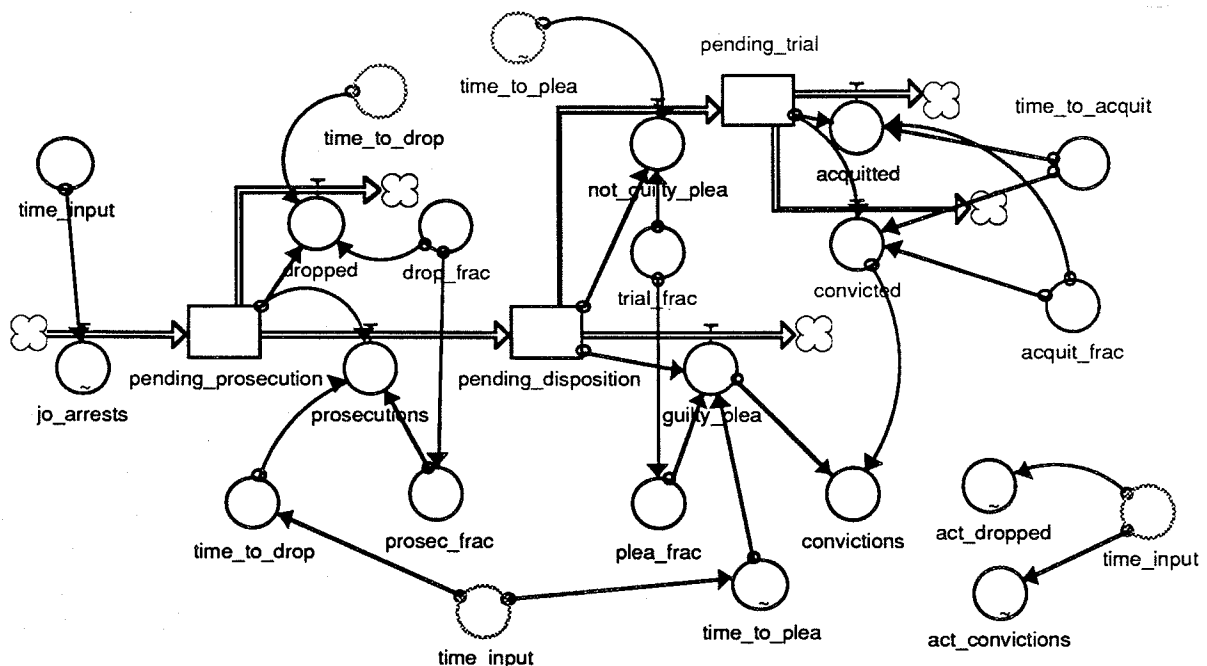


FIGURE 2  
INITIAL EXOGENOUS MODEL

Each of the branching ratios were estimated from data provided by the New York State Division For Criminal Justice Services (DCJS) Offender Based Tracking System containing records for every person fingerprinted upon arrest in the state and adjusted to fit the data. Some adjustment is required, because there are differences between arrest cohort and disposition cohort values, and the model requires continuous processing proportions for cases backlogged in each level rather than "fraction of arrests disposed via ...". Each output rate from the backlogs are assumed to be a function of the number of cases backlogged at any point in time, times the branching ratio, divided by the time to process through the backlog. For example, the number of cases prosecuted per month is the number of cases pending prosecution times one minus the fraction dropped, divided by the time to dispose of cases via dismissal or failure to prosecute. The time to drop and time to prosecute are assumed to be the

same. Of course, the backlog at any point in time equals the previous value of the level  $\pm$  the difference between input and output between values.

The full initial model diagram requires that all initial conditions (all equal 0), branching ratio (fraction), and processing time variables be specified. Exogenous "time series" inputs are designated by the "tilde" in the variable and are fed by "time\_input". These exogenous variables are "jo\_arrests" and "time\_to\_plea". To compare model output to historical data, "act\_convictions" and "act\_dropped" were added as exogenous "time series" data streams.

The parameters were set from the DCJS data and estimates were as follows:

- |  |  |
|--|--|
| the fraction acquitted is a constant 33%               | the conviction fraction is a constant 67%  |
| the fraction dropped is a constant 73%                 | the prosecution fraction is a constant 27% |
| the trial fraction is a constant 4%                    | the plea fraction is a constant 96%        |
| the additional time to acquit is a constant 0.2 months |  |

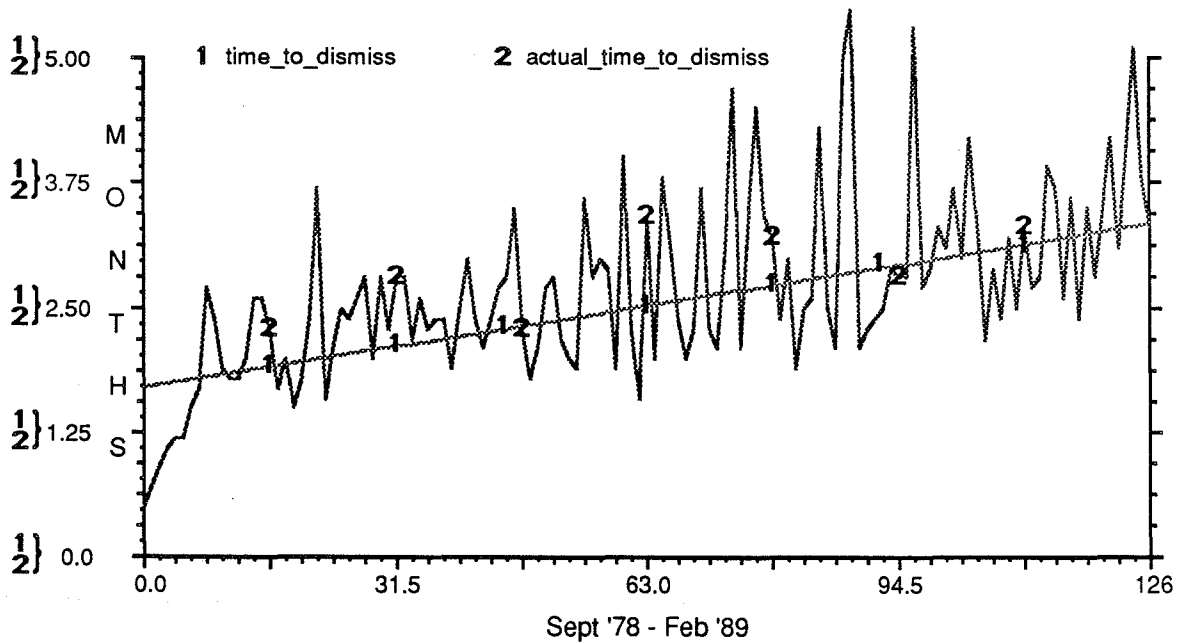


FIGURE 3  
ACTUAL AND LEAST SQUARES  
TIME TO DISMISS

Since approximately 7% of all arrests are never disposed (i.e., disposition is missing), the number of cases dropped includes the number with no disposition by arrest date. The time to dismiss cases has grown linearly throughout the period as shown in Figure 3. The regression equation for the least squares line shown is:  $1.8547 + .01293(t)$  with  $t_0 =$  month 11 (July 79)

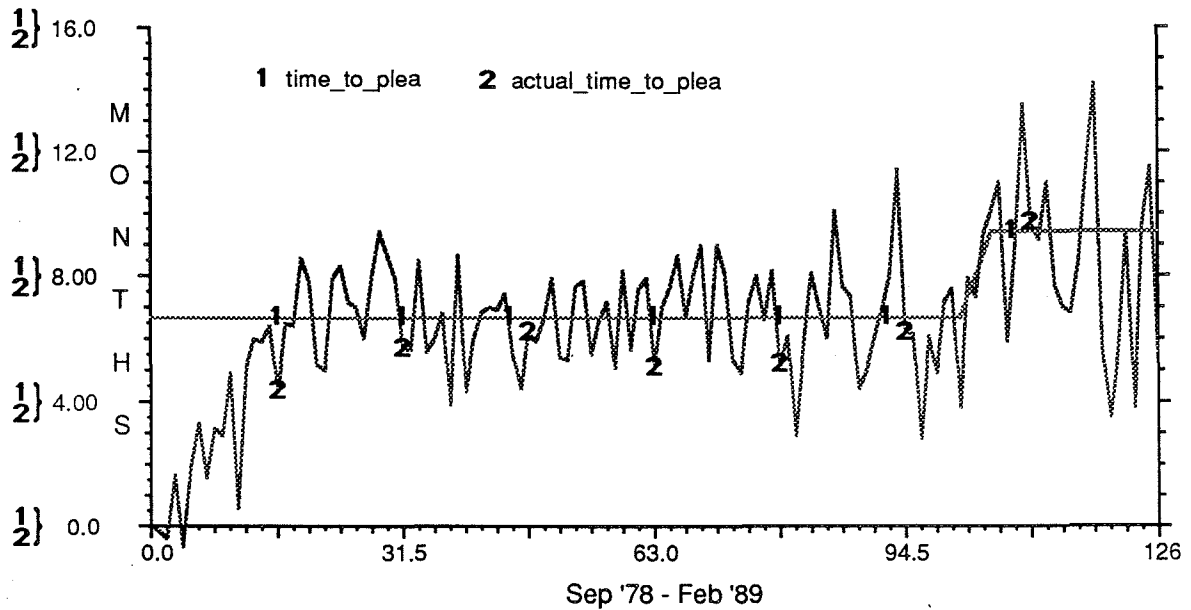


FIGURE 4  
ACTUAL AND ESTIMATED TIME TO PLEAD

The time to dispose of a case by guilty plea was more variable as shown in Figure 4. The disposition time increased somewhat linearly through month 99 (Nov. '86). The disposition time seems to have taken a "step" increase from 9 months to 11.5 months by month 103 (March '87). It was assumed that the trends after this is of the same slope as prior to month 99.

Since all cases disposed via plea were also prosecuted (using time to drop), time to drop was subtracted from time to dispose via plea to produce the additional "time\_to\_plea". The gradual slope for the period before and after the step increase in time to dispose via plea matches that of the slope in time to drop. For this reason, time\_to\_plea is a constant 6.67 plus time\_to\_drop prior to the step, and 9.45 plus time\_to\_drop after the step. The time during the step is linearly interpolated across 3 months.

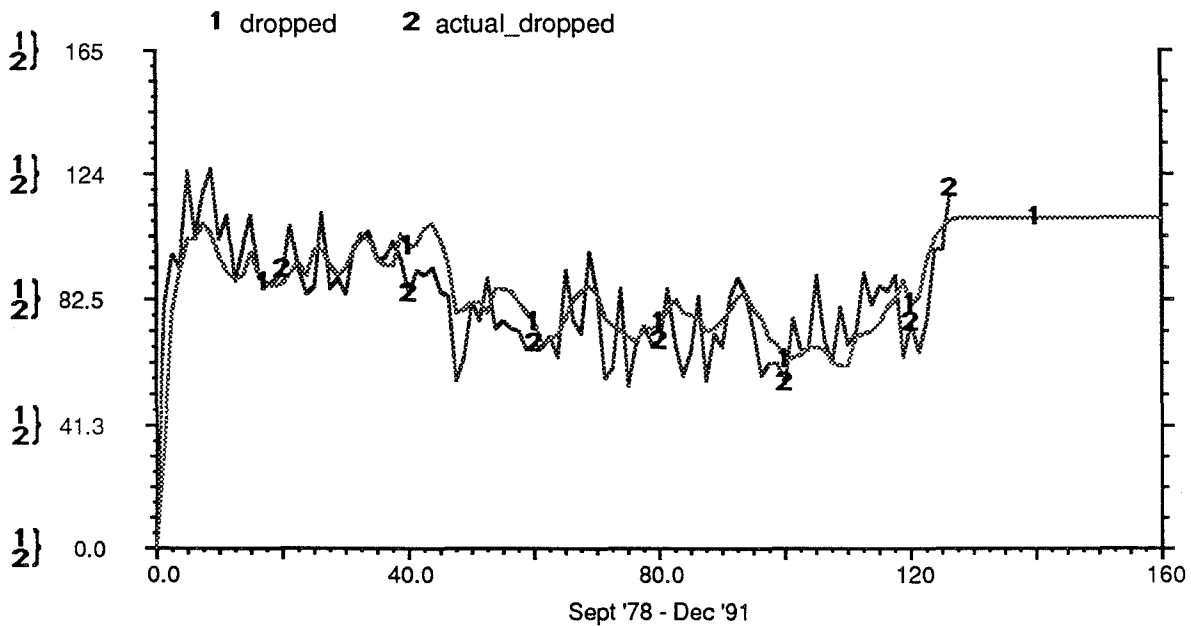


FIGURE 5  
ACTUAL VS SIMULATED CASES DROPPED

The model output was compared to the actual data to test the validity of the model. As shown in Figure 5, the number of cases dropped matches the data very well though all but the end of the time period. Since the number of cases dropped is expected to be artificially inflated because of data censoring, this was taken to be a good fit to the data.

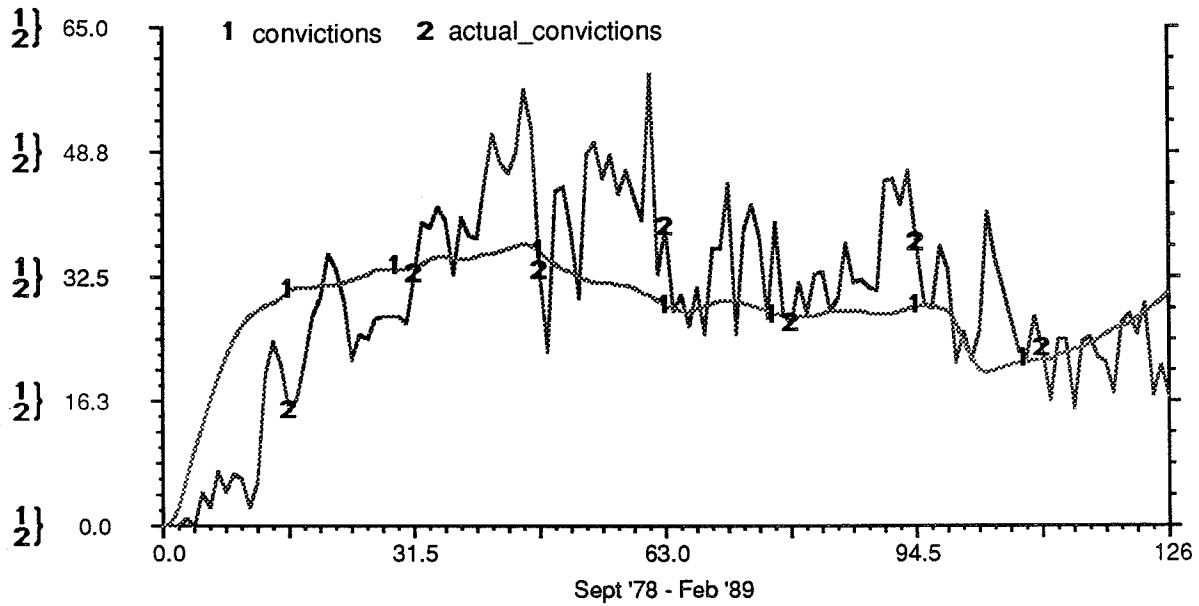


FIGURE 6  
SIMULATED AND ACTUAL CONVICTIONS

When simulated, the initial startup for convictions is quicker than the actual convictions as shown in Figure 6. Because of this response time misfit, the increase in simulated convictions during the final year of simulation may be unduly influenced by this quick response time. In order to adjust the system response time, another order of lag was added, and this delay time was estimated to be 6 months\*. This produces a slower system response time such that the initial growth in convictions matches more closely the actual convictions.

\* I tested whether the differences might be due to the order of the processing time (i.e., the skew of the log-normal distribution) by maintaining the total time to plea through several orders of lags. This not only did this not produce the slower system response, but it created "overshoot". For this reason, there seems to be some other system lag not discernable from the data. I estimated the length of this additional "system response" time to be 6 months through trial and error.

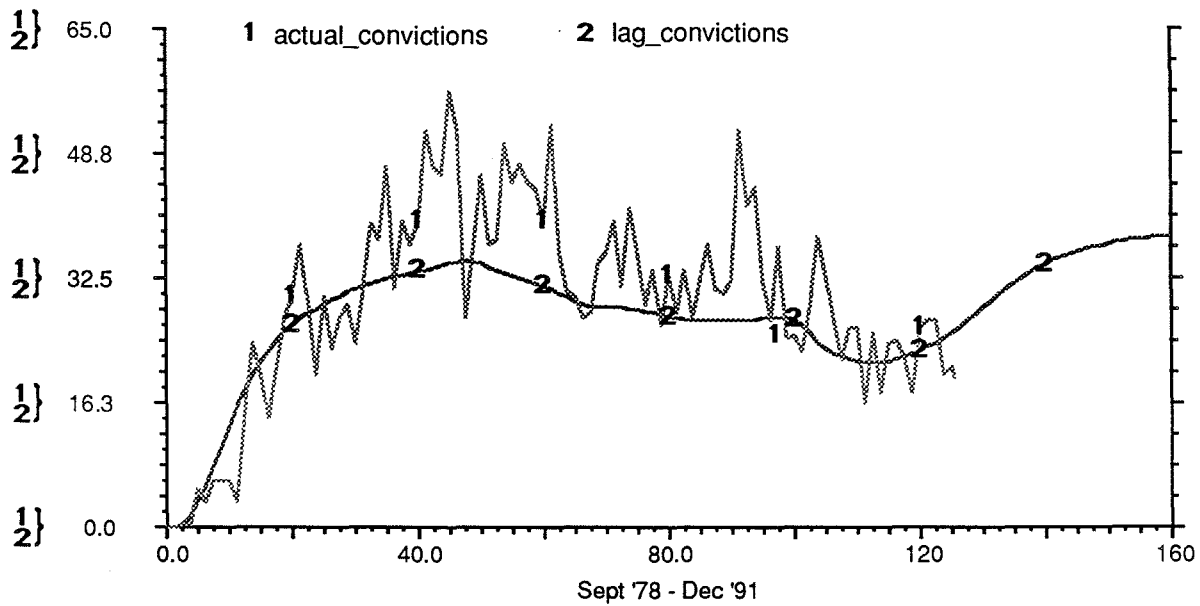


FIGURE 6  
 ACTUAL AND SIMULATED CONVICTIONS  
 WITH 6 MONTH DELAY OF SIMULATED CONVICTIONS

The simulation was run 20 months past the data to demonstrate the dynamic inertia contained in this structure. The result of this additional processing lag is shown in Figure 7.



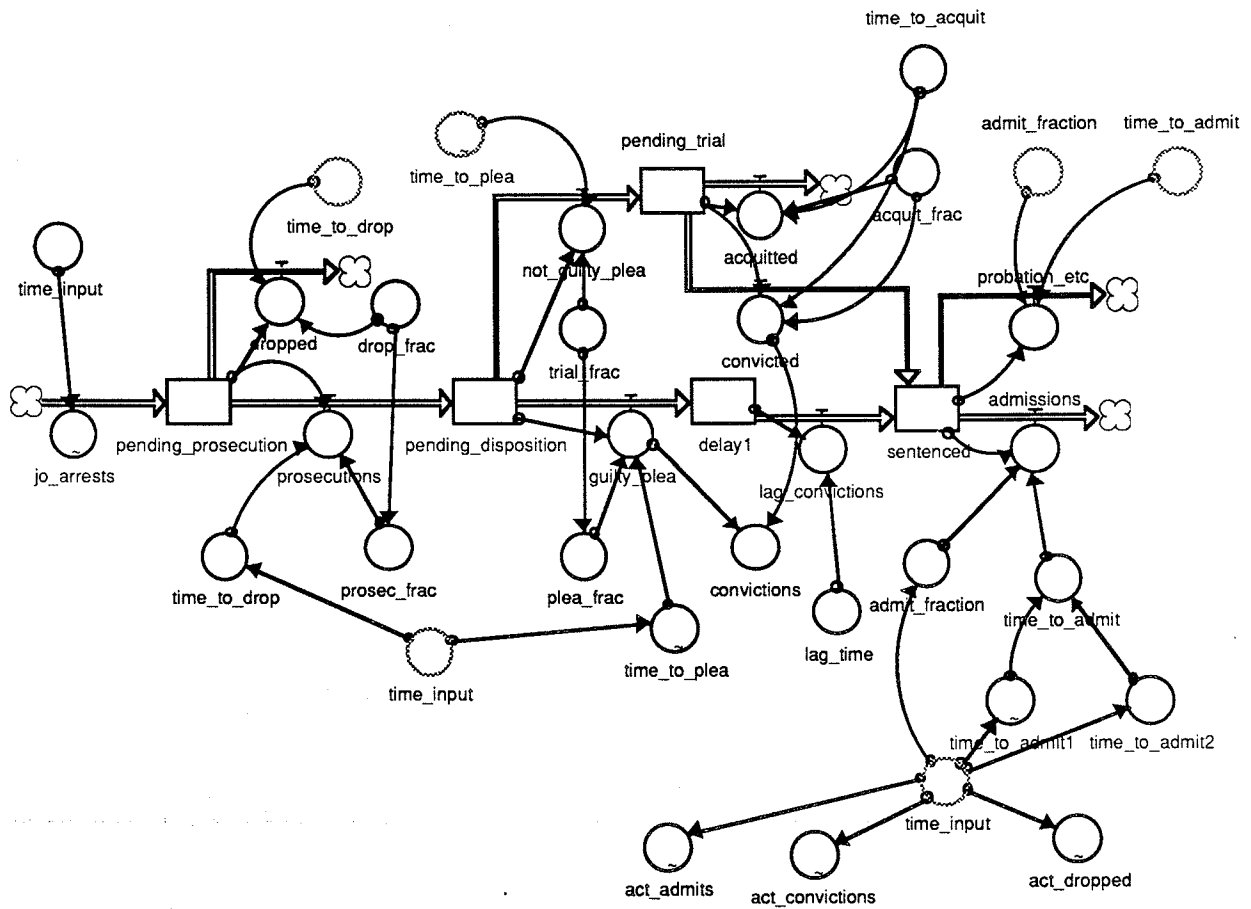


FIGURE 8  
FINAL MODEL STRUCTURE

The full JO processing model was constructed with the 6 month system lag, and included an additional system accumulation (sentenced) leading to DFY admission. This final model structure with all exogenous time series variables is shown in Figure 8.

The addition of the admission structure require two additional parameters be estimated: fraction placed with DFY and time to admit. Since the data for the admission rate is from the division's on line data base, it is unaffected by the data censoring discussed earlier.

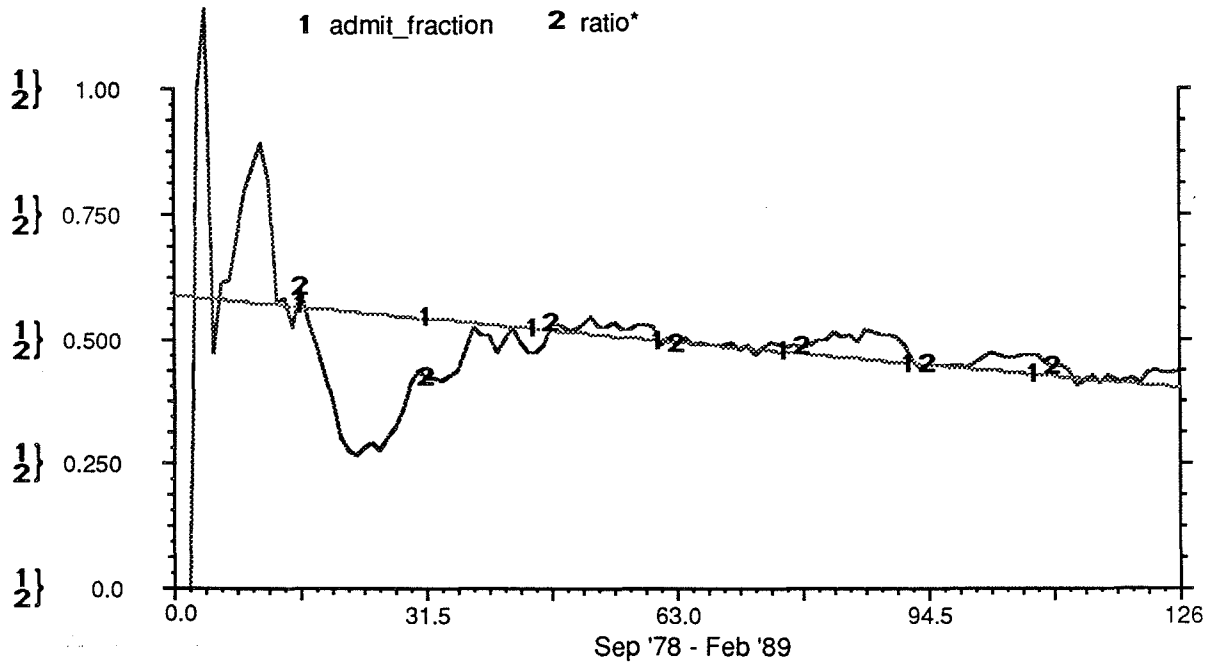


FIGURE 9  
 ACTUAL AND ESTIMATED ADMIT FRACTIONS  
 \*ratio = smooth(act\_admits,12)/smooth(act\_conv,12)

The fraction of convicted cases admitted to DFY was calculated by taking the ratio of the 12 month moving averages of admissions per month and convictions per month. The least squares trend of this parameter is used in the model for the values calculated over the stable period of January '83 (month 53) and February '89 (month 126) as shown in Figure 9. The formula for this trend is:  $5106 - .0015t$ , where  $t_0=53$ rd month. The fraction of convictions admitted range from 58% (9-78) to 41% (2-89).

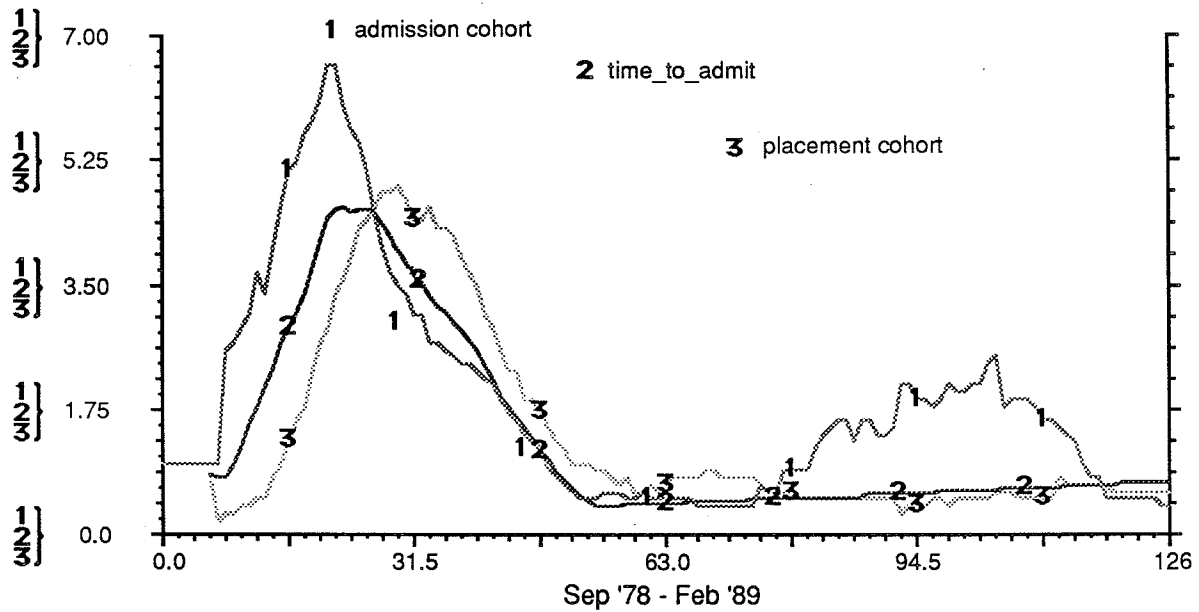


FIGURE 10  
ACTUAL AND ESTIMATED TIME TO ADMIT  
12 MONTH MOVING AVERAGES FOR COHORT DATA

Since the time from placement to admission has been non-linear since 1978 as shown in Figure 10, two periods were used to estimate this parameter. For the period prior to month 55 (March '83), the average admission time of placement and admission cohorts was used. For the period following March '83, the least square fit for the more stable line (placement cohort) was used. The formula for this line is:  $.4063 + .0047t$ , where  $t_0 = 55$ th month (March '83)

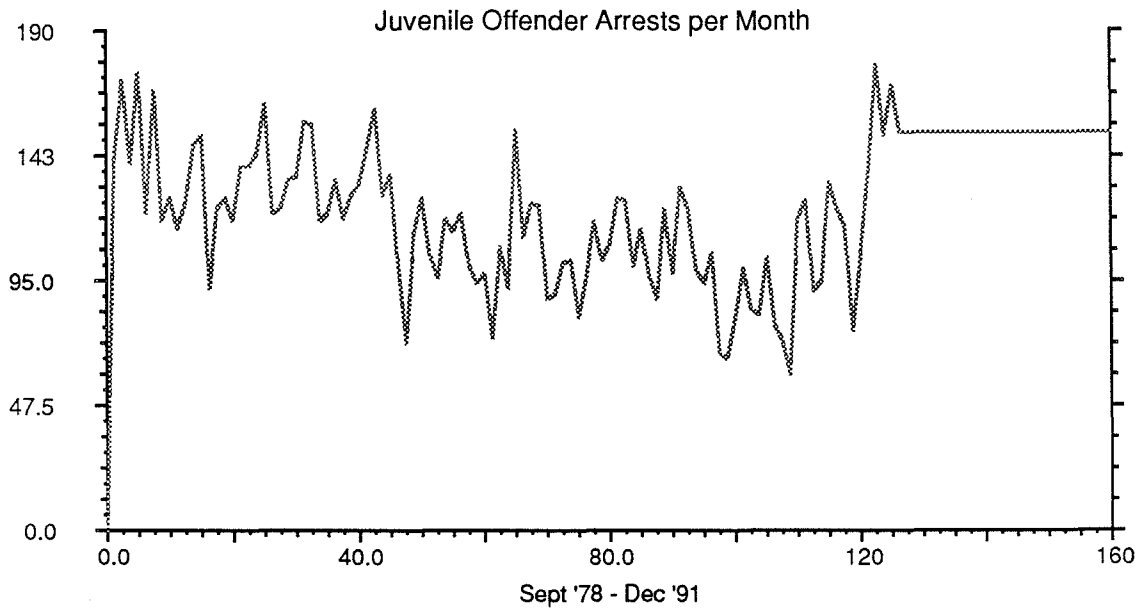


FIGURE 11  
EXOGENOUS MODEL INPUT

## RESULTS

The completed model was run for a total of 160 months (Sept '78 - Dec '91). The STELLA software holds constant the final value listed in any of the table functions (exogenous inputs). The actual arrests per month was used as input and the lagged convictions was used as convictions. Since the number of arrests during the most recent month available was higher than recent historical averages, the model assumes that arrests will continue at the increased rate as shown in Figure 11.

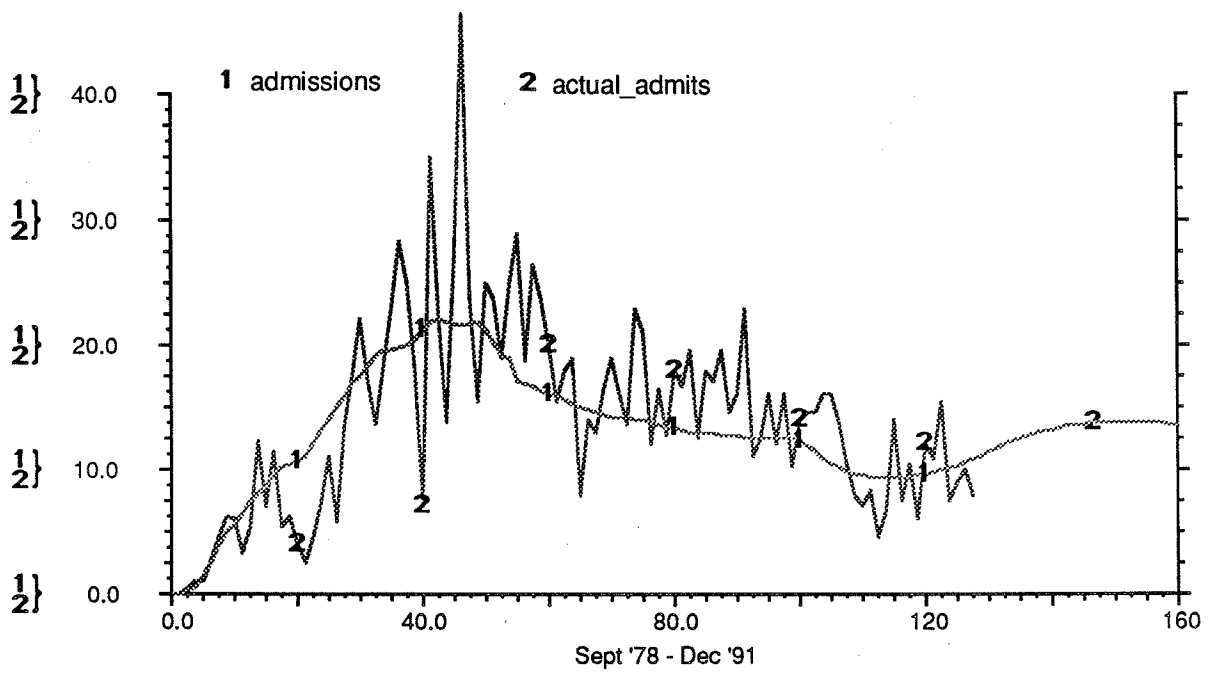


FIGURE 12  
FINAL MODEL OUTPUT AND VALIDITY TEST

Of course, the recent trend suggests that JO arrests might continue to increase, so the results should not be taken to be a forecast of our JO admission rate. As shown in Figure 12, the simulated admission rate closely matches the actual (uncensored) admission rate.

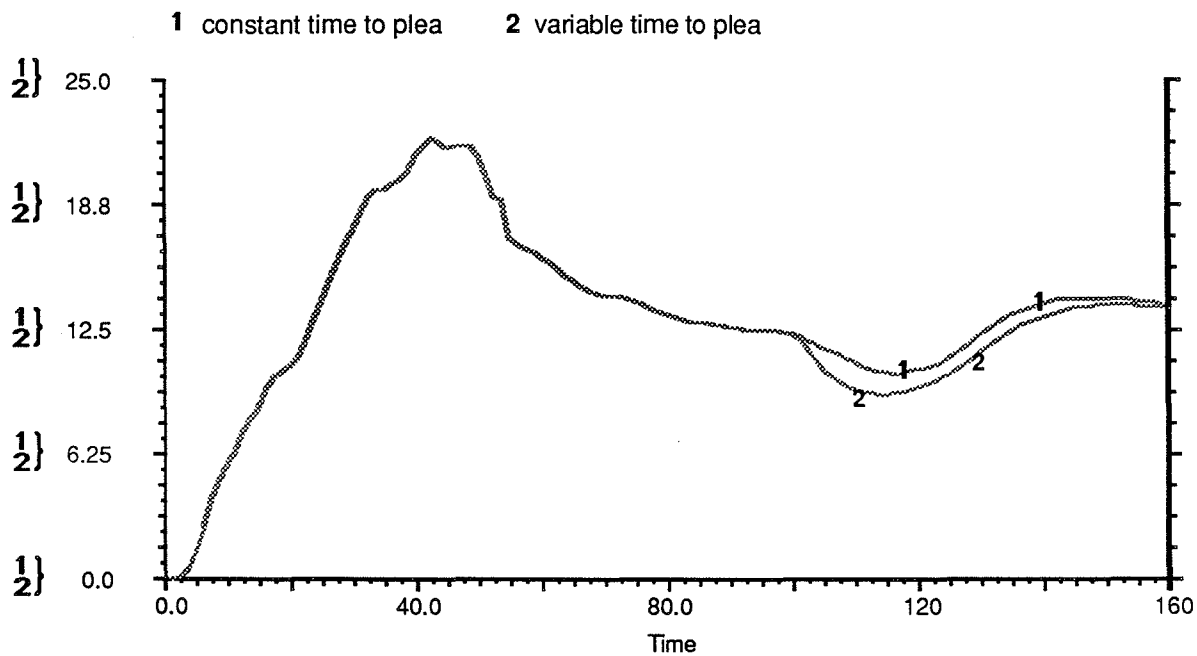


FIGURE 13  
MODEL SENSITIVITY TEST

For the present purpose, the concern is the cause of the decline in admissions during the most recent years. In order to test the sensitivity of the admission rate to the recent increase in processing time, time to plea was held constant at the pre-November '86 value of 6.67 months. The results of this run is compared with the previous run in Figure 13.

The results suggest that had the processing time not taken a 3 month increase, the admission rate would still have fallen off though not as much. Generally, the admission rate is insensitive to sudden changes in processing time as the differences between these two runs never exceeds 1.5 admissions per month. While the constant processing time produces a growth in admission more proportionate to arrest trends, the differences is insignificant.

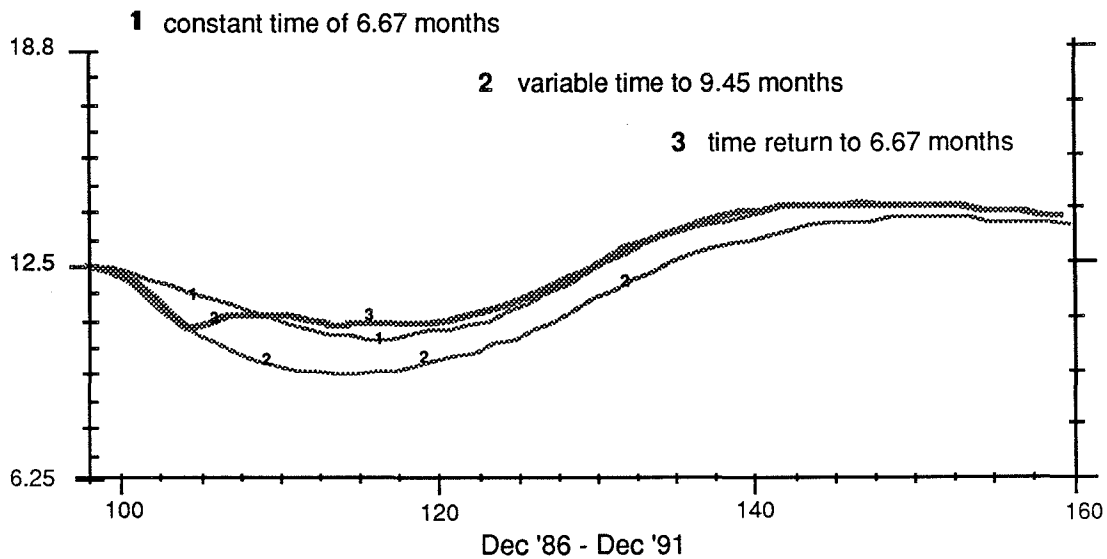


FIGURE 14  
FINAL MODEL SENSITIVITY TEST

To test the possible effect on admissions should the processing time suddenly fall to its previous value, another run of the model was conducted such that the time to plea returns to 6.67 after month 105 (May '87). This assumption is compared with the others in Figure 14. The difference is not dramatic.

## CONCLUSION

It is unnecessary to explain the lack of growth in admissions during the recent time period by resorting to either assumed effects of changing processing proportions or processing time. It seems clear that the recent decline is the lagged results of a previous decline in arrests, in spite of other system changes. The results of testing the model for numerical sensitivity to changes arrests and processing time reveals that the growth in admissions was proportional to the growth in arrests without requiring any processing ratio changes. The JO admission rate can be expected to grow proportional to the growth in arrests. The model with constant or linearly changing processing parameters seems able to explain most of the changes in admission rates. Further, the model proved to be numerically insensitive to changes in processing time, even when the time was suddenly decreased to the pre-growth value. The maximum potential for admission "surge" is demonstrated to be negligible.