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Self-destructing prophecies: Long-term forecasting of municipal correctional bed need

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Abstract

Although municipal jails consume a significant amount of resources and the number of inmates housed in such facilities exploded in the 1990s, the literature on forecasting jail populations is sparse. Jail administrators have available discussions on jail crowding and its causes, but do not have ready access to applications of forecasting techniques or practical demonstrations of a jail inmate population forecast. This article argues that the underlying reason for this deficiency is the inherent unpredictability of local long-term correctional population levels. The driving forces behind correctional bed need render local jail population forecasts empirically valid only for a brief time frame. These inherent difficulties include the volatile nature of jail populations and their greater sensitivity when compared with prison populations to local conditions; the gap between the data needed for local correctional population forecasting and what is realistically available to forecasters; the lack of reliable lead variables for long-term local correctional population forecasts; the clash of the mathematics of forecasting and the substantive issues involved in the interpretation of forecast models; and the significant political and policy impacts of forecasts on local criminal justice systems and subsequent correctional population trends.

The differences between the accuracy of short-term versus long-term jail bed need forecasts means that forecasting local correctional bed need is empirically valid for, at best, one to two years. As the temporal cast is extended, longer-term forecasts quickly become error prone. Except for unique situations where jails exist in highly stable local political, social, and criminal justice environments, long-term forecasts of two years or greater are fatally flawed and have little empirical accuracy. Long-term forecasts of local jail bed needs are useful, though, as policy catalysts to encourage policymakers to consider possible long-term impacts of current decisions, but forecasts should be thought of and presented as one possible future scenario rather than a likely reality. Utilizing a demonstration of a local jail forecast based upon two common empirical forecasting approaches, ARIMA and autoregression, this article presents a case study of the inherent difficulties in the long-term forecasting of local jail bed need.

Introduction

> "Those who fail to predict the future are condemned to be surprised by it."

Forecasting municipal correctional bed need

The paraphrase of the popular quote from George Santayana applies well to municipal and county jail administrators who during the 1990s were often unprepared for the enormous growth in jail populations.[1] Although arrests dropped in the United States during the 1990s, the number of local jail bookings rose from

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7.1 million in 1988 to 11.4 million in 1999 (Beck, 2002). With more than ten million men and women annually admitted and released from jails in more than 3,000 jurisdictions, local jails became the dominant correctional institution in the United States (Wallenstein, 1996, p. 78). Jails nationwide rose to 94 percent of their capacity, up from 90 percent in 2001 (Harrison & Karberg, 2004). With this dramatic increase in population came tremendous costs for local government in both operating and capital expenditures as they struggled to keep up with the burgeoning inmate population (Petersilia, Turner, & Fain, 2000). According to the Bureau of Justice Statistics (2002), local government corrections agencies experienced the highest annual average increase in expenditures of any local governmental area, increasing approximately 9.5 percent per year during the 1990s. Due to their high operating costs and continued expected growth, United States jails began to attract significant policy interest. Jail capacity did not increase commensurate with the number of inmates, and historically about a third of all jails experienced lawsuits or other legal action pertaining to overcrowded conditions (Pontell & Welsh, 1994).

Cunniff (2002) suggested that jail admissions rose as a result of decade-long policy trends to increasingly use jails for detention of offenders with outstanding warrants, for pretrial detention, for housing offenders under state or federal jurisdiction, and as a result of increases in arrests for drug violations and simple assaults and increases in the number of offenders revoked from community supervision. As such, the rise in jail admissions reflected the outcome of numerous discretionary decisions that were largely beyond the control of local jail administrators. The expected dramatic increases in jail population and expenditures posed a challenge to local government leaders as they faced the task of managing and financing jails in the twenty-first century (Cushman, 2002). In reality, most jails have no control over who comes through their doors, and they have very little control over how long anyone stays (Cunniff, 2002). Therefore, despite declining national crime and arrest trends, projections suggest that most United States jails will need more beds while some jurisdictions will experience declining jail populations over the next decade (Beck, 2002, pp. 9, 13; Butterfield, 2004).

A valuable tool for practitioners facing this ambiguity would be reliable long-term forecasts of local correctional bed need. Unfortunately, not all phenomena, even ones easily empirically tracked like the number of inmates housed in a local correctional facility, are inherently predictable over the long-term (Rescher, 1998). It is herein argued that local jail bed need is one such unpredictable phenomena falling prey to prediction spoilers. Spoilers include "*chance*"—random events that continually break discernible empirical patterns; "*chaos*"—irretrievably probabilistic trends that are unpredictable by their nature; and "*choice*"—unforeseeable conscious or arbitrary decisions that change a trend in unexpected ways. Unlike explanation aimed research in which an event occurs and the researcher strives to construct the causes of the event, the forecaster's task is to assemble a model which harbingers an event. The elements of a forecast model need not be causes of the forecast event. In prediction, the initial conditions are given, and their effect has not yet taken place and is to be determined (Pedhazur, 1997, p. 195).

Pursuant to these considerations, this article discusses the forecasting of correctional bed need at the municipal level and demonstrates a county jail ten-year bed need forecast utilizing SPSS Trends software. The case study of municipal correctional bed needs demonstrated that even with sophisticated forecasting techniques such as autoregression and ARIMA,[2] the full cooperation of local correctional personnel, and access to a wide range of local correction, social, and political time series data, the construction of a reliable long-term forecast of local correctional bed needs was not possible.

The current state of jail population forecasting

Despite the obvious benefits that would accrue from reliable forecasts, the forecasting of jail populations has not been a priority in the field of criminal justice. While there is an extensive set of technical literature that deals with simulation modeling and forecasting techniques, the knowledge has not been normally applied to jail populations. Historically, the forecasting of prison populations has been more common and partly reflects both the visibility of these larger institutions and the greater availability of data to construct forecasts. Today a number of states regularly forecast their prison populations and prison population forecasting has advanced to the point where sophisticated forecast models are regularly constructed and are sufficiently accurate to be administratively useful.[3] The prison population forecasts established the ability of variously configured forecast models to account for the impacts of policy shifts on prison populations and produce reliable forecasts.[4]

Regarding jail population forecasts, although more jurisdictions were undoubtedly involved in the forecasting of their jail populations as part of extensive master plans, few discussions were readily available in the general academic literature.[5] Besides inaccessibility, the major deficiency with this literature was that these materials did not demonstrate actual jail population forecasts. While it was a reasonable assumption that a number of unknown jurisdictions were currently involved in forecasting their jail populations, it was a fact that actual forecast examples were not available to practitioners outside of the forecasting discipline. Unlike prison populations, there were no readily accessible demonstrations of the capacity to actually forecast jail populations. Why is it that long-term prison populations forecast exist while long-term forecasts of jail populations were notably absent? The reason there are no reports of long-term forecasts of local jail populations is that a combination of factors renders long-term jail bed need an unpredictable phenomenon and their pursuit a fool's errand.

A forecasting demonstration of municipal correctional bed need

As part of a wider assessment of local jail issues, a forecast of bed need was conducted in late 2000 for the Orange County Florida Corrections Department. Orange County, Florida Corrections maintained one of the largest jail systems in the country with an average daily population of approximately 4,500 inmates. Like most large urban jails, the Orange County jail operated well over its designed capacity of 3,426 (as of August, 2000). The demonstration forecast utilized two general data sources to forecast bed need. The first source was the Orange County Corrections Department, which collects and maintains all of the in-house correctional data. The second general source of forecasting data was from a set of varied state and local organizations that collect county-level information. In this forecast effort, data on correctional bed need in the Orange County Corrections system was compiled beginning in January 1993 and ending in June 2000 from the county in-house database. The resulting time series data set consisted of ninety monthly time units for model estimation, fitting, and forecasting. Bed need was operationally measured as the average daily head count of inmates with length of stays greater than twenty-four hours. Utilizing the forecast generated in 2001 and comparing it with actual jail bed need over the subsequent three plus years, the forecastability of local jail bed need is discussed.

The demonstration forecasting of correctional bed need began with an examination of the bed need sequence chart. Fig. 1 provides the sequence chart for average monthly bed need since 1993. Reflecting a nonstationary series, or one that does not fluctuate consistently about its overall mean, bed need was fairly stable through 1997, thereafter showing an upward trend.

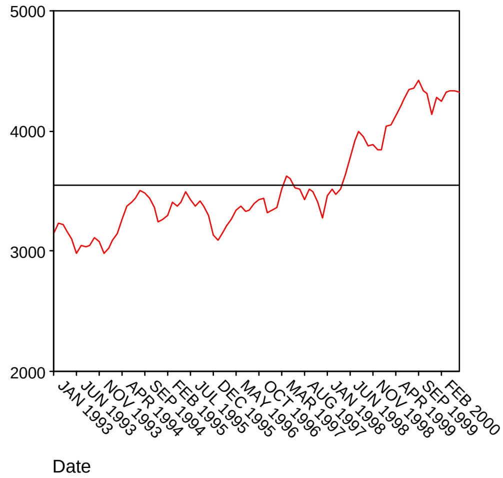


Fig. 1. County correctional bed need—January 1993 to June 2000.

Recalling that the forecast was constructed in late 2000 and was based on monthly data through June 2000, the first step was to divide the sample into two portions: an initial portion called the "use" sample within SPSS was used for forecast model estimation, and a smaller validation portion, termed a "predict" sample, was used to assess the estimated model's fit and adequacy as a forecast method. In essence, the estimation sample fits a model to the historical data and the predict sample checks how well this model fits the most recent data. For the case study, the first seventy-two months (January 1993 to December 1998) comprised the estimation or "use" sample. The eighteen months (January 1999 to June 2000) were the validation or "predict" sample. July 2000 to September 2004 provided a post-forecast comparison in which the accuracy of the original forecast could be assessed against the actual jail bed need over the subsequent four-plus years. Two forecast techniques were employed, autoregression and ARIMA, with both techniques developed with and without lead variables. Thus, four July 2000 forecast models were constructed with projections generated through December 2009.

Autoregression forecasts

The goal of autoregression, a method that automatically installs an AR(1) parameter into the forecast model, is to account as much as possible for the serial correlation that is commonly found in most time series data and which, if unaccounted for, corrupts the estimation of ordinary least squares regression statistics.

The first forecast model was an autoregression univariate model with time as the predictor variable (equal to the case sequence value for each case). The resulting forecast model was:

$$\text{Bed need} = \text{constant} + \text{AR}(1)^{*}\text{bed need} - 1 + \text{B (Time)} + \text{error}.$$

Bed need was determined as the sum of a constant value, plus the average weight or influence of the most recent past bed need level, plus the overall time trend of the series, plus an error term.

The autoregression model results reported in Table 1 provided a good historical fit with all three model parameters significant. The Table 1 statistics were analogous to those found in a standard regression output table. The log likelihood statistic is a measure of the overall model fit and, although analogous to the overall F value in regression analysis, is not directly interpretable. In general, lower log likelihood values reflect better model fit. The AR(1) factor B value of .86130 suggested that there existed a strong recent case influence regarding correctional bed need or in other words and not surprisingly, recent past bed need levels were highly correlated with current bed need levels. The *Time* B value of 9.13073 suggested that bed need increased about nine beds per month over the length of the data series, beginning from a constant value of 3,064 beds. The fit statistics reported in Table 2 were all based on examinations of the errors or deviations between the four model forecasts and the original series.[6] In this first model (see column 1 in Table 2), collectively the fit statistics showed that the autoregression model did not perform strongly as a forecast tool. For example, while the model fit the data series historically in the "use" sample with an average error of 1.7 percent (see "mean abs pct err"), its error in the predict sample jumped to 9.1 percent. The rms (root mean squared error) is a second valuable statistic for assessing the forecast model performance in the use versus the predict samples. Similar to a standard deviation, it could be seen that the error was more than five times larger in the predict sample (74.4 in the use sample compared to 414.5 in the predict sample). This decay in fit was due to the strong influence of recent cases and the fact that autoregression models did not directly account for any seasonal variation. When information on recent cases was no longer available, the forecast model floundered and depended largely on the overall upward trend. This can be seen graphically in Fig. 2 where the forecast model began to consistently underestimate bed need.

Irrespective of the above weaknesses, the model was refit to the entire series and a bed need forecast through 2009 was generated with 95 percent upper and lower confidence intervals. This autoregression model foretold a correctional bed need of 5,729 with a 95 percent confidence range from 4,764 to 6,693 by the end of 2009. The ACF (auto correlation function) of the error terms from this model, however, showed remaining significant correlations among the errors suggesting that additional model terms were needed.[7]

The main advantage of this initial autoregression forecast was that it was derived totally from the historic bed need series and therefore, was entirely producible by correctional staff. On the other hand, the primary deficiency of this autoregression forecast was its clear demonstration for the admonition that bed need should not be projected simply from past experience (Beck, 2002, p. 13). In practice, unsupplemented autoregression forecasts should be cautiously applied and are not recommended for anything but short-term forecasting. One method of strengthening an autoregression forecast is to include lead variables. The question is whether the

Table 1
Autoregression without lead indicators

Number of cases	72			
Standard error	73.993105			
Log likelihood	−411.20456			
	DF	Adj. sum of squares	Residual variance	
Residuals	69	384945.93	5474.9796	
	Variables in the model			
	B	SEB	T-ratio	Approx. prob.
AR1	.86130	.06002	14.349743	.00000000
Time	9.13073	2.38748	3.824427	.00028430
Constant	3064.00163	104.71424	29.260601	.00000000

Table 2
Forecast models fit statistics

		Auto-regression	Auto-regression with lead variables	ARIMA	ARIMA with lead variables
Deg freedom	Use	69	57	57	39
	Predict	18	18	18	18
Mean abs error	Use	57.60	45.84	63.91	50.21
	Predict	391.60	241.89	75.08	74.20
Mean abs pct err	Use	1.71	1.33	1.84	1.44
	Predict	9.14	5.66	1.76	1.74
SSE	Use	381499.3	201751.5	341453.6	187185.1
	Predict	3092462.4	1193851.6	152979.7	169077.3
RMS	Use	74.4	59.5	77.4	69.3
	Predict	414.5	257.5	92.2	96.9
AIC		828.4	675.4	683.0	554.1
SBC		835.2	683.8	687.1	571.0
Dec 2004 forecast		4,920	5,527	5,138	4,061
Dec 2009 forecast		5,729	7,592	6,175	3,316
2009 95% confidence interval		4,764 to 6,693	6,656 to 8,529	−1,383 to 13,733	−13,425 to 20,057

addition of external predictor variables will produce a substantially improved forecast model.

The search for lead variables

In developing bed need forecast models, it is expected that jail populations will exhibit stable correlations with other time series processes. For example, arrests can often be expected to be correlated with jail population levels and current arrest levels may be good predictors of future jail population levels. Such "*lead indicators*" are valuable forecast tools and can be employed in both autoregression and ARIMA models.

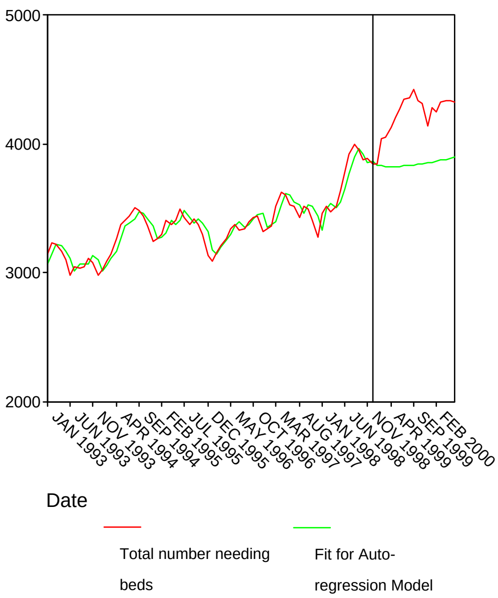


Fig. 2. Bed need and autoregression forecast model fit.

Five substantive Orange County data realms identified in the forecast and correctional literature as data areas that might contain reliable predictor variables external to the Orange County Corrections Department were examined: county crime, court, economic, population, and ethnicity data.[8] In addition, county booking data collected by the corrections department were explored for additional lead indicators of correctional bed need. The resulting data set provided a rich array of demographic and criminal justice based factors for forecasting. In total, more than one hundred candidate lead indicators regarding correctional bed need were available—far too many for a reasonable forecast model. To reduce the number of variables to a parsimonious number and create efficient forecast models, a variable culling process was employed.[9]

Noting that a lead indicator variable was a correlated but not necessarily a causally related variable, the final result was a set of seven candidate lead indicator variables that had the strongest lagged correlations with local bed need: high school Black enrollment percentage lagged twelve months, middle school Black enrollment count lagged nine months, middle school total enrollment count lagged nine months, school district total Black enrollment count lagged nine months, labor force lagged eleven months, second and third degree felony filings lagged nine months, and second and third degree felony bookings lagged nine months. It should be noted that some of the seven surviving predictors obviously shared high multicollinearity levels which would be a concern in the development or testing of a substantive, theoretically grounded forecast model. It is not important for the accuracy of a forecast if the final predictors validate or invalidate a causal model. In fact, it was not easily explained why the above lead variables were good leads of local correctional bed need beyond the fact that they emerged from a non-theoretical culling process as the best empirical survivors. From a pure empirical forecasting point of view, this lack of explanation is irrelevant, but for the pragmatic acceptance of a forecast by politicians and policymakers, substantive logic can be crucial.[10] As this effort was not an attempt to explain jail population shifts, just forecast them, the forecasting model development proceeded to minimize predictor variable multicollinearity and select the final lead variables based solely on empirical criteria (Pedhazur, 1997, pp. 196–197). Of course, if the goal was to not only forecast but to understand jail population levels, then a substantive, causally sensitive model would need to have been developed and tested. The goal herein was simply to generate the strongest empirical forecast model from the time series data available.

Utilizing the seven candidate lead indicator variables developed earlier, a multivariate autoregression analysis was conducted. Examination of a series of autoregression models eliminated nonsignificant lead variables from the above seven variable set to produce the final autoregression model shown in Table 3. Remembering that the model's variables were chosen atheoretically based on their empirical attributes, an AR(1) model with two predictor lead variables, *labor force* lagged eleven months and *second and third degree felony bookings* lagged nine months, provided the following autoregression forecast model:

$$\begin{aligned}\text{Bed need} = & -1347.6\ \{\text{constant}\}\\ & + (.83381^{*}\text{prior month average}\\ & \times \text{daily bed need})\\ & + (-.20578^{*}\text{second and third degree}\\ & \times \text{felony bookings lagged nine months})\\ & + (.01172^{*}\text{county labor force lagged}\\ & \times \text{eleven months}) + \text{error}.\end{aligned}$$

The autoregression model with lead variables reported that as the number of second and third degree felony bookings nine months prior went up, jail bed need subsequently went down. This counter-intuitive relationship between an increase in less serious felony bookings and a lagged decrease in bed need could possibly be connected to some convoluted set of relationships between individuals being booked on less serious felony charges and jail retention. It is more likely the case of the mathematics of the forecasting process masking the true underlying causal processes that generate bed need.[11] As far as the task of pure forecasting is concerned, a logical explanation is unnecessary. The credibility of a forecast based on predictors that have no theoretical or logical connection to jail populations will be questioned however. The best empirical model may conflict with acceptable political sensitivities and undermine the acceptance of even short-term forecasts. In such circumstances, forecasters are presented a forced choice between more substantively understandable predictive lead variables but weaker forecast models and less comprehendible but

Table 3
Autoregression with lead indicators

Final parameters with felony second and third degree bookings lagged nine months and labor force lagged eleven months

Number of residuals	61			
Standard error	58.855772			
Log likelihood	−333.69633			
	DF	Adj. sum of squares	Residual variance	
Residuals	57	201331.89	3464.0019	
	Variables in the model			
	B	SEB	T-ratio	Approx. prob.
AR1	.83381	.07378	11.300821	.00000000
Lagged second and third felony bookings	−.20578	.07901	−2.604312	.01171907
Lagged labor force	.01172	.00151	7.788257	.00000000
Constant	−1347.60749	650.29775	−2.072293	.04277223

more empirically accurate models. In the provided forecast demonstration, the mathematical but obviously non-causal relationship between anticipated jail beds based on the population of Black students would undermine the palatability of any resulting forecast. The distinction between correlation and causation is often lost on policymakers and the public. Black student enrollment in high schools, middle schools, and school districts might be reflective of other measures such as poverty and crime rates, but these more interpretable variables did not perform well as predictors in the example. Further undermining substantive interpretations, White student enrollment levels also performed nearly as well as lead variables as Black student enrollment. In sum, in the demonstration data, models using more substantively meaningful leads performed significantly worse than the ones presented. This reality often leads to a Sophie's choice between model comprehension or model strength in regards to local jail population forecasting.

Even if substantively understandable lead variables also turn out to be the empirically strongest ones available, an additional concern with utilizing lead variables is that they must themselves be forecast to be used for long-term forecasts. In the demonstration forecast, projections beyond nine months relied on forecast values of the lead variables. Local correctional bed need quickly became a forecast generated from another set of forecasts and whatever inaccuracies existed in the lead variable forecasts were passed along. Overall, the lack of reliable lead variables is a serious impediment to the long-term forecasting of local correctional bed need. They may exist but no reliable five-year lead variables, or even two-year leads, had been reported in the correctional forecast literature.

Fig. 3 displays the historic county bed need with the model's fit through the year 2000. As shown, this model's values better fit the county's past bed need than the simple autoregression model, but continued to underestimate bed need in the near term. The fit statistics in Table 2 (see column 2) also indicated this model's improved fit over model 1 with a smaller mean absolute percentage error for the prediction sample of 5.7 percent. The AIC and SBC values for the relative models (see Table 2, columns 1 and 2) provide statistics that can be used to compare different forecast models. Lower AIC and SBC values denote better model fit. When compared, the AIC and SBC showed that the autoregression with lead indicators provided an improved forecast model over the simpler AR(1) model.

With up-to-date values for all variables available, this model provided forecasts directly for nine months

Fig. 3. Autoregression with lead indicators forecast model.

into the future (the lagged value for monthly number of second and third degree felony bookings). Beyond that time frame, a forecast of bed need required a forecast of second and third degree felony bookings and labor force size. The forecast values of the two lead indicators were then utilized to create the bed need forecast. Forecasts of the lead indicator variables can be generated by the forecaster's method of choice, autoregression, ARIMA, or another technique. In this case, forecasts of labor force and second and third degree felonies were generated via an ARIMA process to allow seasonal variations in the lead indicator variables to be taken into account. The two lead variables were projected out to early 2009. Using these projected values, a forecast of bed need was subsequently generated through December 2009. This model forecast a county bed need of 7,592 with a 95 percent confidence interval range from 6,656 to 8,529 for December 2009.

ARIMA forecast models

The second demonstrated forecasting technique employed ARIMA modeling. Using the same approach applied with autoregression, a pure time series ARIMA model was developed first; that is, one without lead indicator variables. Following examination of the autocorrelation functions (ACF) for the differenced series and the exploration of variously configured models, a (0,1,1)(1,1,0) model emerged as the best ARIMA forecasting model.[12] The model reflected that differences were taken at both the seasonal and nonseasonal levels, and that a nonseasonal moving average (1) parameter and a seasonal autoregression (1) parameter were included. The constant was not significant and therefore dropped.

The results of this first true time series ARIMA model are reported in Table 4 and this forecast model produced average errors of less than 2 percent (mean absolute percentage error of 1.84 for the use sample, 1.70 for the predict sample—see Table 2, column 3). Fig. 4 shows that the fit remained strong in both the use and predict samples. Furthermore, the AIC and SBC values were comparable to the autoregression with lead indicators model.

The ARIMA model was refit to the entire series and a forecast through December 2009 was generated. The resulting forecast of bed need depicted a steady increase to the 6,175 level by the year 2010. The forecast, however, had a broad 95 percent confidence level range of −1,383 to 13,733 beds by the end of its forecast period. Clearly, while the point estimate of 6,175 appeared reasonable, the distant forecast values suffered from a decline in expected accuracy as reflected in the spread in the associated 95 percent confidence intervals. It is, of course, impossible for bed need to fall below zero at the end of the decade.

To see if the available lead indicator variables would improve the forecast's long-term performance, a second ARIMA forecasting model using the lead indicator variables was developed. After exploration of various models, a combined ARIMA model (0,1,6)(1,1,0) with labor force lagged eleven months and felony two and three bookings lagged nine months emerged as the best fitting ARIMA forecast model for correctional bed need (see Table 2, column 4 and Table 5).[13] With the best historic fit of the four models demonstrated, this model also had the lowest AIC and SBC values. Despite the fact that the addition of the lead indicator variables slightly improved the model's historic performance over the univariate ARIMA model, the presence of the high order moving average parameters devalued this model. None of the six moving average factors were individually significant, but the overall model turned out to be the closest fit to the then available data and, as will be discussed, the closest forecast to the subsequent bed need trend. Fig. 5 graphically displays the ARIMA plus lead indicator model's fit to the use and prediction bed need samples through the year 2000. The forecast of bed need based on the ARIMA plus lead indicators model reflected that while the prior models forecast a steady growth in bed need, this model alone forecast a decline in bed need by the end of the decade. The ARIMA with lead variables model's December 2009 forecast bed need was 3,316. As with the ARIMA without lead variables model, however, this model had an implausible 95 percent confidence interval range of −13,425 to 20,057.

Fig. 4. ARIMA model without lead indicators.

Table 4
ARIMA model without lead indicators

Number of residuals	59			
Standard error	74.415647			
Log likelihood	−339.49282			
	DF	Adj. sum of squares	Residual variance	
Residuals	57	343393.61	5537.6885	
	Variables in the model			
	B	SEB	T-ratio	Approx. prob.
MA1	−.51207947	.11074689	−4.6238724	.00002208
SAR1	−.56759505	.12884645	−4.4052051	.00004716

Table 5
ARIMA model with lead indicators

Final parameters with felony second and third degree bookings lagged nine months and labor force lagged eleven months

Number of residuals	48			
Standard error	61.870212			
Log likelihood	−268.05695			
	DF	Adj. sum of squares	Residual variance	
Residuals	39	198638.87	3827.9231	
	Variables in the model			
	B	SEB	T-ratio	Approx. prob.
MA1	−.26668983	126.79576	−.0021033	.99833253
MA2	.03997851	40.96487	.0009759	.99922630
MA3	.01213848	21.76516	.0005577	.99955786
MA4	−.06439944	71.44775	−.0009014	.99928542
MA5	.13185229	96.09627	.0013721	.99891223
MA6	−.60613176	88.40493	−.0068563	.99456445
SAR1	−.61348893	.15679	−3.9128877	.00035501
Lagged second and third felony bookings	−.21936166	.09596	−2.2860728	.02776500
Lagged labor force	.00634418	.00405	1.5652804	.12559624

Model comparisons

Fig. 6 shows that the generated forecast models provided December 2009 point estimate bed need values that ranged from a low of 3,316 (ARIMA with lead indicators) to 7,592 (autoregression with lead indicators). The pragmatic question was where to go with such discrepant figures? Despite the fact that based on the diagnostic statistics and the AIC and SBC values designated the ARIMA with lead indicator model as the strongest candidate, its higher order parameters and broad end of forecast confidence interval called for its rejection. The ARIMA without lead variables appeared best as a forecast model. For the corrections department, it avoids the necessity of dealing with external agencies for data and secondary forecasts of lead variables and higher order parameters, explaining counter-intuitive relationships, a low mean absolute percentage error in both the use and predict samples, and comparatively low AIC and SBC values. Based on this model's forecast, the county would expect to need 5,138 beds by December 2004 and 6,175 for December 2009. Its

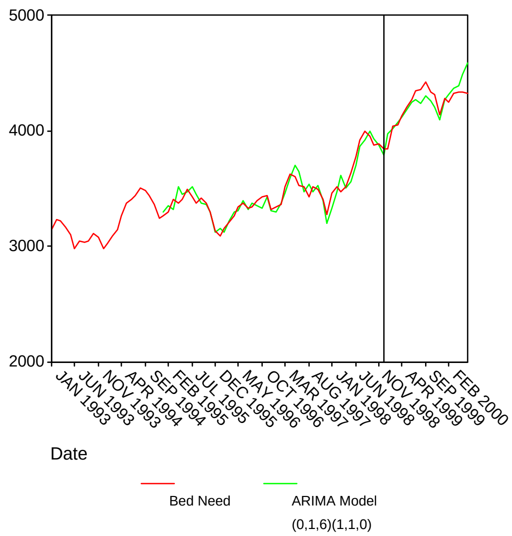


Fig. 5. ARIMA model with lead indicators.

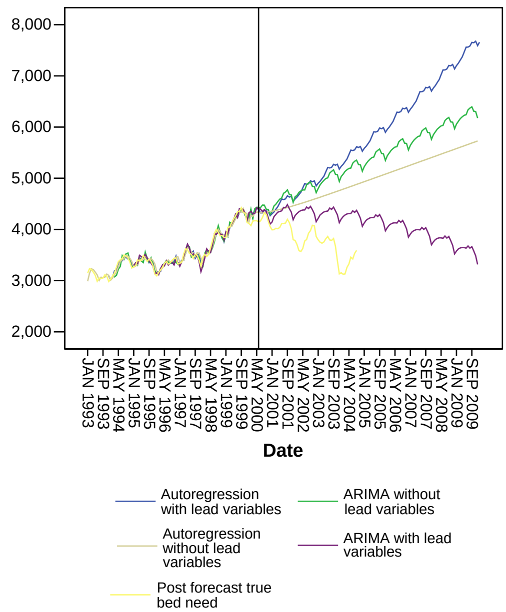


Fig. 6. Model forecasts and post-forecast true bed need.

broad confidence interval at the end of the decade, however, reflects the inherent difficulty of long-term forecasts of jail populations and thus, the forecast figures were presented with the caveat that forecasts beyond two years were highly speculative.[14]

In reality, none of the four models provided good long-term forecasts. The ARIMA model performed statistically best for short-term forecasts, but degraded into negative confidence intervals for long-term ones. The autoregression model without leads quickly degraded temporally. Based upon its avoidance of long-term negative confidence interval values, the autoregression with lead variables model appeared to have the best potential for long-term forecasts if the lead variables can be reliably forecast long-range or leads with greater lagged relationships to jail bed need are discovered. Both requirements are questionable.

Perhaps most damaging to the plausibility of long-term jail population forecasting was that even over the short term, the actual demonstration jail population did not closely follow the forecast models (see Fig. 6). All four models projected jail bed need at higher levels than actual bed need levels came to be (the ARIMA with leads model came the closest). This collective model failure was due to the impact of the forecast on the local criminal justice community. The 2001 release of the forecast occurred during the deliberations of the County's Jail Oversight Commission, a blue ribbon panel of local community and criminal justice system members. The panel had been created in the wake of two highly publicized inmate deaths, but the charge of the Jail Oversight Commission was quickly expanded to include a review of criminal case-processing in order to reduce jail overcrowding. The local media reported the forecast in August 2001 (Bloodsworth, 2001), describing that the jail would need 6,500 beds within ten years. This forecast spurred the Jail Oversight Commission to search for more efficient case-processing at the jail. As the commission wrapped up its business in the spring of 2002, its final report included over 200 changes to either jail operations or the criminal justice system itself. Within that report, the Jail Oversight Commission included an in-house analysis that showed that the forecast's prediction of a bed need of 6,500 could be avoided if the case-processing changes were implemented. Specifically, the commission's report indicated that case-processing efficiencies would stabilize or reduce the jail's population such that a new round of jail expansion would be unnecessary, saving Orange County approximately $175 million (Bloodsworth, 2002b).

Concurrent media coverage focused specifically on the forecast's numerical predictions and the need for immediate policy changes to avoid the forecast's predicted outcomes (Bloodsworth, 2002a). For example, an Orlando Sentinel editorial on April 6, 2002 noted, "If population and crime trends continue, the projections show that the population would grow to at least 6,500 in eight years" (Porter, 2002, p. A17). Another article concluded, "The jail will be 43 percent above its capacity in 2010 if nothing is done to address the underlying problems in the system" (Steinman, 2002, p. B1). The commission's entire report was accepted by local government and was to be implemented beginning in May 2002 (Steinman & Bloodsworth, 2002).

By the spring of 2003, however, only fifteen of the thirty-nine case-processing changes called for were made (Colarossi, 2003a). In late June of 2003, the Jail Oversight Commission met on the one-year anniversary of their final report to check on progress being made within the local criminal justice system on its recommendations. The lack of action on the case processing changes, combined with the forecast's prediction of a large population expansion, was covered by local television and newspaper reports over several days after the commission's reunion (Colarossi, 2003a). In fact, the follow-up report issued at the meeting bluntly indicated that several case processing changes, if implemented, would avoid the negative consequences spelled out by the forecast. Local media also seized upon the upper limits of the original forecast, indicating that the jail's population could grow much larger than the bed need of 6,500. Following this coverage, by September 2003 most of the major case-processing recommendations were fully implemented (Colarossi, 2003b). The jail's average daily population rapidly began to decrease in late September, a time usually marked by significant increases in the inmate population. In fact, in every recorded year prior to 2003, the jail's population had increased in October. The population, however, decreased by over 150 inmates in October 2003 and by an additional 250 inmates in November 2003. By mid-December, "the jail had about 732 fewer inmates than it did in the middle of December 2002" (Colarossi, 2003b, p. B1).

The jail bed need forecast had become a self-destructing prophecy. In reaction to the widely publicized forecast values, the county instituted a number of efforts to reduce the jail population and avoid the predicted boom in bed need. In gist, the demonstration forecast highlighted the problems inherent in forecasting local jail bed need, a task feasible over the short-term and impossible over the long-term. Four reasons for the inherent long-term unpredictability of local jail bed need emerged.

Four inherent difficulties in long-term forecasting of local correctional bed need

The long-term forecast of a local correctional jail population demonstrated the inherent difficulties of constructing such projections. Even with the full cooperation of local criminal justice agencies, access to varied historical long-term data, and the application of sophisticated forecasting techniques, the generated forecasts failed to produce reliable long-term numbers. Forecasting local jail bed need emerged as feasible over the short-term and impossible over the long-term. This inability is credited to four inherent properties of local correctional populations that render their long-term forecasting impossible.

Inherent volatility of local jail populations

The reason for the absence of long-range jail population forecasts lies first in the volatile nature of jail populations. As a forecast lengthens in time, the intervention of prediction spoilers—chance, chaos, and choice—increases. Thus, jail populations regularly shift due to the effect of unpredictable chance events (a spike in arrests following public celebration of a sports championship for example) that continually break the historical pattern. Fluctuations in arrests also exhibit a degree of chaos and, like the stock market, are partly random walk processes that are irretrievably probabilistic and unpredictable. Jail population levels are also clearly susceptible to the unpredictable influences of human choice. Unforeseeable conscious or arbitrary decisions that change trends in unexpected ways are unfortunately common in the environments of most local jails and new legislation and policies are significant but unpredictable influences on jail population levels.[15] Additionally, there may arise completely new processes, such as a stream of new immigration, which cannot be foreseen. The influences of unanticipated change, chaos, or choice are inevitably less over short-time horizons. Hence the prospects of short-range predictions for most phenomena are bound to be better than long-range ones (Rescher, 1998, p. 77). The longer the time-span the greater the risk for perturbations and their consequences to amplify and for jail forecasts to collapse.

In comparison, having inmates with longer sentences and fewer entry and exit avenues, prison populations are less directly sensitive to local demographic shifts, economic conditions, and political trends and are therefore less volatile and more trend stable. At the end of the criminal justice system, it simply takes longer for social and political shifts to impact prison populations than jails. It is also easier to empirically assess and forecast effects from single legislative and sentencing changes. Thus, the few forecast models that are constructed for local jails are more likely to examine statewide legislation and policies while ignoring local factors, and still are often excessively convoluted and complicated.

Jail forecasting data—needs versus availability

In order to construct valid empirical predictions, the first requirement is available data. The practical reality of jail population forecasting is that even if the inherent volatile nature of local jails can be overcome, the data to produce good long-term forecasts are rarely available. The data described in the literature as related to substantively understanding jail crowding frequently are not available while the available data frequently does not address substantive questions related to local jail population levels. Wooldredge (1991; see also Bureau of Justice Statistics, 2000), for example, lists sources into broad groups of criminal justice system factors, internal jail variables, and social/demographic factors concerning economic conditions and population trends.

The main difficulty is obtaining access to data covering the necessary time units. External data sets must be aggregated to similar temporal values such as months and cover time spans similar to the corrections bed need series. Agencies and businesses without an interest in the forecast must be tapped and encouraged to provide time series data. Even when external agencies are cooperative, it is frequently the case that government and business organizations do not maintain time series databases. Their meeting forecast-related data requests often requires programming and reformatting data files that are structured along case file lines into ones that are compiled along temporal time-series lines. The first, and often the longest step in a multivariate forecast, is the acquisition of external temporal data sets due to the costs of compiling the data and data compatibility issues.

An additional data obstacle to long-term jail population prediction is uncertainty regarding the measurement of present conditions. Whenever one cannot determine the present condition of things, then one cannot foretell the future state that will evolve (Rescher, 1998, p. 135). Thus, while current and past bed need can be accurately measured, and internal data forecast models can be relied upon and should be accurate over the short-term, long-term predictions require the accurate identification and measurement of various external phenomena whose present condition are beyond one's ability to measure. For example, current discretionary attitudes toward arrest by line police officers vary by time, agency, and individual. As jails are often the recipients of arrests from multiple agencies and thousands of arresting officers, trends in "arrest discretion" cannot be accurately determined to the precision needed for reliable long-term forecasts. Economic conditions are another phenomenon that exemplifies measurement issues. Unemployment data normally reflects only those actively seeking work and not those who have ceased job searches, and therefore, only partially measures the level of idle workers in a community. In practical impact, even when demographic, economic, crime, and criminal justice trend data are available, as in the demonstration example, reliable long-term forecasts will not be forthcoming.

Lack of reliable lead indicators

Predictions often come bundled with other necessary pre-predictions (Rescher, 1998, p. 153). There are no reliable long-term lead indicators of jail population reported in the literature. Therefore, while forecasts that employ external data sources should have an advantage by directly tapping into processes that harbinger shifts in the jail population, the discovery of universal lead indicators of local jail population levels should not be expected (Cunniff, 2002, p. 10). It is always possible that a local idiosyncratic reliable lead indicator of a jail population will be discovered that will help to produce a reliable long-term county population forecast in a specific locale, but even with such a fortunate discovery, the forecasting would still be swimming against the tide of the inherent volatility of jail populations and the influences of the prediction spoilers. In reality, the survival of long-term lead indicators of jail populations is undermined by the social-political environment in which jails exist. If not extinct, viable lead indicators are likely short-lived. Lead indicators can also be politically sensitive. Due to the common misunderstanding between best predictors of jail populations and causes of jail population shifts, a good forecast model may be rejected by policymakers due to the lead variables not being logically tied to jail population levels. Or conversely, a forecast model may be embraced as a causal explanation of jail populations shifts (Pedhazur, 1997, pp. 230-236). Both results are consequences of a lack of understanding of the uses and limits of forecasting.

Self-destructing prophecies

A final major problem in evaluating the accuracy of jail population forecasts is that policymakers can react to a forecast and make changes to the underlying system. In particular, forecasts of dire population growth and associated financial ruin are likely to generate strenuous policy efforts to avoid the forecast's fulfillment. This alters the assumptions operating within the forecast model and makes the initial forecasts appear to be inaccurate. Clearly, in the demonstration, the forecast was used to spur changes in how criminal cases were processed. By forecasting an undesirable future, the forecast numbers generated an environmental shift where those numbers were no longer an accurate depiction of how the Orange County jail's population would manifest itself. It can be expected that forecasts, particularly dire ones, will often spur action. As such, jail population forecasts will frequently be self-destructing prophesies. In the discussed example, the very policymakers who ordered the development of the forecast made changes to the system and altered the assumptions upon which the forecast was based. While this reality will frequently render jail population forecasts inaccurate, as the impact on local criminal justice policy in this demonstration showed, it will not render them useless.

Conclusion

Jail bed need is seen as volatile and influenced by local conditions not normally available in time series data sets. Noting that this study's jail population forecast was limited to one Florida county over a limited time span, whether the barriers to long-term forecasting discovered herein exist in other locales and more recent times needs to be further explored. While the jail examined was not unique in any obvious ways, replications and additional long-term jail population forecasts should be pursued to determine if jail population forecasts are universally self-destructing. The additional requirements of forecasting lead variables add to the difficulty of creating jail population forecasts. Collectively these factors are felt to render jail population forecasting beyond the near future impossible. Despite the fact that forecasts beyond a two-year span are inaccurate, jail administrators continue to demand longer-term forecasts because the lead time required to fund, plan for, and build additional jail capacity and associated support structures is much longer than two years. Long-term forecasts of local jail levels cannot be achieved, but an increased understanding of the forecasting process would increase understanding of its benefits and limitations. Recognition that empirical forecasts will be of minimal use in long-range planning is a required first step for the proper utilization of forecasting in local corrections.

To cope with this impredictability, local correctional administrators should reduce ignorance of local dynamics and history, share the risk of flawed projections to reduce the impact of unexpected developments while remembering that over-planning is inherently flawed because of unpredicted events (Rescher, 1998, p. 237). What is recommended is to plan for the unexpected. For example, build flexible facilities that have multiple purposes or where bed space can be expanded or contracted as needed. For a continuous forecasting ability, correctional personnel need to periodically re-fit forecast models and compare forecasts with the actual emergent bed need. In order to be useful and reliable, forecasting local bed need must be a continuous effort and it is important to employ repeated short-term forecasts. One-shot forecasts quickly lose their usefulness.

Forecasts of more than a two-year span are really quantitatively disguised policy statements, not descriptions of likely eventualities. They describe where the local correctional vehicle will end up if the population wheel is not turned. For jails, because so many have their hands on the wheel, the likelihood of no one turning the wheel is close to nil. Unless and until this reality alters, a long-term forecast is best utilized as a catalyst for generating policy discussions rather than a tool to plan correctional needs. Despite their empirical inaccuracy, long-term jail population forecasts remain useful tools to prod criminal justice personnel to focus on the future probabilities and away from past problems. In the forecast demonstration, the forecast and its associated broader study of the local jail pointed out that disaster was looming unless policy changes were made.

While much is predictable, the fact remains that very much of interest is not. An irony of human nature is that humans more often find matters interesting exactly because they are hard to predict. When prediction is beyond one's capacities, often this is because the objective conditions requisite for predictability are not realized (Rescher, 1998, pp. 245–246). Society lives in a substantially impredictable world and local jail populations emerge as examples of inherent impredictability. The forecast methods described can provide accurate short-term forecasts for bed need. Practically, these figures would be useful for planning annual budgets, negotiating with neighboring counties to house possible overflow populations, or arranging for other short-range, elastic concerns. Viewing the long-term forecasts as practical for planning projects as immutable as construction of new jail space is risky. The wide variation and uncertainty of long-term jail bed need forecasts suggests they might be better put to use spurring searches for deeper local understanding. The ultimate challenge is for local jail administrators to establish a method for predicting the behavior of criminal justice decision-makers (Cunniff, 2002, p. 16). This is an unlikely event in the foreseeable future and why constant forecast re-assessments are necessary. In the interim, quality forecasts of correctional bed need out to a two-year time frame are accurate enough to be employed in planning and funding decisions. The further beyond that span one forecasts, however, the larger the grain of salt the forecast should be taken with.

Notes

1. Those who cannot remember the past are condemned to repeat it. George Santayana.

2. More sophisticated than common simple time-trend line analysis, autoregression uses time as a predictor of population augmented by the addition of an autoregression (1) model. Still more sophisticated was the time-series analysis introduced by Box and Jenkins (1970): ARIMA modeling. The name ARIMA signifies Auto Regressive Integrated Moving Average models. See also Clements and Hendry (1998, 1999). Although further advancements in forecasting were achieved in the past decade, models beyond those presented here were likely to be impractical for jail forecasting. It was instructive that Cushman (2002) recently suggested jails should "*begin* building a jail population analysis system" (emphasis added). The models presented here can be produced using readily available software, thus they are most likely to be useable by jail administrations with limited data analysis expertise.

3. The more sophisticated approaches used ARIMA based analysis to obtain base line projections that were then adjusted for policy and underlying assumption changes (see Lin, MacKenzie, & Gulledge, 1986). Three recent forecast approaches from Iowa, Colorado, and Washington State exemplified the current state of prison inmate population forecasting. In Iowa, a forecast was based on new and readmissions taking into account average inmate length-of-stay and the release rate for varied prison population groups (Mande, 1990). Colorado employed a more complicated six-step method. The six steps incorporated three internal projections: projected commitments by offense, projected commitments by time to serve, and projected prison population (Office of Research and Statistics, 1999). Scenario building on the empirically based forecast model was also done to assess the impact of possible new legislation and correctional policy changes. Colorado's forecasters reported an ability to accurately forecast the state's prison population level, consistently forecasting within a 5 percent error range. Generating monthly forecasts, Washington State forecasted its prison population based on a formula which factored in the existing inmate population, a projection of the future population of inmates, and the impact of pre-sentencing guidelines (Caseload Forecast Council, 2005).

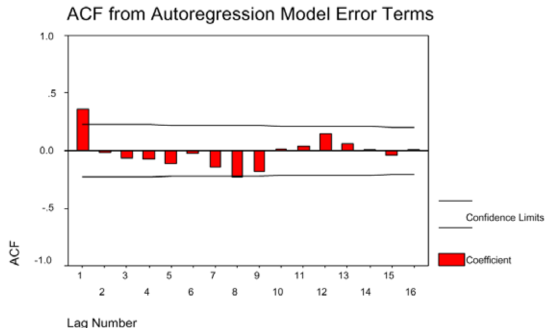
4. Studies that looked at the impact of a specific new correctional or sentencing policy on inmate populations included a Washington State study of the impact of new sentencing guidelines on its prison population (Olson, 1992). Another looked at the impact of the "three-strikes-and-you're-out" legislation using a simulation model. In this manner, different impacts of the legislation on prison populations were forecast based on different scenarios (Schmertmann, Amankwaa, & Long, 1998). A third study looked at "mandatory minimum" legislation using two forecast components: number of admissions for mandatory minimums under three scenarios of low, medium, and high growth and the average length of stay (Bales & Dees, 1992). A final policy impact study looked at the impact of "truth in sentencing" legislation in Mississippi on prison populations (Grimes & Rogers, 2000).

5. The NCCD Prophet program was utilized in a number of jurisdictions. Virginia utilized an "at risk" customized simulation model and Georgia used a Simul8 model. Examples of what was easily available in the literature was a Virginia plan on how a jail forecast capability could be created (Department of Criminal Justice Services, 1991) and a reference to a multi-step jail population forecasting process from Colorado (Office of Research and Statistics, 1999).

6. Fit statistics

- *Mean Absolute Error (MAE)*—uses absolute value for each error to determine average error. In this application, the average of how much each model's forecasts differ from the series values on how many beds are needed.
- *Mean Absolute Percentage Error (MAPE)*—obtained by computing the absolute error for the entire time period, dividing the absolute error by each series value and multiplying by 100, and summing and dividing by the number of values. Often used as it measures the percentage prediction error and, as a percentage varies between 0 and 100, provides an easily interpreted model comparison statistic.
- *Sum of Squared Error (SSE)*—squaring each error and summing, minimizing the SSE is known as the least squares method common in ordinary least squares regression.
- *Root Mean Squared Error (RMS)*—the square root of the MSE. The RMS can be interpreted as the standard deviation of the error terms. A small RMS is preferred since this signifies that the error terms do not have a large spread.
- *AIC and SBC*—AIC (Akaike's Information Criterion) and the SBC (Schwartz Bayesian Criterion) are statistics which reflect a forecast model's goodness-of-fit to the data taking into account the number of parameters in a forecast model. That is, these criteria penalize models with more parameters (or variables) compared with equivalently performing ones composed of fewer parameters. Models with lower AIC or SBC values are preferred. The AIC and SBC do not have interpretative meaning in themselves, but are useful when comparing their values between models fitted to the same data set. See Makridakis, Wheelwright, and Hyndman (1998) for discussion.

7. The ACF or autocorrelation function of the forecast error is used to examine for remaining pattern in a model's residuals. Significant autocorrelations in the errors indicates that the forecast model can be improved by additional parameters. As shown in the following figure of the ACF for the autoregression forecast model, the model's error terms are significantly correlated at one lag and the further refinement of the forecast model is indicated.



8. Crime data—local law enforcement agencies supplied monthly data beginning in January 1993 through December 2000 for the number of reported offenses for the UCR index crimes.

- *Court data*—the clerk of the courts office provided monthly data beginning in January 1993 and ending in March 2001 on the number of first degree felony filings, second and third degree felony filings, misdemeanor filings, traffic filings, and trials.
- *Economic data*—economic trends and development had long been credited with affecting crime levels and by extension bookings and bed need. County economic data was obtained from January 1993 to July 2000 from the Florida Bureau of Economic and Business Research (BEBR). Monthly data was obtained for summed total gross sales revenues in the area of food and beverage, lumber and building materials, general merchandise, total covered employment, total labor force, employed, unemployed persons, unemployed rate, single-family housing starts, multi-family housing starts, multi-family housing permits, and single-family housing permits.
- *Population data*—demonstrating a problem inherent in acquiring time series data for forecasting, a surrogate measure of county population based upon data from utility companies had to be utilized in this forecast. One of the first steps in data collection effort was to call the University of Florida Bureau of Economic and Business Research (BEBR) for county-level population data. Although annual data broken down by age, gender, and race was readily available, monthly population values were not. Contacts with a number of county agencies further revealed that none collected or estimated monthly population values for the county. The number of utility customers as a surrogate measure for monthly county population values was recommended by an analyst at the BEBR. The inferior alternative was to simply extrapolate monthly values between annual measures. The resulting monthly county population measure ran from January 1993 through August 2000.
- *Ethnicity data*—the county school board supplied bi-weekly school enrollment figures that were used as county ethnic surrogate measures. These enrollment summaries contained enrollment data on regular senior high schools, middle schools, elementary schools, and special schools broken down by White, Black, Hispanic, and other ethnic groups. Vacation months were estimated by linear extrapolation from the provided previous and subsequent values. Data for student enrollment were obtained from January 1993 through February 2000.
- *Booking data*—county corrections department bookings were included as possible predictors of county correctional bed need. The monthly number of prior felony and total bookings broken down by five offense categories (felony first degree, felony second degree, misdemeanors, traffic, and other) were compiled.

9. The culling process involved a variation of the blockwise selection process described by Pedhazur (1997, p. 227). First, each of the five substantive domain areas was examined separately with the best predictor variables from each area identified via cross-correlation functions. A cross-correlation function examines a variable's association with prior values of another variable. For example, the correlation of bed need with the unemployment rate for each of the preceding twelve months was computed and charted. Cross-correlations provide a means of determining candidate lead indicator variables, or variables whose current values can serve as predictors of the subsequent values with which they are cross-correlated. Thus, if unemployment rates twelve months ago are significantly cross-correlated with bookings, then unemployment lagged twelve months could serve as a lead indicator variable. The examination of the cross-correlation functions between county correctional bed need and the domain areas revealed few temporally deep correlations. Nine-month lagged predictors were the most common. The second step involved entering the domain area candidate variables into stepwise forward and backwards ordinary least squares regressions. Ignoring problems with serial correlation at this point, a reduced set of candidate lead indicator variables were identified as significant for each of the five domain areas. Third, the candidate variables from each domain area were then combined into a single variable set, collectively examined, and culled again through forward and backwards regressions to produce a final group of candidate lead variables.

10. Confusion between causal and forecast analysis and the incorrect interpretation of predictions as explanations is unfortunately common in the social sciences. A forecaster of jail population levels can expect to be asked to substantially explain "why" his predictor variables work or see her prediction model used to explain changes in jail populations. Thus, wherever plausible, predictors which also are theoretically linked to the forecast phenomena are preferred (Pedhazur, 1997, chap. 8).

11. The inverse relationship between jail beds and the lagged measure of felony 2 and 3 bookings could reflect the situation where collinear measures produces significant higher-order coefficient that are opposite in sign to the zero-order coefficient and highlights the need to incorporate theory into prediction wherever possible (see Pedhazur, 1997, chap. 8). While not an issue in the empirical forecasting of bed need, it defies attempts to produce a rational sounding explanation of the type often expected from administrators to "explain" this relationship. The same problem applies to the relationship between jail beds and the lagged measure of labor force participation. The relationship is positive and powerful, yet there is no theoretical explanation of why lower unemployment rates coincide with greater use of jails. Speculations that lower unemployment could be attracting more marginally employed individuals to the county who also have personal histories that result in more arrests or that lower unemployment results in more purchases and expendable income that coincides with more thefts or social behaviors like drinking that result in more arrests are strained and convoluted at best. Multicollinearity can also result in very high values for overall model strength even though every relationship is insignificant in the same model, a result that did not appear in these models.

12. Notation denotes a first differenced moving average 1 (0,1,1) and a seasonal first differenced autoregressive 1 model (1,1,0). Space precludes providing a detailed discussion of the ARIMA procedure. Readers are directed to the SPSS Trends manual and Clements and Hendry (1998, 1999); Hanke, Wichern, and Reitsch (2001); or Makridakis et al. (1998).

13. Notation denotes a first differenced moving average 6 (0,1,6) and a seasonal first differenced autoregressive 1 model (1,1,0).

14. Concerns with individual forecast model weaknesses often lead to the common practice of combining forecasts (Hanke et al., 2001; Newbold & Harvey, 2002). The thought is that the combination of forecasts will balance out weaknesses existing in the generation of individual forecasts.

15. Such choices can be considered as time specific treatment effects. Two events were considered and examined in the demonstration case study. Neither was found significant.

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