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Forecasting prison populations using sentencing and arrest data

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Aim: *To develop a method for forecasting the NSW remand and sentenced prisoner populations.*

Method: *Autoregressive Integrated Moving Average (ARIMA) models with other time series as input variables were employed to estimate and forecast changes in the remand and sentenced prisoner populations. Models were tested by estimating model parameters over the period January 1998 – December 2010 and then comparing model forecasts with actual prison population trends over the period January 2011 – March 2013. Comparison of actual with forecast remand and sentenced prisoner numbers revealed that both models provide fairly reliable predictions of prison population trends over a three year time horizon.*

Results: *Barring any significant change to policing and penal policy, the prison population is expected to rise in the first half of 2013 and then to drop steadily over the next three years. Although modelling suggests an uptrend in the remand prisoner population, this should be more than offset by a decrease in the sentenced prisoner population over the next thirty-three months.*

Conclusion: *Although the models developed here provide accurate forecasts in retrospective testing, they should not be used as the sole basis for projecting future prison numbers. Future projections of prisoner numbers should also be based on advice from correctional administrators, police prosecutors, legal policy analysts, and others on the likely effects of any proposed change to policing, bail or sentence policy. Construction of a simulation model may help in quantifying the effects of these changes.*

Keywords: *prison population forecast, ARIMAX model, remand population, sentenced prisoner population, seasonal effects, simulation model.*

INTRODUCTION

Between 2000 and 2009, the prison population in NSW rose by 30 per cent. In the three years that followed, it fell by 13 per cent (Australian Bureau of Statistics, 2013). There are indications now that it may now be rising again (NSW Bureau of Crime Statistics and Research, 2013). Rapid changes in prison populations pose significant problems for Government. When prison populations rise significantly, correctional administrators often have little choice but to start building new prisons. Capital works planning in a correctional setting, however, is fraught with risk. If correctional administrators move too quickly in response to a growth in demand for prison accommodation, and the surge in demand turns out to be transient, they can find themselves with spare prison capacity. This wastes scarce public resources. If they move too slowly, on the other hand, demand for prison accommodation can outstrip capacity, leading to prison overcrowding.

Not surprisingly, much time and effort has been expended trying to work out how best to respond to the uncertainty surrounding prison population growth. One common approach is to build a computer *simulation model* of the factors affecting the prison population (e.g. crime, arrests, proportion of arrestees imprisoned, average prison sentence length etc) and use it to explore the impact on the prison population of changes in these factors. The simplest models define a set of states (e.g. crime, arrest, court, prison) and make assumptions about the rate at which individuals flow between these states. These sorts of models are useful in answering 'what if' questions, such as what

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will happen to the prison population if the arrest rate increases by 10 per cent or sentence lengths increase by 20 per cent. On their own, however, simulation models provide no information on *whether* the factors that influence the prison population (such as arrest rates or sentence length) will change. To find out what is likely to happen to a prison population or the factors affecting it, researchers have turned to *forecast models*. The simplest forecast model of prisoner numbers is a linear extrapolation of past trends but it is possible to construct forecast models which capture more subtle features of past prisoner numbers, such as seasonality. Forecast models provide information on likely changes in the prison population, if factors not included in the model (e.g. changes to sentencing policy) remain the same.

There are several ways of constructing a forecast model of prisoner numbers. One approach is to identify the factors that influence a prison population and try to forecast their future behaviour. This is difficult because the future behaviour of factors that influence the prison population is generally hard to predict. One factor whose future behaviour is fairly predictable, however, is the age structure of the population. Demographers are fairly good at predicting future trends in the number of males and females in different age groups. Since most offenders are young (aged 20-40) a number of researchers have attempted to use demographic forecasts as a basis for predicting demand for prison accommodation (see, for example, Barnett, 1987; Walker, 1986). The predictive accuracy of these models, unfortunately, turned out to be very low. Blumstein, Cohen and Miller (1980: p. 18-20), for example, used age structure trends to forecast Pennsylvania prison population. They projected that the prison population would increase from 5,982 in 1975, peak at 10,300 in 1990, and then decline to 10,100 by 1994. Instead of reaching 10,300 in 1990, the Pennsylvania prison population reached 22,281. Instead of falling to 10,100 by 1994, it reached a new high of 28,294 (Marvell, 1997). The problem, it turned out, was not that age structure has no effect on the prison population, but that other unmeasured (and in some cases unmeasurable) factors had even bigger effects which swamped the effects of age (Marvell, 1997, p. 123).

This is not surprising. The size of a prison population is not just a function of the proportion of young people in the population or the crime they commit. It is also influenced by the ways policy makers respond to changes in crime. When prison remissions were abolished in response to a crisis over law and order in NSW in 1989, the NSW prison population rose by 47 per cent in the space of four years (Gorta & Eyland, 1989). The introduction of mandatory minimum terms in NSW had similar effects (Poletti & Donnelly, 2010). Rather than trying to identify the underlying determinants of prison population trends, recent research opted instead to model future prison population trends in the basis of past trends. Lin et al. (1986) illustrate this approach. They compared three forecasting methods that relied solely on past trends in prisoner numbers to predict future trends: segmented regression, exponential smoothing and autoregressive integrated moving average (ARIMA) models. The first and simplest method is essentially a linear extrapolation of the trend since the last turning point in the prison population series. The second method is similar but assigns more weight to more recent observations of the prison population than to more distant observations. The last method explicitly captures any cyclical behaviour or serial dependence in past observations of the prison population and then uses this information to forecast future trends. This is especially useful where time series show seasonal effects or when the next observation in a time series is strongly correlated with those immediately prior to it. Prison populations show both these characteristics. Not surprisingly, the ARIMA model performed best out of the three models compared by Lin et al. (1986).

In this bulletin, we present a forecast model for the NSW prison population, based on the approach adopted by Lin but with a number of additional features. The univariate forecasting models explored by Lin et al. (1986) make no distinction between the remand and sentenced prisoner populations. This is unfortunate because the custodial arrangements for remand (unconvicted) prisoners differ from those for offenders serving a sentence of imprisonment. Remand and sentenced prisoner populations are also affected by different factors. The size of a remand population is strongly influenced by the way in which police and courts exercise their discretion in relation to bail. The sentenced prisoner population is (not surprisingly) strongly influenced by the way in which courts exercise their sentencing discretion. The forecasting models explored by Lin et al. (1986) also have another significant weakness from our perspective. They make no use of information on inputs to the criminal justice system, such as the number of persons arrested for breaching their bail conditions (a common reason for being placed on remand) and the proportion sentenced to a term of imprisonment. In this report we discuss two models: one of which links the size of the remand population to actions taken by police for breach of bail conditions; and the other of which links the size of the sentenced prisoner population to the number of prison sentences imposed by the Local Court. Both models also capture seasonal effects. While both models have limitations (which we discuss), testing reveals both provide fairly reliable predictions of prison population trends over a three year time horizon.

METHOD

DATA

Data for modelling were obtained from three sources: the Offender Integrated Management System (OIMS), maintained by Corrective Services, New South Wales; the Computerised

Operational Policing System (COPS), maintained by NSW Police, and the Re-Offending Database (ROD), maintained by the NSW Bureau of Crime Statistics and Research.

OIMS data were used to construct the two dependent variables: number of sentenced prisoners and the number of remand prisoners held in the correctional centres managed by Corrective Services. These two variables were measured on the first Sunday of each month. Data on the number of persons proceeded against by police for breach of bail were obtained from COPS. Data on the number of persons given a sentence of imprisonment and the number of persons who were bail refused were obtained from ROD. Monthly time series on each of these variables were constructed over the period January 1998 to March 2013.

MODELLING STRATEGY

To obtain the best model for forecasting remand prison population, the data series was broken down into two parts: (1) the estimation period: January 1998 – December 2010 and (2) the validation period: January 2011 – March 2013. A twenty-seven month validation period (15% of the total sample) was chosen. This is a little lower than the percentage (20%) commonly employed. We used a slightly higher proportion of the time series for estimation because it increased the accuracy of prediction in the validation period. The estimation period and validation periods for the sentenced prison populations were January 1998 – December 2011 and January 2012- March 2013, respectively. We used a shorter validation period for sentenced prison population to increase the prediction accuracy because there is a turning point in the series around middle of 2009. Data from the estimation period was used to estimate the models. Data from the validation period was held out for comparing model predictions with observed data on prison population trends.

The Autoregressive Integrated Moving Average (ARIMA) model with other time series as input variables was employed to estimate and forecast the prison population. This type of model is known as ARIMAX model. The ARIMAX models tested here treat the size of the remand or sentenced prisoner population as a function of its own past values, past errors and current and past values of the other time series (breach bail and number of offenders given a custodial sentence). ARIMAX models are usually characterised as ARIMAX(*p*, *d*, *q*), where *p* is the number of autoregressive (AR) terms (lagged values of the series) included in the model, *d* the number of differences employed to render the series stationary (one is usually sufficient) and *q* the number of lagged random errors in the model. Diagnostic checking of the ARIMAX model includes significance of model parameters and autocorrelation of residual errors. The t-test was used to test the significance of the model parameter. A small p-value less than .05 indicates the parameter is significant. The Ljung-Box test was used to test if the residual errors are significantly different from white noise. That is, they must not be autocorrelated. A p-value larger than .05 indicates the residual errors are not significant different from white noise. Model selection was based on the root mean square error (RMSE) and the mean absolute percentage error (MAPE) in the validation period. Root mean square error (see equation 1) is the square root of the mean square of the difference between the observed and predicted values. Mean absolute percentage error (see equation 2) is the mean of the absolute value of the percentage change of the predicted values relative to the actual values. Both of these statistics are commonly used to assess the accuracy of prediction models.

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}(y_t - \hat{y_t})}{n}} \qquad (1)$$

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{y_t - \hat{y_t}}{y_t}\right| \qquad (2)$$

A few ARIMAX models were fitted to the remand prison population from the estimation period using forward selection technique for selecting relevant independent variables. Two candidate models were found and the model comparison was reported in Appendix Table A1. The model, with smaller RMSE and MAPE, chosen to predict the remand prison population was an ARIMAX (4,1,12) model with three independent variables and monthly dummies (m_j=1 if month=j) (see equation 3). First differencing (Δ) was applied to the remand prison population series to remove its non-stationarity (d=1). Two AR terms at lag 1 and lag 4 (r_{t-1} and r_{t-4}) and one MA term at lag 12 (e_{t-12}) were included to capture the dependence structure in the past values and errors. The large p-value in the Ljung-Box test up to lag 24 (p=.819) showed that the model was adequate as the residual errors were not significantly different from white noise. The three independent variables included lag1 of the number of breach of bail (br_{t-1}), lag 2 of the rolling sum of the Local courts imprisonment penalties over the last twelve months ($s12imp_{t-1}$) and the year-to-year change in the remand prison population ($d12r_t$). Parameter estimates of the chosen model are given in Table A2 in the Appendix.

$$\begin{aligned}\Delta r_t = b_0 + b_1\Delta br_{t-1} + b_2\Delta s12imp_{t-2} + b_3\Delta d12r_t \\ +b_4\Delta m_1 + \cdots + b_{14}\Delta m_{11} + a_1\Delta r_{t-1} \\ +a_2\Delta r_{t-4} + e_t + c_1 e_{t-12} \qquad (3)\end{aligned}$$

Two candidate ARIMAX models were found when modelling the sentenced prison population and were summarised in Table A3 in the Appendix. The ARIMAX (8,1,0) model with the smaller

RMSE and MAPE was selected as the best model. Again first-differencing was applied to the sentenced prison population because of its non-stationarity (*d*=1). One AR term at lag 8 (s_{t-8}) was included in the model to account for the dependence structure in the sentenced prison population. The independent variables included lag 1 of the remand prison population (r_{t-1}), lag 1 of the rolling sum of the Local Courts imprisonment penalties over the last twelve months ($s12imp_{t-1}$), the change in trend starting on July 2009 ($chgtr_t$=0 before July 2009 and 1 otherwise) and some monthly dummies (see equation 4). In the diagnostic checking, the large p-value (p=.533) in the Ljung-Box test up to lag 24 indicated that the residuals were not significantly different from white noise. Parameter estimates of the ARIMAX (8,1,0) model are given in Appendix Table A4.

$$\Delta s_t = b_0 + b_1 \Delta r_{t-1} + b_2 \Delta s12imp_{t-1} + b_3 \Delta m_1 + \cdots + b_7 \Delta m_5 + b_8 \Delta chgtr_t + a_1 \Delta s_{t-8} + e_t \quad (4)$$

After selecting the best model, the chosen model was re-estimated on the complete data set before forecasts were calculated. Based on the re-estimated model, dynamic *h*-step-ahead forecasting method was employed to predict the sentenced and remand prison population from April 2013 to December 2015. The dynamic forecasting method began by using the estimated coefficients, the lagged values of the dependent variables, and the lagged value of any independent variables to predict one step ahead for the dependent variable one month later. Then the two-step-ahead forecast was produced by using the one-step-ahead forecast of the dependent variable and the forecasted lagged values of every independent variable using separate ARIMA models. The process continued for thirty-three periods where each step used the prediction of the previous step. The 95% confidence interval for the forecast, also known as prediction interval, was computed to assess the uncertainty in the prison population forecasts. The prediction interval would be useful for prison administrators to ensure there are sufficient resources to accommodate the range of possible outcomes indicated by the interval.

All the analyses were conducted using SAS 9.2 and the results are discussed in the next Section.

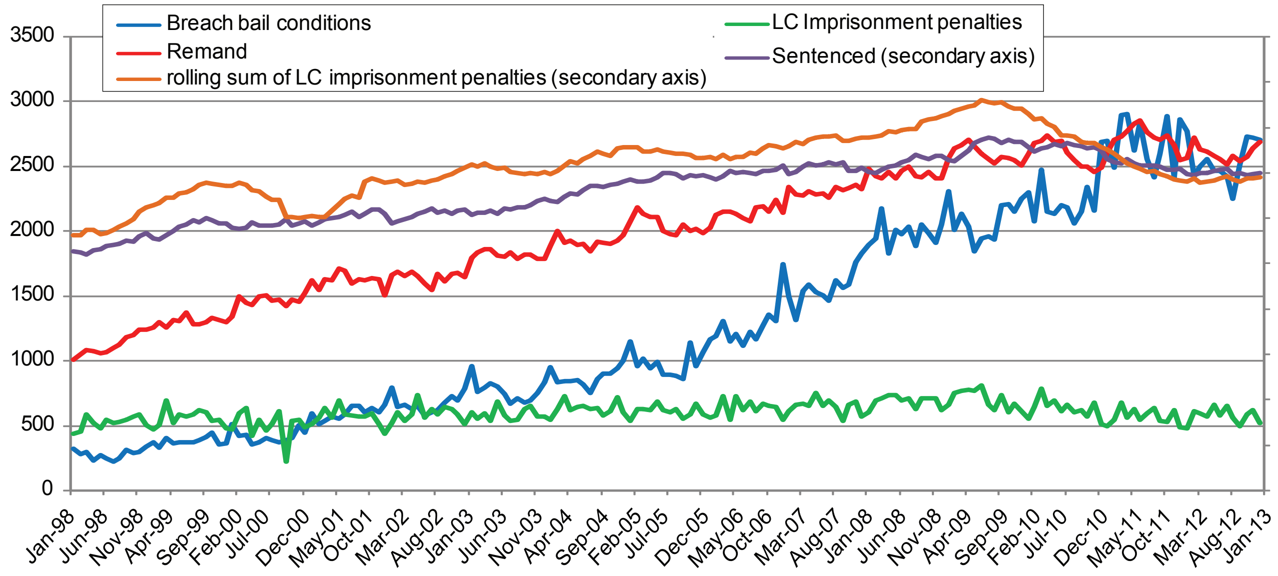
RESULTS

TREND DESCRIPTION

Before presenting the results of the model fitting and forecasts, we examine trends in each of the variables included in the analysis.

Figure 1 shows trends in the size of the sentenced prisoner and remand populations, the number of offenders proceeded against for breaching bail, the number of Local Court penalties of imprisonment imposed on offenders and the rolling sum of Local Court imprisonment penalties over the last twelve months. It can be seen that the number of sentenced prisoners (in purple) rose after 1998 before reaching a distinct turning point in mid-2009

Figure 1. Remand and Sentenced Prison population in NSW



after which it fell. It continued to fall until early 2012 and then fluctuated between 6,900 and 7,100 thereafter.The remand prisoner population (in red), in contrast, had a steady linear upward trend until the end of 2008. The upward trend in remand prisoners slowed down after this point and the remand population also became more volatile during 2009 to early 2013.

As with the remand series, the number of breach bail offences (in blue) rose rapidly after 1998.Like the remand population, the trend stabilized around 2011. The correlation between the first-differenced number of breach bail offences and lag 1 of the first-differenced remand population (0.33) is moderately high. This is not surprising since a large number of those held on remand are probably on remand for breaching their bail conditions. The rolling sum of the number of imprisonment penalties issued in Local Courts over the last twelve months (in orange) demonstrated a similar increasing trend as the sentenced prison population with a peak at July 2009 and gradually went down afterwards. The correlation between the first-differenced size of the sentenced prisoner population and lag 1 of the first-differenced rolling sum of Local Court prison sentences (0.26) is moderately strong, but not as strong as that between breach bail and the remand population.

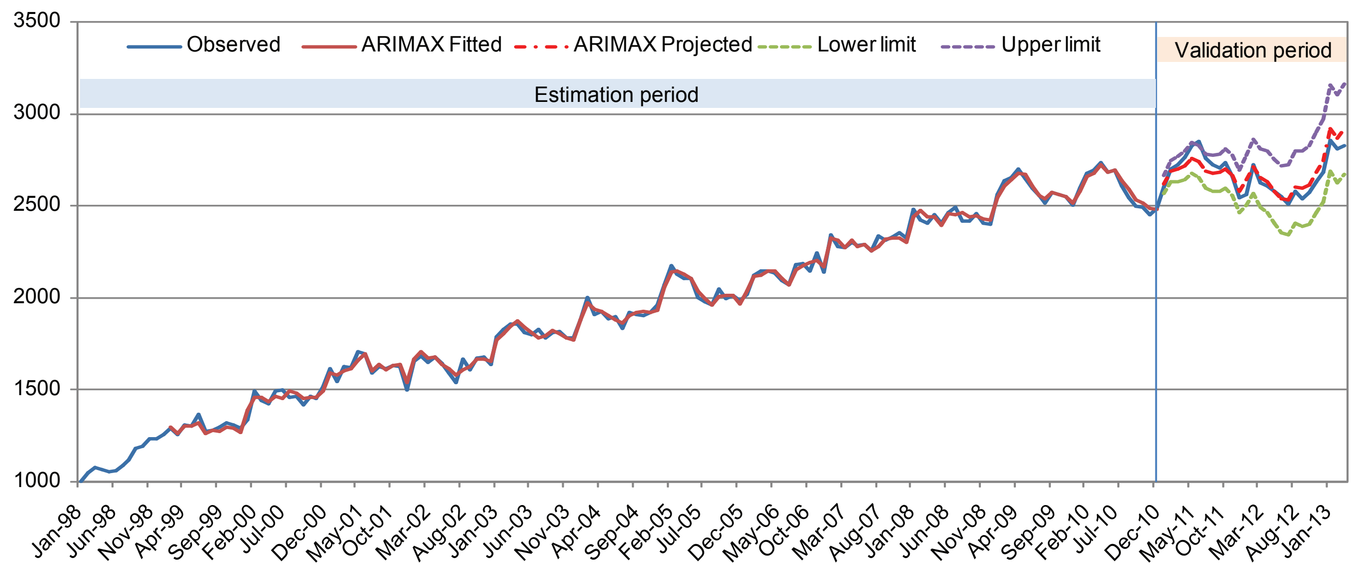
REMAND AND SENTENCED PRISONER FORECASTS

Figure 2a plots the predicted and observed values of the remand populationin both the estimation and validation periods. The projected series in the validation period follows the observed series reasonably well, with only one observation lying outside the upper prediction interval. The root mean square error and mean absolute percentage error were 49.19 and 1.52% respectively for the chosen ARIMAX model as shown in Table A1 in the Appendix.

After re-estimating the ARIMAX model, the dynamic h-step-ahead forecasts and their 95 per cent prediction intervals (upper and lower limits) are plotted in Figure 2b. The remand prisoner population is predicted to rise in the next quarter following March 2013 and then drop in the remaining months of 2013. It is expected to rebound at the beginning of 2014 but drop back to the peak level of 2013 at the end of the year. The remand prison population is expected to reach a new peak in early 2015 and then to return to the peak level of 2014 at the end of the year. The forecast upward trend is less marked than that observed in the last decade and the remand prison population is expected to be less volatile in the next thirty-three months compared to the previous four years. The forecasts also show some seasonal patterns with higher number of prisoners in the first half of each year. The prediction interval widens as the forecast horizon lengthens because of the errors at each time point build up in a cumulative way. The minimum value of the lower limit is 2,643 and the maximum value of the upper limit is 3,285. These upper and lower bounds help us to estimate the number of beds required to accommodate the remand prison population in the next thirty-three months by accounting for the uncertainty in prediction.

Figure 3a plots predicted and observed values of the sentenced prisoner population. The small gap between the predicted

Figure 2a. Remand prison population in the estimation and validation periods



values and the actual values in the estimation and validation periods suggested the best model had a good fit to the observed data. None of the observationsis lying outside the 95 per cent prediction interval. The root mean square error (RMSE) and the mean absolute percentage error (MAPE) for the predicted and observed series are 28.42 and 0.37% respectively as shown in Appendix Table A3.

The chosen model is re-estimated on the complete data set. Based on the re-estimated model, the dynamic h-step-ahead forecasts and their 95 per cent prediction intervals are plotted in Figure 3b. The dynamic forecasts suggest that the sentenced prisoner population will continue to rise till June 2013 and fall in the remaining months of 2013. In 2014; the sentenced prisonerpopulation will drop further in the first two months before a rebound occurs in March. By the middle of 2014, it will

Figure 2b. Remand prison population with forecasts

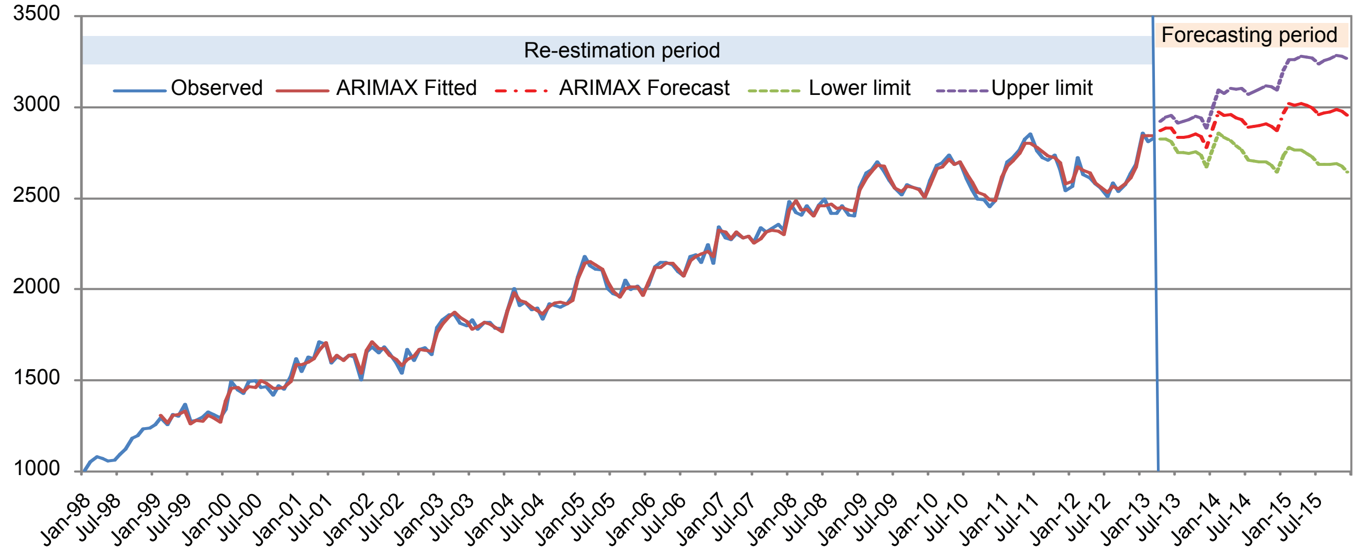
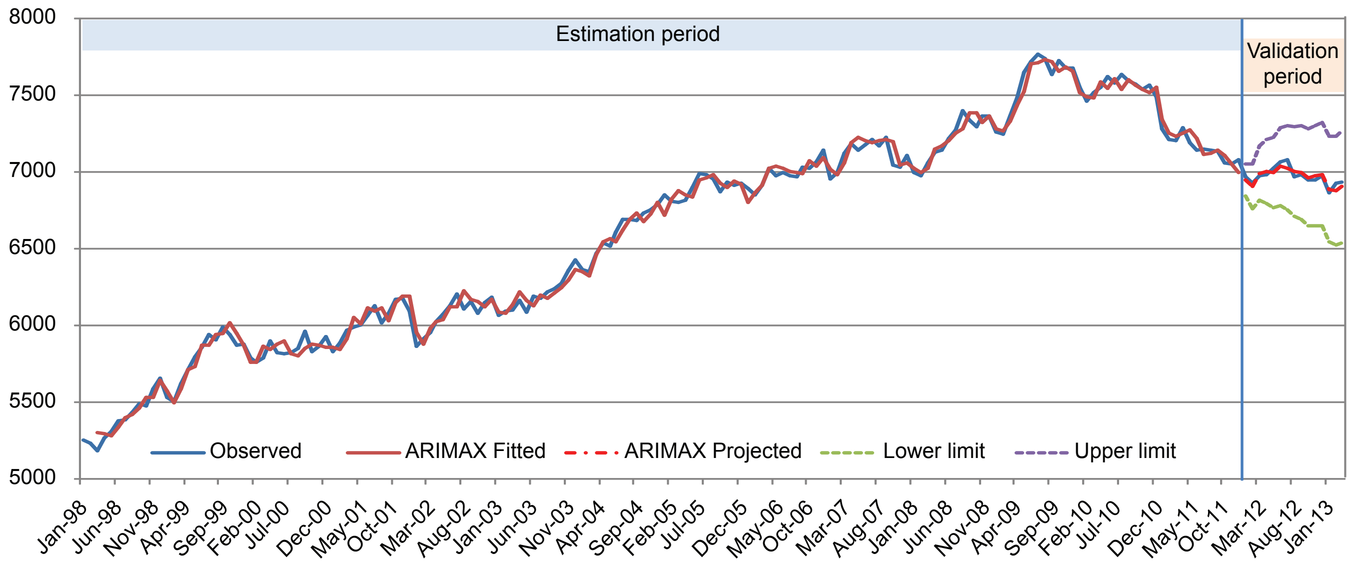


Figure 3a. Sentenced prison population in the estimation and validation periods



start to fall again towards the end of the year. The population will continue to fall in 2015 with a trend pattern similar to that of 2014. The forecasts show a seasonal pattern, with a lower number of sentenced prisoners in the summer months. The maximum value in the upper bound of the prediction interval is 7,310, giving us an idea on the number of beds required to accommodate the decreasing sentenced prison population in the next thirty-three months.

TOTAL PRISON POPULATION FORECAST

Forecasts for remand and sentenced prisoners were combined to produce a total prison population forecast. Figure 4 shows the combined series of the observed values and forecasts. As shown in Figure 4, the total population peaked in July 2009 and started to fall in 2010. Despite a small rebound in the first half of 2013, the total prison population is expected to drop steadily over the

Figure 3b. Sentenced prison population with forecasts

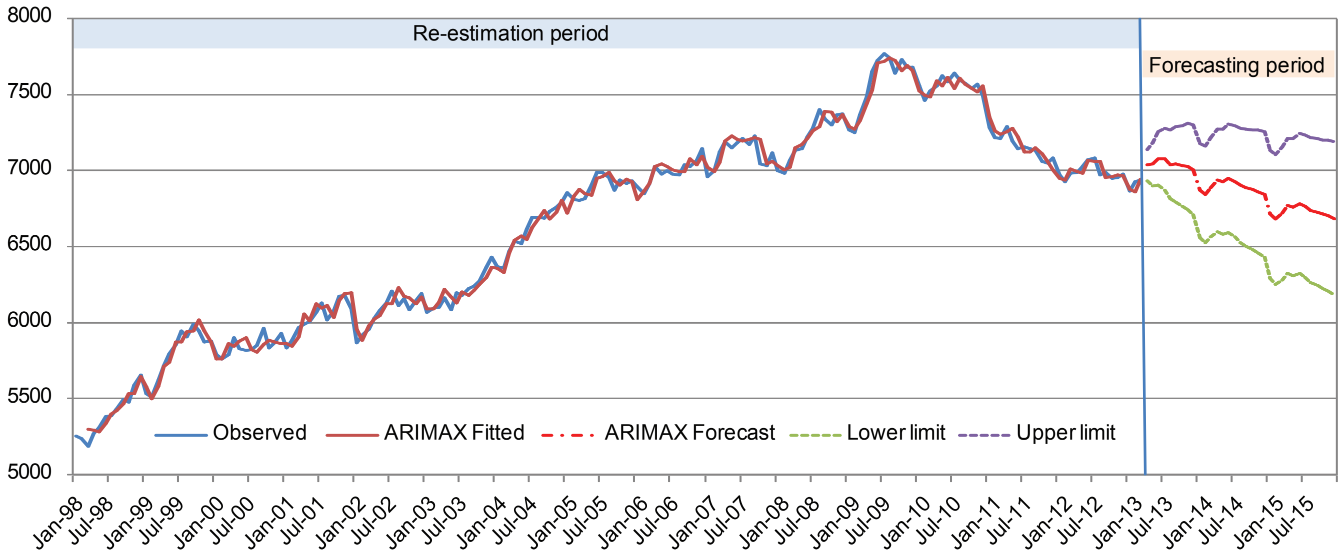
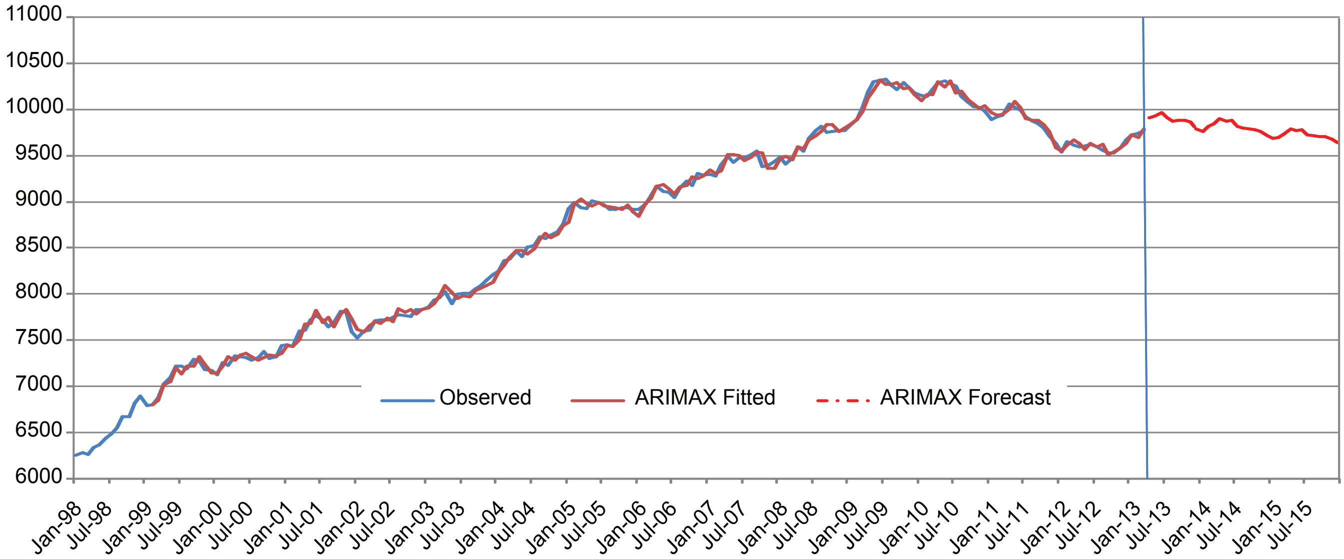


Figure 4. Total prison population with forecasts



next three years. This decreasing trend is mainly driven by the downward trend in the sentenced prisoner population although there is an uptrend in the remand prisoner population. The decreasing rate of the sentenced prison populationis expected to be greater than the increasing rate of the remand prison population over the next thirty-three months.

DISCUSSION

The results presented above show that it is possible to construct reliable forecast models of remand and sentenced prisoner population growth, without having detailed information on the determinants of that growth. Indeed, ARIMAX models, such as the one developed here, have been found to outperform more sophisticated structural models (i.e. models based on assumptions about the causes of prison population growth) in terms of short-run forecasting ability (Meyler, Kenny & Quinn, 1998). A thirty-three month forecast may be insufficient time to build a new prison but it is sufficient to make many other decisions concerned with staffing and resources. The forecasts can also be used to obtain early warning of changes in prison numbers that are out of keeping with expectations and/or as an input to policy on matters likely to affect the prison population.

Notwithstanding all this, we do not recommend that the NSW Government base decisions about correctional spending solely on the forecasts generated by these models. Forecast models of the type developed here tell us the likely trend in prison numbers if existing policies remain unchanged (see Federal Sentencing Reporter, 2007). Criminal justice policies and other external factors influencing the criminal justice system, however, rarely remain unchanged. In developing prison population projections, therefore, Governments need to consider prison population forecasts against the backdrop of advice from experts on whether existing or new policies are likely to alter the flow of people into prison or the length of time they stay. This is where simulation modelling can be very useful. To illustrate, suppose that a forecast model predicts the prison population will fall by 10 per cent over the next three years, from 10,000 to 9,000. Consultation with senior officials and other experts within the criminal justice system, however, suggests that a new policy under consideration by Government will increase sentence lengths for a particular class of offender. Simulation models can be used to quantify the likely effect of an increase in sentence length on prisoner numbers and the prison population forecast can be adjusted to take this effect into account. This is essentially the approach adopted by the Ministry of Justice in the United Kingdom (Ministry of Justice, 2012).

Although the current models give accurate predictions over the short-run, there are ways in which they could be improved. The current remand model makes only limited use of data the number of people arrested by police (viz. number proceeded against for breach bail) and makes no use of information on offence seriousness or prior convictions, although both these variables would be expected to affect the size of the remand population. The sentenced prisoner model also makes no use of information on offence seriousness or prior convictions despite the fact that both would be expected to affect the likelihood of a custodial sentence and the length of the sentence imposed. A further limitation is that, although male and female prisoners are housed in different prisons, both models ignore the role of gender. A model that makes more extensive use of information on the profile of people entering the justice system could potentially give earlier warning of changes to the male and female custodial populations. The feasibility of a model linking arrests to prison populations was demonstrated by Wan (2011) in a study of the impact of police arrests on correctional workload in NSW. She found that a 10 per cent increase in the number of male arrests resulted, over the long term, in a 4.0 per cent increase in male sentenced prisoners, while the same size increase in female arrests produced, over the long term, a 3.7 per cent increase in female sentenced prisoners. It would be useful to embed these empirical relationships in a model which also takes into account seasonal and other known influences on the prison population.

NOTES

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REFERENCES

Australian Bureau of Statistics (2013). *Prisoners in Australia 2012*, Cat. No. 4517.0. Canberra: Australian Bureau of Statistics.

Barnett, A. (1987). Prison populations: A projection model. *Operations Research*, 35, 18-34.

Blumstein, A., Cohen, J. & Miller, H. (1980).Demographically disaggregated projections of prison populations. *Journal of Criminal Justice*, 8, 1-25.

Federal Sentencing Reporter. (2007). Public Safety, Public Spending: Forecasting America's Prison Population (2007-2011). Federal Sentencing Reporter, 19(4), 234-252.

Gorta, A. & Eyland, S. (1990). *Truth in Sentencing: Impact of the Sentencing Act 1989*, NSW Department of Corrective Services.

Lin, B-S., Mackenzie, D.L. & Gulledge, T.R. (1986). Using ARIMA models to predict prison populations. *Journal of Quantitative Criminology*, 2(3), 251-264.

Marvell, T.B. & Moody, C. (1997). Age-structure trends and prison populations.*Journal of Criminal Justice*, 25(2), 115-124.

Meyler, A. & Kenny, G. & Quinn, T. (1998). Forecasting Irish inflation using ARIMA models. *Central Bank and Financial Services Authority of Ireland Technical Paper Series*, 1998(3), 1-48.

Ministry of Justice (2012). Prison Population Projections 2012-2018 England and Wales.Ministry of Justice Statistics Bulletin. Retrieved from: http://goo.gl/DmXn1h

NSW Bureau of Crime Statistics and Research (2013). *New South Wales Custody Statistics: Quarterly Update: March 2013*. Sydney: NSW Bureau of Crime Statistics and Research.

Poletti, T. & Donnelly, H. (2010).*The impact of the standard non-parole period sentencing scheme on sentencing patterns in New South Wales*. Sydney: Judicial Commission of New South Wales.

Walker, J. (1986). *Forecasting prisoner numbers: A computer model for correctional administrators*. Canberra ACT: The Australian Institute of Criminology.

Wan, W-Y. (2011). *The relationship between police arrests and correctional workload*. Crime and Justice Bulletin (No. 150). Retrieved from NSW Bureau of Crime Statistics and Research website: http://www.lawlink.nsw.gov.au/lawlink/bocsar/ll_bocsar.nsf/vwFiles/cjb150.pdf/$file/cjb150.pdf

APPENDIX

Table A1. Model comparison for remand prison population

Model	Variables	RMSE	MAPE
Best model	lag 1 of number of breach bail conditions offence	49.19	1.52%
	lag 2 of rolling sum of Local Courts imprisonment penalties in previous 12 months		
	year-to-year change in remand prison population		
	Monthly dummies		
	AR(1),AR(4), MA(12) terms		
Competitive model	lag 8 of number of persons who were bail refused in Local Courts	51.95	1.60%
	lag 2 of rolling sum of Local Courts imprisonment penalties in previous 12 months		
	year-to-year change in remand prison population		
	Monthly dummies		
	AR(1),AR(4), MA(12) terms		

Table A2. Parameter estimates of ARIMAX (4,1,12) model for remand prison population

Variable*	Estimate	SE	p-value
lag 1 of number of breach bail conditions offence	0.029	0.014	.047
lag 2 of rolling sum of Local courts imprisonment penalties in previous 12 months	0.031	0.014	.027
year-to-year change in remand prison population	0.493	0.019	<.001
January	89.821	12.856	<.001
February	123.305	14.759	<.001
March	116.088	16.500	<.001
April	115.273	17.973	<.001
May	99.612	17.557	<.001
June	76.624	18.437	<.001
July	36.675	17.189	.035
August	41.897	18.021	.022
September	42.507	16.091	.009
October	44.358	13.943	.002
November	29.197	12.935	.026
Constant	9.829	2.199	<.001
AR(1) term	-0.369	0.081	<.001
AR(4) term	-0.265	0.081	.001
MA(12) term	-0.800	0.075	<.001

*All the independent variables are first-differenced in the ARIMAX (4,1,12) model.

Table A3. Model comparison for sentenced prison population

Model	Variables	RMSE	MAPE
Best model	lag 1 of remand prison population lag 1 of rolling sum of Local Courts imprisonment penalties in previous 12 months change in trend term at July 2009 monthly dummies AR(8) terms	28.42	0.37%
Competitive model	lag 1 of remand prison population lag 1 of rolling sum of Local Courts imprisonment penalties in previous 12 months year-to-year change in sentenced prison population Monthly dummies MA(12) terms	76.87	0.86%

Table A4. Parameter estimates of ARIMAX (8,1,0) model for sentenced prison population

Variable*	Estimate	SE	p-value
lag 1 of remand prison population	0.251	0.081	.002
lag 1 of rolling sum of Local Courts imprisonment penalties in previous 12 months	0.208	0.056	<.001
January	-108.384	13.981	<.001
February	-156.053	17.975	<.001
March	-110.763	19.438	<.001
April	-43.169	17.554	.015
May	-39.857	13.556	.004
Change in trend	-18.311	10.26	.076
Constant	9.596	4.091	.020
AR(8) term	-0.195	0.083	.020

* All the independent variables are first-differenced in the ARIMAX (8,1,0) model.

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