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APPLICATION OF DYNAMIC PROGRAMMING MODEL TO CRIME CONTROL (A CASE STUDY OF BENIN CITY METROPOLIS)

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ABSTRACT

It is quite consensual that the police patrolling can be regarded as one of the best well-known practices for implementing public-safety preventive policies towards the combat of an assortment of urban crimes. Deploying adequate police patrol to hotspots areas based on available patrol units is even huge challenge. In time past, Nigerian police employed heuristic approaches to deploy crime preventive police patrol teams to the hotspots. These approaches are not necessary expected to yield optimal solutions to the problem of effectively allocating police patrol efforts across various hotspots. In this work, we present how dynamic programming can be used to bring about optimal solutions to the police patrol allocation problem. Data were collected from the Nigerian Police Command Headquarter, Benin City on crime statistics across eight precincts. These data were analyzed using the dynamic programming to determine the optimal solutions to the effective deployment of crime preventive police patrol force across the eight precincts.

Keywords: Programming, Crime & Control.

INTRODUCTION

Decision making involves several decisions that needs to be taken at different time. The mathematical techniques to optimize such a sequence of interrelated decisions over a period of time are called dynamic programming. It uses the idea of recursion to solve a complex problem, broken into a series of interrelated (sequential) decision also called (sub problems) where the outcome of a decision at one stage affects the decisions at each of the following stages. The word dynamic has been used because time is explicitly taken into consideration. Dynamic progranming (DP) difers from linear programming (LP) in two ways:

1. In DP, there is no set procedure (algorithm) as in LP to solve any decision Problem. The DP techniques allows to break the given problem into a sequence of easier and smaller sub problems, which are then solved in a sequential order(stage).
2. LP approach provides one-time period (single stage) solution to a Problem where as DP approach is useful for decision-making over time and solves each sub-problem optimally.

Crime Control and Policing

In many fundamental respects, the investigation process, though showing some advances, seems to have been relatively uninfluenced by significant changes in policing the crime problem and technological advances made in the past thirty years. It is our view that progress in police criminal investigation efforts remains largely isolated from broader police efforts to respond more effectively, more efficiently, and more resolutely to the crime problem in general. Over the last three decades, policing has gone through a period of significant change and innovation. In a relative by short historical time frame, the police have reconsidered their fundamental mission, the nature of core strategies of policing. and the character of their relationships with the communities they serve. This reconsideration is now broadly conceived of as community and problem-oriented policing. Within the community and problem-oriented policing paradigm shift, many innovations have developed, including broken windows, hot spots, pulling levers, compstat and other policing approaches (Weisburd and Braga, 2006). These changes and innovations grew out of concern that policing tactics did not produce significant impact on crime and disorder. There is now growing consensus that the police can control crime when they are focused on identifiable risks, such as crime hot spots, repeat victims and very active offenders, and when they use a range of tactics to address these ongoing problems (Braga,2001,2008, Skogan and Fryd., 2004; W Neisburd and ECK, 2004). In the United States, these police innovations have been implemented by uniformed patrol officers rather than criminal investigators. In most police department, the fruit of an investigation is the arrest and subsequent conviction of a criminal offender. Indeed, the work of criminal investigators in apprehending serious offenders can be incredibly creative, involve dogged persistence and include acts of heroism. We believe that the fruit of their labor can be the investigative knowledge and actions into crime- control strategies. Crime investigators have special expertise in the following areas:

- Interviewing skills for interviewing victims, witnesses and offenders.
- Developing and managing of informants.
- Conducting convert surveillance, including the use of advanced Surveillance Technologies.
- Identifying and locating potential witnesses and sources of intelligence.
- Preserving and developing evidence Preparing cases for prosecution and liaising with prosecutors in the lead-up to, and conduct of a trial.
- Protecting, managing and preparing witnesses for trial.
- Sequencing of investigative steps in an inquiry so as to optimize of Success. Maintaining knowledge of and in some cases relationships with, criminals and criminal groups.

Apart from the last one, all these skills are general much more concentrated among investigators than uniformed patrol officers. For the last one, the investigators crime "Knowledge" tends to be more offender-centric, whereas patrol officers knowledge is more naturally place-centric, victim-centric and crime-type-centric. Many of the skills above contribute to the ability of investigators to handle a case from start (crime incident report) to finish (conviction), which patrol officers usually cannot do except in really simple case, because the structure and schedule of normal patrol operations generally do not allow it. With their special knowledge and skill set, investigators can advice uniformed patrol officers on the nature of local crime problems and supplement their crime-control efforts with their expertise in conducting surveillances, doing undercover work, and interviewing victims and offenders. Investigators can also collaborate with analyst to develop in-depth descriptions of recurring crime problems. Our point is that criminal investigators are not being fully utilized by most police departments in their management of recurring crime problems. In essence, the 'crime control loop' is not complete without the participation of criminal investigators in the problem-solving process (Sparrow, 2008).

Statement of the Problem

The problems of Nigerian Police in exercising its duties are both logistic and moral, over the years. In logistic terms, the force maintained by the federal government has not had enough equipment. The quantity of weapons, arms and ammunition available in most mobile squadron units in the country are hardly enough. There are some instances where the force cannot stand the counter firepower of armed bandit.

Aims and Objectives of the Study

Indeed, it appears that what is in Nigeria today is tantamount to a serious crime problem; hence, the main objective of this project is;

1. To educate members of the public on the role and powers of the police, and the significance of the public cooperation with police in order to promote an overall individual, community and natural security.
2. To give an insight into how optimal allocation of available number of police patrol units can effectively combat or intercept crime in some major street in Benin city.
3. To offer suggestions and recommendation on how to have responsive police force in Nigeria.

Looking closely into the objectives, our aims of the project is to develop a dynamic programming model for effective allocation of crime preventive patrol force (available) to a number of precincts or hotspots. With the above aim in mind, analysis will be carried out on data collected, using the developed mathematical expression for the overall objective of the problem from the dynamic programming model developed

Approaches to the study of dynamic progranming and crime cotrol exist. The papers reviewed in this chapter can be classified into the following headings:

(1) Dynamic programming

(2) Crime control

Further, dynamic programming can be examine under two main headings.

(a) Approximate dynamic programming approach

(b) Discrete choice dynamic programming. Crime control is divided into

(a) Crime control and crime prevention

(b) Media and policing in crime control Approximate Dynamic Programming Approach Nadarjah et al (2011), propose a novel family of approximate dynamic programs (ADPs) for the Markov decision process (MDP) based on portioned surrogate relaxation of an approximate linear program, used in conjunction with information relaxation and duality approach for Markov decision process. Their approximate dynamic programs estimate lower and upper bounds to the value of storage within a Monte Carlo simulation of the natural gas forward curve. They estimated lower and upper bounds that either match or improve those available in the literature. Further, their approach subsumes the ADP available in the literature corresponding to those known estimated bounds, and sheds additional light on the performance of heuristics used in practice. Nadarajah et. al. (2011) work has broader relevance for the valuation of storage of other commodities, and the modeling and solution by approximate linear programming of intractable MDPs with state variables that include high-dimensional exogenous information such as a forward curve. Approximate dynamic programming has received substantial attention in the recent literature. George and Powel (2006) address the problem of determining optimal step sizes for estimating parameters in the context of dynamic programming. In their work, they stated that most applications on dynamic prograrmming, observations for estimating a value functions typically come from a data series that can be initially highly transient. The degree of transience affects the choice of step size parameters that produce the fastest convergence. In addition, they are of the opinion that the degree of initial transience can vary widely among the value function parameter for the same dynamic programming.

In most approximate dynamic programming algorithms value of the future state of the system are estimated in a sequential manner, where the old estimate of the value $\left(\overline{V}^{n-1}\right)$ is smoothed with a new estimate based on Monte Carlo Sampling $\left(\hat{X}^{n}\right)$. The new estimate of the value is obtained using one of the two equivalent forms.

$$\overline{V}^{n} = \overline{V}^{n-1} - \alpha^{n}\left(\overline{V}^{n-1} - \hat{X}^{n}\right) \quad (1)$$

$$= \left(1 - \alpha^{n}\right)\overline{V}^{n-1} + \alpha^{n}\,\hat{X}^{n} \quad (2)$$

Where α^{n} is the quality between 0 and 1 and it is commonly referred to as step size. The size of α^{n} governed the rate at which new information is combined with the existing knowledge about the value of the state (see George and Powel 2006).

Theorem 2.1.1

Let $\{\alpha^{n}\} n = 1, 2, \ldots,$ be a sequence of step sizes $\left(0 \le \alpha^{n} \le 1\right), \forall_{n} = 1, 2, \ldots$ that satisfy the following condition.

$$\sum_{n=1}^{\infty} \alpha^{n} = \infty \quad (3)$$

$$\sum_{n=1}^{\infty} \left(\alpha^{n}\right)^{2} < \infty \quad (4)$$

If $\{\hat{x}^{n}\}$ $n = 1, 2, \ldots$ is a sequence of independent and identically distributed random variable with finite mean, θ and variant, σ^{2}, then the sequence, $\{\theta^{n}\}$ $n = 1, 2, \ldots$, defined by the recursion,

And with any deterministic initial value, converges to almost surely (See Goerge and Powell 2011) Bethke (2008), devise a new strategies for multi-agent planning and control problems, especially in the case where the agents are subject to random failures, maintenance needs, or other health management concerns, or in cases where the system model is not perfectly known. He argue that dynamic programming techniques, in particular Markov decision process (MDPs), are natural framework for addressing these planning problems, and present an MPD problem formulation for a persistent surveillance mission that incorporates stochastic fuel usage dynamics and the possibility for randomly-occurring failures into the planning process. Bethke (2008), shows that the problem formulation and its optimal policy lead to good mission performance in a number of real-world scenarios. Furthermore, adaptive solution framework is developed that allows the planning system to improve optimal policy in problem formulation over time, even in the case where true system model is uncertain or time-varying. Keles and Hartman (2007), model the portfolio management problem for multi-stage investment projects, such as those routinely associated with research and development projects, with stochastic dynamic programming. As the recursion is intractable for large-scale problem instances, they present an approximation scheme which allows for the solution of long horizon problems in order to ensure good time zero decisions when maximizing the discounted, expected worth of decisions over time. Additionally, the approximation approach provides two estimation of the probability of making the best decision at time zero and providing

additional information to the decision maker. Numerous examples illustrate the models ability to examine different budget levels, delay options (lengths, penalties, and cost), initial portfolios, project returns, ad interaction effects of projects in the pipeline, while previous research focusing on single project analysis has highlighted the importance of the delay option. Kelas and Hartrman (2007) illustrate how critical thie option is when one considers a portfolio of projects over time especially when projects late in the review process may fail or budgets are small.
De Faries (2002) offer bounds that characterize the quality of approximate product by the linear programming approach and the quality of the policy utimately generated. In addition to providing performance guarantees, the erro bounds and associated analysis offer new interpretations and insights pertaining to the linear programming approach. Among other things, this understanding to some extent guides selection of basic functions ad "State-relevance weights" that influence quality of the approximation.
Approximate linear programming involves solution of linear programs with relatively few variables but an intractable number of constraints. He propose a constraint sampling scheme that retains and uses only a tractable subset of the constraint, under certain assumptions, the resulting approximation is comparable to the solution that would be generated if all constraints were taken into consideration.
Haugh and Kogan (2008), propose approximate dynamic programming -based methods for constructing and evaluating good approximate their problem. They describe how duality and approximate dynamic programming method can be used in financial engineering. Haugh and Kogan (2008), focus on America option pricing and portfolio optimization problems when the underlying state space is high-dimensional. In general, it is not possible to solve these problems exactly due to the so-called "curse of dimeneionality and as a result, approximate solution techniques are required. The approximate linear programming formulation provides an approximation to the portfolio policy as well as an upper bound on the value function. This approach is computationally intensive and its ability to handle large-scale practical problems still needs to be evaluated. Some encouraging results in this direction are obtained by Han (2005).
Frazier (2011), considers the role of dynamic programming in sequential learning problems. These problems require deciding which information to collect in order to best suppot later actions. Such problems are ubiquitous, appearing in simulation, global optimization, revenue managerment, and many other areas. Dynamic programming offers a coherent framework for understanding and solving Bayesian formulations these problems. He present the dynamic programming formulation applied to a canonical problem, Bernoulli ranking and selection. Frazier (2011), then reviews other sequential learning problems from the literature and the role of dynamic programming in his analysis. However, dynamic programming (DP) is a recursive optimization approach to solving a sequential decision problems. Dynamic programming is mainly used in problems requiring a sequence of related decisions and it is based on Belman's principle of optimality. Principle of optimality: An optimal policy has the property that regardless of the decision taken to enter a particular state in a particular stage, the remaining decision must constitute an optimal policy for leaving that state (Bronson and Naadimutu, 2004). In a similar manner, Carmen et al (2001) treated dynamic programming in mathematical optimization by simplifying a decision into a sequence of step and defined a sequence of value functions V,,V,.., with an augument y representing the state of the system at time i from 1 to n. They define V,) as the value obtained in state at the last time n, ri=n-1, n-2,..2,1, and concluded that V, at the initial state of then system is the value of the optimal solution. The optimal value of the decision variables can be recovered by tacking back the calculations already performed.

Discrete Choice Dynamic Programming

Szabołcs (2005), introduced preference persistence into a dynamic discrete choice model of demand for durables. This persistence may arise, for example, when the product can be categorized into a few numbers of formats which involves special knowledge, maintenance and upgrade. The standard optional slopping problem of when to buy a new product Rust (1987), Melnikor (2000) is completed by the upgrade problem. Customers who already have a product may choose to upgrade it but this upgrade is format specific. Hence the expected future upgrade qualifies for different formats must be taken into account already of the purchase decision, of a new product. The model is estimated on a data set of low-end computer servers, are presented by operating systems. The resut suggests that the model is better able to capture main tendencies in the segment than a static or a simple optional slopping model. For this application, the model can be considered as a proxy of a computer network building customer who cares not only about the likely future quality of the individual computers, but also about the direction of evolution of the network, that induces even stronger forward booking behavior than a simple optional slopping problem.

Keane and Wolpin (1994), explore the performance of approximate solution of DDP problems. Their approximate method consists of;

1. Using Monte Carlo iteration to simulate the required multiple integrals of a subset of the state points, and
2. Interpolating the non-simulated values using a regression function. The overall performance of the approximate method appears to be excellent, both in-tems of the parameters estimates it generates when embedded in an estimation algorithmn. Over the past decades, a substantial iteration on the estimation of discrete choice dynamic programming (DC-DP) models of behavior has developed. However, this literature now faces major computational barrier. Specifically in order to solve the dynamic programming (DP) problems that generate agent's decision rules in DC-DP models, high dimensional integrations must be performed of each point in the state space of the DP problem. A major impediment of the application of this approach is computational like static discrete choice Models, the dimension of the integration that must be performed to calculate the choice probabilities that are necessary for estimation is directly related to the size of choice set. However, in the dynamic setting, integrations of that dimensional must be performed not only to solve the dynamic optimization problem itself. Moreover, those integrations must be performed at all values of the state space (discrete or discredited if continuous) upon which is what Bellmen (1967) called the curse of dimensionality". Pan and Zhau (2008), study the mull period and continuous optional consumption investment choice model, and given an optional solution to the model. Their result can be regarded as the generalization of the portfolio selection north monotone. Utility functions, based on a non-monotones utility function. Dynamic portfolio choices consist of the discrete time model and the continuous-time model which were studied by Merton (1973) and Lucas (1978) how to generalized a one-period portfolio model to the multi-period one is important subject in the financial field, the significance of their study was to determine that the modem financial decision needs to reflect a complex integration of the investment environment for multi-period portfolios, the investors often choose investment stage, their purpose are the total maximizing functions of the end of investment stage. If these portfolio stages are not correlative, then the multi period strategy can be divided by many single periods, if these portfolio stages are correlative, then many investment choices become more complex. It is well know that in the practical investment environments, the returns of asset distributions changes with the time. Therefore, how to adjust investmet strategies based on changes of the environment is the practical problem that every investor must be facing. The result of the practical problem provides an important background for multi period research investment portfolio. Arcidiacono et al (2009), provides a method of estimating dynami discrete choice models (in both single and multi agent settings) in which time is a continuous process. The advantage of working in continuous time is that state changes occur sequentially, rather than simultaneously eliminating a substantial coarse of dimensionality that arises in multi agent setting eliminating this computational bottleneck is the key to providing a seamiess link between estimating the performing post-estimation counter factual. In the case of complex discrete games, the models that applied researchers typically estimate (where the curse of dimensionality is broken by using

two step approaches in which agents belief-conditional choice probabilities (CCPs)-are estimated in a first stage)often do not math building on the theoretical framework developed by Doreszelski and Judd (2008) Arcidiscono et al (2009) propose an estimation strategy for continuous time discrete choice model that can be implemented either via a full solution nested fixed point algorithm or using a cop-based approach. They also consider estimation in situations with imperfection sampled data, such as when there is an unobserved choice, for example a passive decision to not invest or when data is aggregated over time, such as when only discrete- time data are available at regularly-spaced intervals.
Pantano and Zheng (2010), introduce a novel approach to allow for unobserved heterogeneity in two-step structural estimation strategies for discrete choice dynamic programming models (i.e. strategies that avoid full solution methods). They contribute to the literature by adopting a fixed effects approach, rather than identifying an unobserved heterogeneity distribution, Pantano and Zbeng (2010) actually reveal the true unobserved type of each observation in a first step. They do so by exploiting the tight link between the conditional choice probabilities that are derived from the economic model and Just two subjective self-reported assessments about future choice probabilities such as those commonly elicited in major surveys. They uncover the unusual power of ideal expectations data to identify unobserved types for different classes of models of more enpirical relevance, they show that their results hold when they allow these subjective future choice probabilities to be elicited in less than ideal circumstances, such as for example, when self- reports display substantial "heaping" at "focal" reference values.
Bhowmik (2010), introduced fundamental working principles, and major area of applications of dynamic programming. The strengths which make it more prevailing then the others is also opened up. Focusing the imperative drawbacks afterward comparison study of this algorithm design technique in his paper brings a general awareness to the implementation strategies, Esteban-Bravo and Nogales (2008), introduced a decomposition methodology, based on a mathematical programming framework to compute the equilibrium path in dynamic models by breaking the problem into a smaller independent sub problems. They study the peformance of the method solving a set of dynamic stochastic economic models. The numerical results reveal that the proposed methodology is efficient in terms of computing time and accuracy. Discrete-time optimal control problems arise naturally in many economic problems. Despte the rapid growth in computing power and new developments in the literature, many economic are still quite challenging to solve. Economists are aware of the limitations of some of these approaches for solving these problems due to memory and computational requirements. However, many of the economic models present some special structure that can be exploited in an efficient manner. Other approaches involve converting the problem into a mathematical programming problem in which al the states and controls were decision variables and the dynamic equations formed part of the constraint set (Bergounioux et al (1997). But these methods lead to problems with large numbers of variables and constraints. Estaban-Bravo and Nogales (2008) address this problem by splitting it into manageable pieces (sub problems) and by coordinating the solutions of these sub problems.

Crime Control and Crime Prevention
Males (2011), states that the draconian nature of the three strike and you're out" law offers a unique opportunity to test the selective incapacitation effect of massive incarceration. The results of this 2011 analysis, updated from the original 1998 report, continue to present a starting departure from traditional assumptions about crime and crime control. The effects of more imprisonments for lengthier terms should be greatest in countries and within population groups where the "three strikes" law was most invoked. However, analyses of strike sentencing and crime trends by age group and county consistently showed this was not the case. Virtually no evidence could be found supporting the law's deterrent or selective incapacitation effect on targeted population or in the jurisdictions most affected. Further, many countries use the "three strikes" law to sentence mainly

non violent offenders, which is possible given the flaws in the current law but is not consistent with its intent as publicized by advocates. Both direct county comparisons and statewide correlational analysis shows the 1994 "Three strikes" law has had no demonstrable effect on violent crime levels or trends. The populations that demonstrated the greatest decline in violent crime rates since 1884 were youthe and youg adults, which experienced the last strike sentencing, while those ages 40-5 9, which experienced much heavier strike sentencing, have shown little or no improvement in violent crime rates.
Cozens et al (2005), critically review the core findings from recently published place-based crime prevention research. They evaluate the available evidence on the contribution of crime prevention through the optimal solution is not optimal also of the optimal path, because all other paths have measure zero. Hence the optimal solution is characterized as follows: An optimal decision has to be optimal only on the optimal path, but not at node that have probability zero, i.e. that are off the optimal path. Therefore there is muitiplicity of optimal solution if the solution is changed on the complement of the support of the controlled process. To conclude, one can say that dynamic programming solves actually a more general problem, because in optimal control, we require a solution only to be optimal along the controlled process.

Characteristics of Dynamic Programming Problems

Dynamic programming is a computational method that can be used when making a sequence of interrelated decisions. It finds an optimal combination of decisions by breaking up the overall problem into a sequence of easier sub problems. Below are the characteristics of dynamic programming problem:

1. The problem can be divided into stages with a policy decision required at each stage.
2. Each stage has a number of states associated with it. The number of states may be finite or infinite.
3. The effect of policy decision at each stage is to transform the current state into a state associated with the next stage. The transformation may be deterministic or stochastic.
4. Given a current state, an optimal policy for the remaining stages is independent of the policy adopted in the previous stages. This is the principle of optimality.
5. A recursive relationship identifies the optimal policy for each stage, given the optimal policy for each state in stage n+1 is available. The form of the recursion is problem dependent. Choosing the right kind of recursive relation is where the skill lies.
6. The solution procedure typically begins by finding the optimal policy for each state of the last stage i.e, we use a backward solution technique. Sometimes a forward procedure makes more sense. Then, the recursive relationship, the solution procedure moves backward (in a backward formulation) stage by stage each time finding the optimal policy for that stage.

Multistage Decision Process

A multistage decision process is a process that can be separated into a number of sequential steps or stages which may be completed in one or more ways. The options for completing the stages are called decisions, A policy is a sequence of decisions, one for each stage of the process.

$m_j(u)$ = **Optimal return from completing the process beginning at stage j in state u**

$d_{j(u)}$ = **Decision taken at stage j that achieves $m_j(u)$**

Table 3.1

	u				
	0	1	3	…….	
$m_n(u)$					Last stage
$d_n(u)$					
$m_{n-1}(u)$					Next to last stage
$d_{n-1}(u)$					
………….	…….. ……….	…………	……………		
$m_1(u)$					First Stage
$d_1(u)$					

The entries corresponding to the last stage process are generally straight forward to compute. The remaining entries are obtained recursively; that is, the entries for the jth stage (j =1, 2…,n-1) are determined as functions for the (j+1)st stage. The recursion formula is problem dependent, and must be obtained new for each different type of multistage process. For simplicity, table 3.1 has been drawn as though each stage had the same set of states. While this can always be brought about artificially (by suitably penalizing the The return function), it is often more natural to use different state variables, each saith its Own range of values, for the different stages, Such use, of course, In way alters the application of the principle of optimality.

Mathematical Model

Optimize: $z=P_1(x_1)+ P_2(x_2)+...t \quad P_n(x_n)$

Subject to:

$$X_1 + x_2 + x_3+ ..... + x_n \geq b$$

where $P_1(X_1)$, $P_2(x_2)$, ... $P_n(x_n)$ are known weighted probabilities of a single variable and b is a known nonnegative integer. Models are important class of multistage decision processes. Here the number of stages is n. Stage 1 involves the specification of decision variable x, with a resulting contribution s() to the total return; the states are 0, 1, 2, 3,...b, representing possible values for the number of units available for allocation. All stages after the first have these same states associated with them, stage 1 has the single state b. representing possible values for the number of units available for allocation. All stages after the first have these same states associated with them, stage 1 has the single state b.

Police patrolling is an important instrument for implementing preventive strategies towards the combat of criminal activities in urban centers, mainly those involving violence aspects (such as Kidnapping, Armed Robbery, Burglary and Stealing, Murder, Arson and, OBT- Obtained money under force pretence etc.). An underlying hypothesis of such preventive Work that, by knowing where the occurrences of crime are curently happening and the reasons associated with such, it is possible to make a more optimized distribution of the police resources available to control or intercept the overall crime rate. In view of this, we attempted to develop a dynamic programming model for optimal allocation of police patrol units to intercept these crimes. For illustration, crime data were collected from police command headquarters, Benin City, for eight precincts and the model was used to allocate ten police patrol units.

CONCLUSION

Since certain heuristic approaches are what the Nigerian Police uses to deploy a crime preventive police patrol force to a number of precincts or hotspots, this may always not guarantee the maximum crime intercepts in the various precincts. The utilization of dynamic programming in rescoperations research problem always Guarantees optimality (Tongo 2010 and Gudn et al 2007). Hence we can be assured that the 0.0317 cumulative weighted probability of police patrol initiated intercept obtained from the eight precincts in this study is the best value that any heuristic method of allocation will ever produce.

RECOMMENDATIONS

Because of the superiority of dynamic programming over any heuristicapproach, it is recommended that efforts towards the use of dynamic programming in the deployment of crime preventive patrol units to various region should be employed by the Nigerian police in general and in particular, Benin City Police Command Headquarter.
Though the manual computation may become very difficult as the number of precincts and patrol units increases, computer packages can be used for such computations. Hence, this study can be extended to wider coverage of Benin City and additional assumptions can be introduced to stimulate the model. This is recommended for further research.

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