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# A simulation model for the procedure of psychiatric patients' diversion at william r. sharpe, jr. hospital using flocking algorithm for input modeling

Aida Rabiee Gohar

# A SIMULATION MODEL FOR THE PROCEDURE OF PSYCHIATRIC PATIENTS' DIVERSION AT WILLIAM R. SHARPE, JR. HOSPITAL USING FLOCKING ALGORITHM FOR INPUT MODELING

**Aida Rabiee Gohar**

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**Feng Yang, Ph.D., Chair**

**Majid Jaridi, Ph.D.**

**Wafik H. Iskander, Ph.D., P.E.**

**Department of Industrial and Management Systems Engineering**

**Morgantown, West Virginia**

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## ABSTRACT

The high rate of civil commitment in West Virginia indicates that the bureau of mental health in the state has been inefficient and unproductive at facilitating the procedures of mental health system delivery, to the point that the two state hospitals of West Virginia are often at their full capacity and incapable of admitting any new cases. This inadequacy at managing psychiatric emergencies causes frequent diversion of civil committed patients from the state psychiatric hospitals to other community psychiatric units, and ultimately costs the state an un-budgeted $4 million annually.

The main objective of this research is to contribute to the improvement of the mental healthcare system in West Virginia for psychiatric patients, as well as employees and all the other involved parties which benefit. This is done by optimizing capacity-related decisions at William R. Sharpe, Jr. Hospital, one of the main assigned centers for psychiatric issues in the state.

In order to achieve this outcome, this work intends to first model the arrival process of different psychiatric patients to William R. Sharpe, Jr. Hospital based on data-driven simulation for complex multi-dimensional time series, by applying a flocking algorithm to the available dataset. Including the scheme of simulating patient arrivals, a simulation model is developed to model the patients' arrivals, stay, and departures at the hospital. Sensitivity analysis has been performed to investigate the impacts of various variables such as the capacity of the hospital, the number of patient arrivals of a particular category, etc.

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| | |
|---|---|
| NSDUH | National Survey on Drug Use and Health |
| AMI | Any Mental Illness |
| SMI | Serious Mental Illness |
| MEPS | Medical Expenditure Panel Survey |
| MH | Mental Health |
| SA | Substance Abuse |
| CDC | Centers for Disease Control |
| i.i.d. | Independent and identically distributed |
| (NHPP) | Non-Homogeneous Poisson Process |
| ecdf | Empirical Cumulative Distribution Function |
| cdf | Cumulative Distribution Function |
| CI | Confidence Interval |
| SAMHSA | Substance Abuse and Mental Health Service Administration |

# Chapter 1

# Introduction

## 1.1 State of Mental Health in the U.S.

Mental disorders, a.k.a. mental illness or psychiatric disorders refer to a wide range of mental health disorders which cause suffering or have a negative effect on the normal abilities or daily functioning such as thinking, feeling, communicating with others, etc. More than any other group of illnesses, including cardiovascular diseases and cancers, mental disorders account for a large proportion of disability in developed countries.

Although mental disorders can involve people of any age, religion, race or income, the good news is that they are treatable and people do recover. Even people with serious mental disorders can be treated successfully by regularly taking part in their individualized plans. Based on the research done on psychiatric epidemiology, mental disorders are prevalent throughout the United States. They affect tens of millions of people annually, and only a fraction of those are able to receive treatment. According to the most recent data from the National Survey on Drug Use and Health (NSDUH), in 2012 about 43.7 million adults (representing 18.6% of all U.S. adults) aged 18 or older were affected by any mental illness (AMI), of which 9.6 million of them (4.1% of all U.S. adults) suffered from a serious mental illness (SMI).

Based on a report by the Medical Expenditure Panel Survey (MEPS) in 2008, mental disorders were ranked third among the most costly medical conditions for women and among the top ten most costly conditions for men [1]. The information provided by MEPS in 2006 presents the total expenditures for mental health services, the number of Americans who have been receiving mental health services and the average cost for each person who has received the mental health services. Based on this study, 36.2 million people in the U.S. have paid a combined $57.5 billion for mental health services. Thus the average cost per person is about $1,591.

In 2008, mental health (MH) disorders or substance abuse (SA) disorders accounted for 1.8 million inpatient admissions in the U.S. (4.5% of all hospitalization in U.S.). Put together, MHSA disorders are the primary reason for $9.7 billion worth of hospitalization costs, accounting for 2.7% of total inpatient hospital costs in the U.S. [4].

A study conducted from 1988-1994 shows that a high percentage of patients diagnosed with mental disorders have had inpatient care [2]. Based on a report from the Centers for Disease Control and Prevention (CDC), 2.7 million mental disorder patients have received at least 24 hrs of inpatient treatment, which is very costly and requires a huge portion of mental health resources. 4.67 million patients have been released in less than 24 hrs. About 10%, or 266,000, of the total inpatient treatments have been done at state and county mental hospitals [3].

### 1.2 State of Mental Health in West Virginia

Deinstitutionalization, which began in 1955, is defined as the policy of moving severely psychiatric patients, also known as SMI patients, out of large state institutions and then closing some or all of those institutions. In 1994, West Virginia led the deinstitutionalization of psychiatric patients, along with states such as Rhode Island, New Hampshire and Massachusetts, with an effective deinstitutionalization rate of 95.9%. These patients, who would have previously been hospitalized for a long time in state hospitals, were discharged and returned to their communities [5]. Currently a large number of mental health service centers and facilities, regardless of their funding source, are encouraged to keep psychiatric patients out of hospitals.

According to a study done by the NSDUH, from 2005-2006 West Virginia was among the states with the highest rates of serious psychological distress and major depressive episodes in the country for the population age range of 18 and older. Over that same age range, West Virginia had among the highest rates of patients diagnosed with AMI nationally, at 21.4%, and was the first state in the category of SMI patients, accounting for 5.5% of such diagnoses in the U.S. This led to a combined direct and indirect fiscal impact of $3.6 billion, or 6.7% of the 2006 gross domestic product of West Virginia.

According to the Office of Health Facility Licensure and Certification (OHFLAC), in West Virginia there are 66 licensed hospitals, including 4 psychiatric hospitals and only 11 Psychiatric/Chemical Dependency Units. Moreover, there are 13 community mental health centers, 75 mental health-related companies/facilities based on the Manta website and, according to National Substance Abuse Index, 43 substance treatment centers.

Currently there are two state-funded acute inpatient psychiatric hospitals in West Virginia, with a total capacity of 240 beds. Each hospital has a designated catchment area with corresponding Community Mental Health Centers. The William R. Sharpe, Jr. Hospital is a 150-bed facility located in Lewis County, and serves 42 of West Virginia's 55 counties. Mildred Mitchell Bateman Hospital, located in Huntington, has 90 beds covering the remaining 13 counties. Both hospitals only accept involuntary patients, either through civil commitment or through court order via the judicial system.

### 1.3 Motivation

According to the data from the "Commission on Mental Hygiene Reform, Final Report," from 1995-2003 the rate of involuntary commitment among psychiatric patients has increased by 447%, and has continued to increase since then [6]. As a result, state-owned psychiatric hospitals lack the available beds for the involuntarily-committed patients most of the time, which results in the diversion of these patients to community psychiatric units, which costs the states millions of dollars annually. The records from William R. Sharpe, Jr. Hospital indicate that they have been constantly faced with a lack of available beds, or over-capacity of their 150 beds, since 2002.

The lack of available beds in hospitals, which sometimes results in overcrowding, has very destructive consequences on patient care and employee health, especially in the case of psychiatric hospitals. Increased use of PRN mediation due to patient aggression and violence, increased stress level among hospital staff (which in some cases is associated with special mental disorders such as depression due to the increased workload), and increased staff burnout and job dissatisfaction are some of the significant effects of overcrowding or over-bedding in psychiatric hospitals [7].

As mentioned before, diverting patients to other psychiatric units has been occurring frequently in the two state-funded psychiatric hospitals as a provisional solution to their overcrowding problem. Although patient diversion might momentarily solve the problem, there are some problems with applying this solution:

1) It doesn't have a considerable effect on improving the quality of patient care.

2) Bed availability, location remoteness and selection criteria are some of the problems That routinely limits the use of diversion as the primary solution for over bedding.

3) It is very costly in the long term.

Thus heavy reliance on community hospital diversion may well not be the least costly solution, much less a solution that leads to high- quality patient care. So far no significant research has been done to systematically investigate the cause and solutions to the overcrowding problem in West Virginia mental hospitals.

## 1.4 Research Objective

The main objective of this work is to perform statistical and simulation-based analysis to assist capacity-related decisions at the state psychiatric hospitals.

## 1.5 Research Approach

Some basic statistical analyses were first performed on the historical data at William R. Sharpe, Jr. Hospital over the past seven years. A simulation model was developed to model the patient flows through the hospital. In the model, a flocking algorithm was employed to simulate patient arrivals. Multiple simulation replications were performed for performance evaluation and sensitivity analysis.

## Chapter 2

## Literature Review

Simulation is known to be able to model practically any real systems. The challenge involved in building a simulation model representing the patient flows through the hospital lies in the simulation of patient arrivals, which are non-stationary multivariate time series. In this part, a review is provided for the non-parametric flocking algorithm for time series simulation, which was adopted in this work as part of the simulation model.

The flocking algorithm is originally a technique developed to simulate the flight paths of a flock of birds, also called boids. This concept was proposed for the first time in 1987 by Reynolds, in computer science and social emergent behavior modeling. Reynolds considered the emergent behavior of the flock to be the result of interactions between simple rules, and modeled a few of these simple rules. These models were then used to simulate flocks. The rules of Reynolds' simulation were: 1) collisions must be avoided, 2) each boid should fly with the same speed and in the same direction as the other boids (velocity matching), and 3) the boids' intention is to fly around the centroid of its neighbors (flock centering) [13]. The simplicity of these rules allows extending the use of such self-organized behavior to more useful purposes, such as data visualization. Proctor and Winter in 1998 added a fourth rule to Reynolds' rules, which was about modifying the motion of individuals considering some similar measure which can be derived from a set of data. They defined the concept of information flocking in such a way that each individual boid is associated with a single data item. This flocking motion allows visualizing the similarities between the data items [13]. Moere in 2004 made a significant extension to the concept of information flocking and the models initiated by Proctor & Winter. A creative way to visualize time-varying datasets was proposed, in order to map boids' paths for the stock market prices of different companies. To achieve this goal, he used the emergent characteristics of self-organization and dynamic behavior simulation.

In order to simulate non-stationary multivariate time series, Schruben and Singham in 2010 developed an algorithm using the concept of flocking. The basic was to generate a flock of boids whose flight paths follow one or more leaders. It is assumed that there is only one leader, called the *alpha boid*, whose path is determined by the trace data available. After generating the flock of boids, the path of each boid within the flock can be used to create replications for the simulation model. The results of these replications may be very similar to the trace data. In order to improve the accuracy of the input's simulation model, multiple replications are used to minimize the uncertainty associated with a single input stream. In 2011, Schruben and Singham applied the flocking algorithm to model inputs for an agent movement simulation. In the absence of real data, software programs have been designed to simulate complex situations, such as the movement of forces in combat situations, often using agent base modeling. The agents' desired paths are shown by waypoints, and users should make decisions in advance of the waypoints. In cases where the objectives of agents are obvious, it is often difficult to code these waypoints into the model. In order to design a patrol system to prevent crossing, it is necessary to simulate the possible waypoints in such a way as to be able to test the capabilities of the patrol strategy. Schruben and Singham presented the flocking algorithm as their approach for simulating these waypoints. There are red agents in a border crossing model who intend to move forward undetected across the border, whereas the blue agents patrol back and forth along the border. They refer to the waypoints of the red agents as the trace data, whose paths will be used to generate new paths (alpha boid). New waypoints tend to follow the alpha boid, with respect to the affinity factor considered in the model, while trying to keep the properties of trace data, such as dependence. The inverse direction of red agents is also considered in the model. The final step is to run the model using the simulated biods' paths to see how well the program does, and also to determine which types of paths are more probable to result in an agent's success.

# Chapter 3

# Methodology

## 3.1 Problem Statement

Inside the U.S., both the state and local governments take responsibility for the evaluation and treatment of involuntarily-committed psychiatric patients, while the overall process is governed by state laws, regulations and budgeting choices. While there are some differences between the state and local bureaucratic processes for involuntary psychiatric commitment, state-run psychiatric facilities are almost always in charge of taking care of involuntary psychiatric commitments so that immediate inpatient care and treatment to be provided for this population. Therefore, almost all state psychiatric hospitals are struggling with the patient over-bedding problem, leading to the diversion of patients to community hospitals.

Correspondingly, the two state-funded psychiatric hospitals of West Virginia, with a total 240 beds, have repeatedly faced this challenge and had to divert patients to community centers as a result. This temporary solution carries several drawbacks, several of which were mentioned in Chapter 1. Each of these two state psychiatric hospitals has its own designated catchment area, and they both only accept involuntary patients either through civil commitments or court order. Civil commitments fall into two categories: initial commitment (IC) and final Commitment (FC). Initial commitment is also called Probable Cause, indicating an involuntary hospitalization of patients for up to 30 days. After this period of inpatient care, any sign of imminent self-harm or danger to others will result in final commitment (FC) of the patient for further hospitalization.

According to previous records of the studied state hospital, since 2002 William R. Sharpe, Jr. Hospital has regularly been above its designed capacity of 150 beds, which provided a strong motivation to investigate the cause and solution to the over-bedding problem. In order to approach this issue, statistical analysis was performed on historical data from the hospital to provide input for designing a computer simulation model to replicate the hospital's daily admissions, releases, diversions and lengths of stay in order to achieve an approximate rate of diversion. Then, as the final part of this work, sensitivity analysis was carried out.

## 3.2 Materials and Methods

This study was conducted at William R. Sharpe, Jr. Hospital. with the total capacity of 150 beds, the hospital is one of the two state-funded acute inpatient psychiatric hospitals in West Virginia in which Psychiatric patients are admitted to the hospital only thorough court order as forensic patients or involuntary commitment. The hospital serves 42 counties out of total 55 counties of West Virginia which is about 65% of West Virginia's population. At the beginning of this study there were about 75 forensic patients and 75 civil committed patients at the hospital, so that half of the hospital's beds were occupied by involuntary civil committed patients who were all 18 or older. The legal status for civil commitments fall into two categories of initial commitments and final commitments, and both will be extended if patient is an imminent threat to self or others. This study concentrates on the admission's procedure of involuntary civil commitments, and all court order commitments will be excluded from this study.

### 3.2.1 Data Collection Methods

The original copy of historical data for this study includes an Excel spreadsheet recorded and maintained by the hospital's admission office. This document contains basic admission data, including medical record number, name, age, gender, county in which the patient was committed, legal status, admission date and discharge date. A new Excel database was created with de-identified personal data by removing their name, age, and gender; the medical record numbers were hashed into new item numbers. The new item numbers were matched to patients to distinguish those who had more than one admission during the duration of this study.

The new modified data was stored on a password-protected laptop which was designated for this research only. This research study was approved by the hospital research committee and West Virginia University institutional review boards, and was granted a waiver regarding the requirement for obtaining informed consent and Health Insurance Portability and Accountability Act authorization.

**3.2.2 Data Analysis and Simulation**

Different categories of patients, based on the legal status and the county of commitment, were taken into consideration as the key factors for this research study. The study window for the admission dates starts from 1/2/2007 and ends on 11/29/2013, a total of 2524 days. The patient's length of stay at the hospital was calculated by subtracting their discharge date from their admission date.

If a patient was still at the hospital, or did not have a discharge date recorded by the end of the seven year study window, it was assumed that he/she was discharged on December 31, 2013 to obtain more precise bed-occupying days for those patients.

The major goal of this research study is to create a simulation model which accurately represents the true admission procedure of patients to William R. Sharpe, Jr. Hospital. The following notations represent the collected historical data in our study:

$T$- The time horizon considered in this study, equal to 2,524 days.

$n_1$- The number of IC patient arrivals during the time horizon, equal to 11,054.

$n_2$- The number of FC patient arrivals during the time horizon, equal to 848.

$\{a_t = (a_{t,1}, a_{t,2});\ \mathrm{t} = 1, 2, 3, \ldots, \mathrm{T}\} -$ The patients' arrivals during the time horizon, where $a_{t,1}$ and $a_{t,2}$ represent the number of arrivals for IC and FC patients, respectively, on the $\mathrm{t}^{th}$ day.

$\{\mathrm{p_i};\ \mathrm{i} = 1, 2, 3, \ldots, \mathrm{n_1}\}$ : The length of stay for the $\mathrm{i^{th}}$ IC patient.

$\{\mathrm{q_i};\ \mathrm{i} = 1, 2, 3, \ldots, \mathrm{n_2}\}$ : The length of stay for the $\mathrm{i}^{th}$ FC patient.

**3.2.2.1 Simulation Model**

A simulation model was developed to model the admission, stay, and departure of patients. The simulation model was designed and implemented in MATLAB, and consists of two major algorithms.

The first algorithm is adapted from the flocking algorithm [12], and is used to simulate the input arrivals of patients. It simulates multivariate time series without requiring the various restrictive assumptions typically required by conventional methods. The historical data of patient arrivals over the time horizon were denoted as the bivariate time series as: $\{a_t = (a_{t,1}, a_{t,2});\ \mathrm{t} = 1, 2, 3, \ldots, \mathrm{T}\}$, and they were used as the input for algorithm 1. The vector $\tilde{a}_t = (\tilde{a}_{t,1}, \tilde{a}_{t,2})$ represents the simulated number of patient arrivals for IC patients, denoted by $\tilde{a}_{t,1}$, and FC patients, denoted by $\tilde{a}_{t,2}$, on the $\mathrm{t}^{th}$ day. Algorithm 1 takes the real historical bivariate time series as the input and generates the non-negative integer bivariate time series denoted as $\{\tilde{a}_t = (\tilde{a}_{t,1}, \tilde{a}_{t,2}), \mathrm{t} = 1, 2, 3, \ldots, \mathrm{T}\}$.

There are two user-specified parameters for algorithm 1: the affinity parameter, which is defined according to the modeler's preference about how similar the generated data are supposed to be to the Alpha boid (real data), and the noise parameter, to model the uncertainty involved in patient arrivals. These two parameters are set at 0.65 and 0.55 respectively in this work. The outputs of algorithm 1 were all rounded to the nearest non-negative integers to ensure that all the elements of the generated bivariate time series are non-negative integers. Multiple realizations of $\{\tilde{a}_t, \mathrm{t} = 1, 2, 3, \dots, \mathrm{T}\}$ can be generated by algorithm 1, and each realization represents a possible scenario for patient arrivals to the hospital over the time horizon. A brief explanation of these two algorithms is presented below.

With $I_2$ being the 2x2 identity matrix and $0_2$ as a two-dimensional zero vector, Algorithm 1 is described as follows.

Algorithm 1:

Inputs:

(a) Real data, which is a historical bivariate time series of patient arrivals denoted as $\{a_t = (a_{t,1}, a_{t,2});\ \mathrm{t} = 1, 2, 3, \dots, \mathrm{T}\}$.

(b) Affinity parameter $\lambda$.

(c) Noise parameter $\sigma$.

Process:

Initialization: randomly sample $\tilde{a}_1$ from multivariate normal distribution $N\ (a_1, \sigma^2 I_2)$.

FOR *t= 2 to T*

Set $R_t$ as the Euclidean distance between $\tilde{a}_{t-1}$and $a_t$.

Randomly sample $\varphi_t$ from $N\ (0_2, I_2)$ and $\varepsilon_t$ from $N\ (0_2, \sigma^2 I_2)$.

Then: $\tilde{a}_t = \tilde{a}_{t-1} + \lambda(\tilde{a}_t - \tilde{a}_{t-1}) + (1-\lambda)R_t\varphi_t + \varepsilon_t$

END FOR

Output:

$\{\tilde{a}_t, \mathrm{t} = 1, 2, 3, \dots, \mathrm{T}\}$.

Figure 1 shows the historical patient arrivals and also the generated patient arrivals by algorithm 1 over a 60-day period. The generated outputs resemble and deviate from the real data on different days.

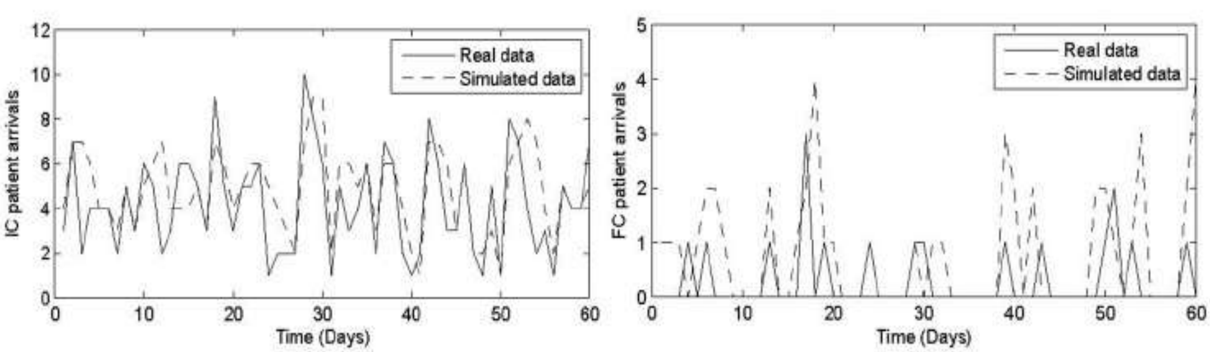


**Figure 3- 1: Simulated patients' arrivals over 60 days.**

Algorithm 2 is a simulation framework which uses the output of Algorithm 1 as its input, and was developed to simulate the whole admission procedure, such as arrival, stay or diversion, and departure of the patients.

In Step 1, algorithm 1 is called to generate the number of arrivals for IC and FC patients over the time horizon. In Step 2, the lengths of stay will be simulated using the bootstrapping resampling method. This method uses the real historical data to simulate a patient's length of stay at the hospital so that a patient's departure time is subsequently determined. According to the hospital policy, FC patients have higher priority to be admitted than IC patients when available beds at the hospital are lacking.

It is assumed that there are no patients at the hospital at the time of initiating the simulation. The time horizon of this study is 2,524 days, so the simulation's length (T) is set to 2,524 days. The diversion rate of patients was computed only during the period ($t_0$, T] and as it is the output of Algorithm 2, it is the performance metric of interest in this work. The warm-up period $t_0$ for this simulation model was set to 365 days.

According to the historical data, there were a total of 11,902 patients admitted to the hospital during the time horizon; however 7,967 of them (about 66.94% of total incoming patients) were diverted to other psychiatric community centers. Later in the next chapter, in order to validate the simulation model, the actual rate of diversion is compared to that estimated from the simulation model.

Algorithm 2:

Inputs:

(a) $N_b$ is the total number of beds at the hospital.

(b) The historical data of patient arrivals, denoted by $\{a_t;\ \mathrm{t} = 1, 2, 3, \dots, \mathrm{T}\}$.

(c) The historical data of lengths of stay at hospital for IC and FC patients, respectively denoted by $\{p_i;\ \mathrm{i} = 1, 2, 3, \dots, \mathrm{n}_1\}$ and $\{q_i;\ \mathrm{i} = 1, 2, 3, \dots, \mathrm{n}_2\}$.

(d) Affinity parameter λ.

(e) Noise parameter σ.

(f) Warm-up period length $t_0$.

Process:

Initialization:

Set $D_t$=0 for $t$=1, 2, …, T, with $D_t$ representing the number of patients discharged on the $t^{th}$ day.

Set $E_t$=0 for $t$=1, 2, …, T, with $E_t$ representing the number of current patients at the hospital at the beginning of the $t^{th}$ day.

Set $K_t$=0 for $t$=1, 2,…, T, with $K_t$ representing the number of diverted patients during the $t^{th}$ day.

Set $E_0$=0 to represent the number of patients at the hospital at the beginning of the simulation.

Step 1: Call algorithm 1 with inputs $\{a_t;\ \mathrm{t} = 1, 2, 3, \dots, \mathrm{T}\}$, λ and σ.

Return the simulated patient arrivals over the time horizon, denoted as: $\{\tilde{a}_t;\ \mathrm{t} = 1, 2, 3, \dots, \mathrm{T}\}$.

Step 2: FOR $t$ =1 to T

Set $E_t = E_{t-1}$

FOR $j$ =1 to $\tilde{a}_{t,2}$

IF $E_t < N_b$ THEN

Randomly sample from real data$\{q_i;\ \mathrm{i} = 1, 2, \dots, \mathrm{n}_2\}$, and assign it to $v$.

IF $v + t \leq T$ THEN

Set $D_{t+v} = D_{t+v} + 1$ and $E_t = E_t + 1$

END IF

ELSE

Set $K_t = K_t + 1$

END IF

END FOR

FOR $j$ =1 to $\tilde{a}_{t,1}$

IF $E_t$ < $N_b$ THEN

Randomly sample from real data$\{p_i;\ \mathrm{i} = 1, 2, \dots, \mathrm{n}_1\}$, and assign it to $u$.

IF $u + t \le T$ THEN

Set $D_{t+u} = D_{t+u} + 1$ and $E_t = E_t + 1$

END IF

ELSE

Set $K_t = K_t + 1$

END IF

END FOR

Set $E_t = E_t - D_t$

END FOR

Output:

The diversion rate, which was estimated as: $\sum_{t=t_0+1}^{T} K_t \,/ \sum_{i=1}^{2} \sum_{t=t_0+1}^{T} \tilde{a}_{t,i}$ .

# Chapter 4

# Results

## 4.1 Statistical Analysis

The information for civil committed patients for ten selected counties, including the top referring counties A-E and the bottom referring counties F-J, is summarized in Table 4.1.

The hospital's catchment area includes 42 referring counties, from which there were a total of 3,935 visiting patients to the hospital from 2007-2013. The total number of bed-occupying days by all these patients was 214,312. The top five counties most utilizing the state psychiatric hospital are denoted by A, B, C, D and E, respectively. All five of these counties individually had the highest contributions to the population of civil committed patients at the hospital in terms of both the number of admissions, ranging from 21.70-4.45% of total civil admissions, and the number of bed occupying days, ranging from 13.18-5.83% of total bed occupying days.

On the contrary, the least referring counties, represented as F, G, H, I and J, had the lowest contributions to the total civil patients at the hospital. The number of admissions ranged from 0.64-0.28% of the total civil admissions, respectively, and the number of bed-occupying days was accordingly within the range of 0.80-0.11% of the total bed occupying days.

It is shown in Table 4.1 that county A, with a total of 2,294 (854+1440) patient visits, had the highest number of visits to the hospital. Of these, 1,440 patients were diverted to other community hospitals due to the lack of available beds, and 854 patients were admitted to the hospital, which was about 21.70% of total admissions during the time window of this study.

County A with 28,240 days of utilizing the hospital beds (or about 13.18%) has the greatest contribution to the total number of bed-occupancy days during the time window of this study.

From Table 4.1, it is also obvious that civil commitment admissions are disproportionately distributed among the listed counties. There is a huge variance between those top referring counties and the bottom counties in terms of number of civil admissions; however it is necessary to take the population of each county into consideration in order to accurately investigate this disparity.

| Counties | Admissions (IC+FC) | Admission Percentage (of total) | Bed Occupancy (days) | Occupancy Percentage (of total) | Admissions | | Bed Occupancy (days) | | Total Diversions | Diversion Percentage |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | IC | FC | IC | FC | | |
| A | 854 | 21.70% | 28,240 | 13.18% | 793 | 61 | 23,321 | 4919 | 1,440 | 62.77% |
| B | 405 | 10.29% | 22,981 | 10.72% | 341 | 64 | 6,254 | 6727 | 212 | 34.36% |
| C | 289 | 7.34% | 16,886 | 7.88% | 213 | 76 | 6,646 | 10240 | 572 | 66.43% |
| D | 218 | 5.54% | 14,422 | 6.73% | 189 | 29 | 11,304 | 3118 | 827 | 79.14% |
| E | 175 | 4.45% | 12,495 | 5.83% | 133 | 42 | 8,218 | 4277 | 723 | 80.51% |
| F | 25 | 0.64% | 1,709 | 0.80% | 22 | 3 | 1,373 | 336 | 15 | 37.50% |
| G | 18 | 0.46% | 1,482 | 0.69% | 14 | 4 | 877 | 605 | 10 | 35.71% |
| H | 16 | 0.41% | 865 | 0.40% | 16 | 0 | 865 | 0 | 7 | 30.43% |
| I | 15 | 0.38% | 241 | 0.11% | 14 | 1 | 228 | 13 | 15 | 50.00% |
| J | 11 | 0.28% | 1,504 | 0.70% | 11 | 0 | 1,504 | 0 | 9 | 45.00% |

**Table 4- 1: Seven-year aggregate admission data of the highest and lowest referring counties**

In order to avoid a false interpretation about the counties' contributions to the total civil commitment admissions, the annual population of each county was collected and listed in table 4.1 to control the sampling size bias. According to the population data recorded by the United States Census Bureau, the ratios of annual civil visits to annual population of each county from 2010-2013 are presented in Table 4.2. These ratios vary from 0.0-0.17 %.

| Counties | Population | | | | Visits | | | | Visits Per Populace | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 2010 | 2011 | 2012 | 2013 | 2010 | 2011 | 2012 | 2013 | 2010 | 2011 | 2012 | 2013 |
| A | 86,982 | 86,844 | 86,657 | 86,569 | 152 | 126 | 69 | 73 | 0.17% | 0.15% | 0.08% | 0.08% |
| B | 69,240 | 69,316 | 69,166 | 68,972 | 75 | 66 | 49 | 27 | 0.11% | 0.10% | 0.07% | 0.04% |
| C | 56,524 | 56,661 | 56,849 | 56,868 | 34 | 40 | 26 | 20 | 0.06% | 0.07% | 0.05% | 0.04% |
| D | 96,776 | 98,671 | 100,527 | 102,274 | 37 | 30 | 20 | 19 | 0.04% | 0.03% | 0.02% | 0.02% |
| E | 78,913 | 79,259 | 79,177 | 78,833 | 20 | 23 | 22 | 15 | 0.03% | 0.03% | 0.03% | 0.02% |
| F | 10,449 | 10,349 | 10,269 | 10,077 | 8 | 1 | 1 | 1 | 0.08% | 0.01% | 0.01% | 0.01% |
| G | 8,693 | 8,765 | 8,778 | 8,650 | 5 | 1 | 1 | 0 | 0.06% | 0.01% | 0.01% | 0.00% |
| H | 5,736 | 5,803 | 5,839 | 5,901 | 1 | 0 | 1 | 4 | 0.02% | 0.00% | 0.02% | 0.07% |
| I | 9,154 | 9,148 | 9,016 | 8,881 | 1 | 1 | 1 | 0 | 0.01% | 0.01% | 0.01% | 0.00% |
| J | 7,574 | 7,608 | 7,581 | 7,577 | 1 | 0 | 2 | 0 | 0.01% | 0.00% | 0.03% | 0.00% |

**Table 4- 2: Annual admission totals and population data of ten selected counties 2010-2013**

From Table 4.2, it is obvious that there is no correlation between the population size of the listed counties and the number of civil visits referred by those counties. While county A remains the first-ranked county by number of civil visits per capita, the ratios of civil commitment visits per capita generally declined across the majority of selected counties from 2010-2013.

A summary of the frequency of patient readmission to the hospital, and the bed-occupying days of patients with respect to the number of readmissions over the entire time window, is provided in Table 4.3. Since it represents the number of individual admission, the diverted patients were excluded from the calculations. The total number of admissions equals 3,935, of which 2,056 patients have only been admitted once to the hospital, covering about 39.35% of total bed-occupying days.

There were 1,879 patients who had more than one admission to the hospital. Of these, 12 patients were admitted 10 or more times, and one person had been admitted 49 times. Readmitted patients had a significant contribution to the total bed occupancy of the hospital, such that 594 patients with more than one admission totally contributed about 60.65% of the total bed occupancy at the hospital. Furthermore, 37.35% of total bed-occupying days were dedicated to the 255 patients admitted more than twice.

| Number of Times Admitted | Number of Patients | Bed Occupancy (days) | Occupancy Percentage (of total) | Average Bed Occupying Days per Patient | Average Bed Occupying Days per Visit |
|---|---|---|---|---|---|
| 1 | 2,056 | 84,326 | 39.35% | 41.01 | 41.01 |
| 2 | 339 | 49,941 | 23.30% | 147.32 | 73.66 |
| 3 | 132 | 26,544 | 12.39% | 201.09 | 67.03 |
| 4 | 54 | 2,565 | 5.86% | 232.69 | 58.17 |
| 5 | 21 | 9,635 | 4.50% | 458.81 | 91.76 |
| 6 | 16 | 13,121 | 6.12% | 820.06 | 136.68 |
| 7 | 8 | 4,295 | 2.00% | 536.88 | 76.70 |
| 8 | 8 | 3,389 | 1.58% | 423.63 | 52.95 |
| 9 | 4 | 1,564 | 0.73% | 391.00 | 43.44 |
| 11 | 1 | 688 | 0.32% | 688.00 | 62.55 |
| 12 | 2 | 1,456 | 0.68% | 728.00 | 60.67 |
| 14 | 1 | 625 | 0.29% | 625.00 | 44.64 |
| 15 | 1 | 699 | 0.33% | 699.00 | 46.60 |
| 17 | 3 | 3,000 | 1.40% | 1000.00 | 58.82 |
| 19 | 1 | 725 | 0.34% | 725.00 | 38.16 |
| 21 | 1 | 445 | 0.21% | 445.00 | 21.19 |
| 28 | 1 | 467 | 0.22% | 467.00 | 16.68 |
| 49 | 1 | 827 | 0.39% | 827.00 | 16.88 |

**Table 4- 3: Seven year readmission frequencies and bed occupancy data**

According to Table 4.3, the average bed-occupying days for the patients who have been admitted only once was 41.01 per patient and also per visit, while almost all the readmitted patients had a greater contribution to the total bed occupancy at the hospital. The rest of the readmitted patients had been occupying the hospital's beds for a longer period. The shortest average number of bed-occupying days per visit belonged to the four patients who were admitted to the hospital more than 18 times.

Table 4.4 presents a summary for different periods of bed-occupying days for all arrivals of IC and FC patients, including diversion. The bed-occupying days for all the patients diverted to other psychiatric facilities were also taken into account. There were a total of 11,730 patient arrivals to the hospital, excluding 172 patients lacking discharge data, among which there were 10,936 IC patients and 794 FC patients. According to this table, 9,862 (90.18% of total IC patients) have been staying at the hospital for less than 30 days, which is the maximum legal period of inpatient care at the hospital for IC patients. The hospitalization period for IC patients varies from 0 to 1,661 days; however, only less than 10% of IC patients had been staying at hospital more than 30 days and had their legal status changed to FC patients.

| Length of Stay(n) In Days | Number of IC Patients | Number of FC Patients |
|---|---|---|
| n<=7 days | 4,128 | 78 |
| 7<n<=30 | 5,734 | 319 |
| 30<n<=182.5 | 994 | 345 |
| 182.5<n<=365 | 55 | 28 |
| n>365 | 25 | 24 |
| **Range of Bed Occupying Days** | | |
| Minimum | 0 | 0 |
| Maximum | 1661 | 2131 |

**Table 4- 4: Summary of IC and FC bed occupancy for all arrivals and diversions**

Regarding those FC patients who were admitted to the hospital for initial psychiatric treatment for greater than 30 days, the length of stay for them (about 83.63%) varied from 7-182.5 days. The maximum length of stay for FC patients was recorded as 2,131 days, and if patients were discharged from the hospital within 24 hours of admission the number of bed-occupying days was set to zero.

### 4.2 Simulation Result

The principle objective of this study was to develop a simulation model in order to investigate the impacts of changing some input variables of the simulation algorithm on the diversion rate of patients. These input variables include the total number of available beds at the hospital, patient arrivals and the lengths of stay at the hospital.

As a point of reference, a benchmark scenario is defined with respect to these three main inputs: (a) $N_b$=75, (b) the historical data for patients' arrivals $\{a_t;\ t=1, 2, \ldots, T\}$ and (c) the historical data of length of stay at the hospital for IC and FC patients, denoted by $\{p_i;\ i=1, 2, \ldots, n_1\}$ and $\{q_i;\ i=1, 2, \ldots, n_2\}$ respectively. This benchmark scenario was performed for 500 simulation replications by running algorithm 2 500 times in order to get 500 different diversion rate estimations.

Using these estimates, the cross-replication average rate of diversion, sample standard deviation and 95% confidence interval (CI) were calculated for this sample size of 500 different diversion rates. The values for the mentioned statistics are 66.96%, 2.23% and [66.76%, 67.16%] respectively, so that the real historical diversion rate of 66.94% was also included in 95% CI.

Alternative scenarios were created by adapting different values for the above three input variables (a)-(c). Each simulation scenario was performed 500 times to obtain 500 replications of the diversion rate in order to compare the statistics mentioned above with the ones from the benchmark scenario. These corresponding statistics for the diversion rate are presented in Table 4.5, Table 4.6 and Table 4.7.

Each table presents the following columns regarding each scenario: “Mean” and “Standard Deviation,” which provide the average diversion rate and standard deviation of the diversion rate across all the replications. The “Reduction” column shows the estimated decrease in expected diversion rate compared to the benchmark scenario and finally the “CI” column represents the 95% confidence interval of the expected decrease.

If the lower band of the CI is greater than zero, the alternative scenario will be considered significantly different from the benchmark with respect to the diversion rates.

### 4.2.1 Increasing the Hospital Capacity

In this section of study, the input (a) is adjusted to three different capacities: $N_b$= 85, 95 and 115, in order to investigate the system’s performance under these three different scenarios accordingly. The results are provided in Table 4.5, and the CI column in this table presents the expected reduction in diversion rates with respect to new increased capacities.

| Beds Available | Mean | Standard Deviation | 95% CI of Reduction |
|---|---|---|---|
| $N_b$=85 | 61.26% | 2.38% | [5.41%, 5.99%] |
| $N_b$=95 | 55.29% | 2.72% | [11.36%, 11.98%] |
| $N_b$=115 | 42.85% | 3.31% | [23.76%, 24.46%] |

**Table 4- 5: Estimated diversion change with adjusted hospital capacities**

### 4.2.2 Reducing the Number of Patients’ Arrivals

Different alternative scenarios were generated by reducing the number of patient arrivals, (b), by 10% and 20%. According to historical data, the top five counties together account for 48.02 % of total patient arrivals, so the reductions were implemented on these five counties. Table 4.6 is provided to present the impacts of reducing patient arrivals on diversion rates. Furthermore, the results of comparing this scenario with the benchmark are also given in this table.

| Reduction Percentage | Counties | Mean | Standard Deviation | Reduction | CI of Reduction |
|---|---|---|---|---|---|
| 10% less patients' arrivals | County A only | 66.21% | 2.29% | 0.75% | [0.47%, 1.03%] |
| | County B only | 66.51% | 2.22% | 0.45% | [0.17%, 0.73%] |
| | County C only | 66.83% | 2.21% | 0.13% | [-0.15%, 0.41%] |
| | County D only | 66.51% | 2.20% | 0.45% | [0.18%, 0.73%] |
| | County E only | 66.59% | 1.98% | 0.37% | [0.11%, 0.63%] |
| | All of the 5 counties | 64.68% | 2.27% | 2.28% | [2.00%, 2.56%] |
| 20% less patients' arrivals | County A only | 65.38% | 2.29% | 1.58% | [1.30%, 1.86%] |
| | County B only | 66.39% | 2.21% | 0.57% | [0.30%, 0.85%] |
| | County C only | 66.23% | 2.08% | 0.73% | [0.46%, 1.00%] |
| | County D only | 66.12% | 2.32% | 0.84% | [0.56%, 1.12%] |
| | County E only | 66.37% | 2.17% | 0.59% | [0.32%, 0.86%] |
| | All of the 5 counties | 62.72% | 2.42% | 4.24% | [3.95%, 4.53%] |

**Table 4- 6: Estimated diversion change with adjusted patient arrivals**

### 4.2.3 Reducing the Length of Stay

To explore the effects of reducing patient length of stay, an alternative scenario was developed by varying the input (c) of algorithm 2. Two reduction rates of 10% and 20% were implemented on the bed-occupying days of IC, FC and both patients to respectively estimate how different the real diversion rates would be in such cases. A summary of results are provided in Table 4.7.

| Reduction Percentage | Patient's Status | Mean | Standard Deviation | Reduction | CI of Reduction |
|---|---|---|---|---|---|
| 10% less length of stay | IC patients | 65.51% | 2.32% | 1.45% | [1.17%, 1.73%] |
| | FC patients | 64.45% | 2.35% | 2.51% | [2.23%, 2.79%] |
| | Both | 62.78% | 2.45% | 4.18% | [3.89%, 4.47%] |
| 20% less length of stay | IC patients | 63.51% | 1.45% | 3.45% | [3.16%, 3.74%] |
| | FC patients | 61.77% | 2.51% | 5.19% | [4.91%, 5.47%] |
| | Both | 57.38% | 4.18% | 9.58% | [9.28%, 9.88%] |

**Table 4- 7: Estimated diversion change with adjusted patient arrivals**

Based on the obtained results presented in Table 4.7, the reduction in the lengths of stay did significantly decrease the simulated diversion rates in comparison to the effects by other alternative scenarios.

## Chapter5

## Discussion and Conclusion

This study is designed to contribute to the development of the mental healthcare system in West Virginia for psychiatric patients, along with employees and all other involved parties which benefit by affecting the capacity-related decisions at one of the main assignment centers for psychiatric issues in the state, William R. Sharpe, Jr. Hospital.

A multitude of factors affect the involuntary state psychiatric hospitalization process and play key roles in the system's efficiency, performance and quality, which makes it more difficult to study. Although it seems that the immediate purpose of this work is to find the key to addressing the current capacity-related problems at West Virginia's state psychiatric hospitals, ideally its underlying purpose is to provide an adaptable framework for facilitating administrative decision-making as well as policy planning regarding the outcome and the maximization of cost-benefit among various healthcare sectors and scenarios.

Hospital managers and policymakers benefit from this research study by receiving different insights into several specific areas when addressing over-bedding problems. In order to address such problems while focusing on the counties with the highest number of commitments, different practical shortcuts might be utilized, such as increasing the number of beds in crisis units to help the patients who only need a brief crisis intervention; collaborating with other community mental health facilities to improve the quality of long-term treatment plans for patients who have multiple admissions, while improving key factors that show enormous effects on mental health, such as family, society support, treatment adherence and relapse, into consideration.

Since dispersion problems are frequent among many state psychiatric hospitals, increasing the number of group homes and assisted living facilities could be considered as another alternative to reducing the lengths of stay at hospitals. This approach helps patients to improve their mental health status by increasing medication compliance and intervention efficiency, while also benefiting from a stable therapeutic living environment.

In terms of hospital expansion and budgeting, this study provides a scientific approach based on historical data and daily census to ascertain the reasonable capacity needed by hospitals to address the over-bedding difficulties. According to the simulation's output, shorter lengths of stay reduce the diversion rate of patients, which is a milestone in facing the over-bedding problem; however, the quality of patients' care must not be sacrificed in the name of shortening patient hospitalization time. When addressing this problem, it is necessary to take both the benefits and limitations of inpatient psychiatric treatments into consideration. A high quality of inpatient care plays a key role to the successful discharge of patients, even in the presence of all possible solutions proposed before.

This study can be easily expanded and adapted to be applied in other healthcare sectors to address similar challenges. With the cost information, decision trade-offs can be evaluated based on the simulation model, and further, optimal (or near optimal) decisions that balance cost and service quality can be obtained.

**Direct References:**


[1] Soni, A. (2011). *Top 10 most costly conditions among men and women, 2008: estimates for the US civilian noninstitutionalized adult population, age 18 and older*. Agency for Healthcare Research and Quality.

[2] M Mechanic, D., McAlpine, D. D., & Olfson, M. (1998). Changing patterns of psychiatric inpatient care in the United States, 1988-1994. *Archives of General Psychiatry*, *55*(9), 785-791.

[3] National Center for Health Statistics (US. (2011). Health, United States, 2010: With special feature on death and dying.

[4] Stranges, E., Levit, K., Stocks, C., & Santora, P. (2011). State variation in inpatient hospitalizations for mental health and substance abuse Conditions, 2002–2008.

[5] Torrey, E. F. (1997). *Out of the shadows: Confronting America's mental illness crisis*. New York: John Wiley.

[6] Williams, Robert D. (2005). A Study of the Effect of an Integrated Continuum of Intensive Crisis Intervention Services (ICICIS), including Assertive Community Treatment (ACT), on Civil Commitments in North Central West. Dissertation submitted to the College of Human Resources and Education of West Virginia.

[7] Virtanen, M., Batty, G. D., Pentti, J., Vahtera, J., Oksanen, T., Tuisku, K., ... & Kivimaeki, M. (2010). Patient overcrowding in hospital wards as a predictor of diagnosis-specific mental disorders among staff: a 2-year prospective cohort study. *The Journal of clinical psychiatry*, *71*(10), 1308-1312.

[8] Biller, B., & Nelson, B. (2000). Modeling and generating multivariate time-series input processes using a vector autoregressive technique. ACM Transactions On Modeling And Computer Simulation,13(3), 211-237.

[9] Biller, B., & Gunes, C. (2010, December). Introduction to simulation input modeling. In *Proceedings of the Winter Simulation Conference* (pp. 49-58). Winter Simulation Conference.

[10] Arkin, B. L., & Leemis, L. M. (2000). Nonparametric estimation of the cumulative intensity function for a nonhomogeneous Poisson process from overlapping realizations. *Management Science*, *46*(7), 989-998.

[11] Härdle, W., Horowitz, J., & Kreiss, J. P. (2003). Bootstrap methods for time series. *International Statistical Review*, *71*(2), 435-459.

[12] Schruben, L. W., & Singham, D. I. (2014). Data-driven simulation of complex multidimensional time series. ACM Transactions on Modeling and Computer Simulation (TOMACS), 24(1), 5.

[13] Proctor, G., & Winter, C. (1998, January). Information flocking: Data visualisation in virtual worlds using emergent behaviours. In *Virtual Worlds* (pp. 168-176). Springer Berlin Heidelberg.

[14] Schruben, L., & Singham, D. (2011, December). Agent based simulation output analysis. In *Proceedings of the Winter Simulation Conference* (pp. 540-548). Winter Simulation Conference.

[15] Gunal, M. M., & Pidd, M. (2007, December). Interconnected DES models of emergency, outpatient, and inpatient departments of a hospital. In *Simulation Conference, 2007 Winter* (pp. 1461-1466). IEEE.

[16] Sood, L., & Owen, A. (2014). A 10-year service evaluation of an assertive community treatment team: trends in hospital bed use. Journal of Mental Health, 23(6), 323-327.

## Indirect References

- Ramberg, J. S., & Schmeiser, B. W. (1974). An approximate method for generating asymmetric random variables. *Communications of the ACM*, *17*(2), 78-82.
- Kuhl, M. E., Lada, E. K., Steiger, N. M., Wagner, M. A., & Wilson, J. R. (2006, December). Introduction to modeling and generating probabilistic input processes for simulation. In *Proceedings of the 38th conference on Winter simulation* (pp. 19-35). Winter Simulation Conference.
- Johnson, N. L. (1949). Systems of frequency curves generated by methods of translation. *Biometrika*, 149-176.
- Gerhardt, I., & Nelson, B. L. (2009). Transforming renewal processes for simulation of nonstationary arrival processes. *INFORMS Journal on Computing*,*21*(4), 630-640.
- Kuhl, M. E. (2011). Nonstationary Input Processes. *Wiley Encyclopedia of Operations Research and Management Science*.

- Reynolds, C. W. (1987). Flocks, herds and schools: A distributed behavioral model. *ACM SIGGRAPH Computer Graphics*, *21*(4), 25-34.
- Moere, A. V. (2004, October). Time-varying data visualization using information flocking boids. In *Information Visualization, 2004. INFOVIS 2004. IEEE Symposium on* (pp. 97-104). IEEE.
- Schruben, L. W., & Singham, D. I. (2010, December). Simulating multivariate time series using flocking. In *Proceedings of the Winter Simulation Conference*(pp. 1048-1054). Winter Simulation Conference.
- Singham, D., Therkildsen, M., & Schruben, L. (2011, December). Applications of flocking algorithms to input modeling for agent movement. In *Proceedings of the Winter Simulation Conference* (pp. 2443-2449). Winter Simulation Conference.
- Schruben, L., Singh, H., & Tierney, L. (1983). Optimal tests for initialization bias in simulation output. *Operations Research*, *31*(6), 1167-1178.
- Fryzlewicz, P., Van Bellegem, S., & Von Sachs, R. (2003). Forecasting non-stationary time series by wavelet process modelling. *Annals of the Institute of Statistical Mathematics*, *55*(4), 737-764.
- Barton, R. R., & Schruben, L. W. (1993, December). Uniform and bootstrap resampling of empirical distributions. In Proceedings of the 25th conference on Winter simulation (pp. 503-508). ACM.
- Center, T. A. (2014). Treatment advocacy center. Retrieved June, 1, 2014.

# Appendix

## Appendix 1:

## Population Information of the Main Counties according to Census estimation

| Counties | 2010 | 2011 | 2012 | 2013 |
|---|---|---|---|---|
| Wood | 86982 | 86844 | 86657 | 86569 |
| Raleigh | 78913 | 79259 | 79177 | 78833 |
| Harrison | 69240 | 69316 | 69166 | 68972 |
| Marion | 56524 | 56661 | 56849 | 56868 |
| Monongalia | 96776 | 98671 | 100527 | 102274 |
| Ohio | 44475 | 44178 | 44046 | 43727 |
| Wetzel | 16557 | 16405 | 16419 | 16204 |
| Marshal | 33064 | 32876 | 32685 | 32459 |

**Table A1- population estimation of different counties based on Census (2010-2013)**

| Counties | 2010 | 2011 | 2012 | 2013 |
|---|---|---|---|---|
| Wood | 391 | 345 | 327 | 285 |
| Raleigh | 140 | 120 | 127 | 93 |
| Harrison | 82 | 114 | 100 | 75 |
| Marion | 137 | 138 | 135 | 126 |
| Monongalia | 141 | 159 | 113 | 150 |
| Ohio | 233 | 252 | 215 | 205 |
| Wetzel | 70 | 68 | 66 | 44 |
| Marshal | 86 | 84 | 70 | 44 |
| Others | 484 | 562 | 503 | 424 |

**Table A2- The number of psychiatric patients at different counties (Diversion included)**