"AN ENHACEMENT OF MCMC ALGORITHEM WITH REDUCTION OF ECONOMICAL COST"

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Abstract

With the higher penetrations of wind power and photovoltaic power in systems, the randomness of their output adds amounts of uncertainty to system generation planning and scheduling. This thesis defines the risk indices of spinning reserve which measure the Costing level of system spinning reserve on the basis of temporal characteristic of the total casting output of wind and photovoltaic power modeled as scenario trees. Then, the economic dispatch model considering risk indices of spinning reserve and interruptible load regarded as spinning reserve to improve the system economy is formulated. The proposed model is solved by MCMC. Finally, the simulation example of system composed of lower costing -units proves the validity of the model.

Keywords- MCMC, Algorithm, Power distribution, solar energy, economic cost

I.INTRODUCTION

The installed capacity of solar photovoltaic panels has grown from 1.5 giga watts (GW) in 2000 to over 70GW in 2013 worldwide with an increase of 74% in 2011 alone (IEA, 2013). Government incentive programs, declining material and installation costs along with a change in political will toward renewable energy have been major influences to this growth. With the introduction of attractive government incentive programs, many home and business owners are now installing photovoltaic panels on building rooftops in urban centers. This has been the case within the City of India optimal secondary distribution systems. For homes and small businesses the return on investment and installation costs are primary drivers in the decision to install rooftop solar power. To achieve a reliable aggregate estimation of cost or return on investment however, the quantity of electricity needs to be accurately calculated. In Canada, there is need for a demonstrated methodology for quantifying rooftop solar power. This thesis sets out to develop such a methodology for the City of India [1].

The City of India, located approximately 100km west of Toronto, is a city experiencing rapid growth in population and building development. India is a diverse city with a variety of mixed land use ranging from high-rise apartments and office towers to sub-urban housing and rural farm land at the city limits. A large portion of the City landscape is dominated by two university campuses along with a large and diverse technology industry. Numerous student residences, high-rise condos, and campus buildings have transformed the urban landscape over the past decade. The growth and expansion of Blackberry (formerly Research in Motion) and other technology.

II.RESEARCH OBJECTIVES

The general objective of this research is to produce a range of values representing the possible electricity output that can be achieved in the City of India if all suitable buildings in the City were outfitted with rooftop photovoltaic solar panels optimal secondary distribution systems. Due to the variability of seasons, weather and solar output and the general complexity of this problem, a range in values from best to least favorable conditions are provided based on several factors [2]. These include:

1) **Suitable rooftop size to accommodate solar panels**

2) **Suitable rooftop angle**

3) **Solar panel angle**

4) **Solar panel direction in relationship to the sun**

5) **Seasonal variability in incoming solar radiation**

6) Shadow from trees, neighboring buildings and other features

7) Rooftop obstacles and physical barriers to construction

8) Size of solar panel array.

III.BACKGROUND

Solar panel development and research has progressed considerably over the past several decades. Major advancements to the manufacturing and performance of solar panels in the 1970's have lead to wide spread use of this technology today. Programs in the U.S., China, Japan and Europe continue to advance this technology further with their research, innovation and implementation of solar power. Today, these countries boast the highest implementation rates of photovoltaic (PV) systems in the world (University of Central Florida, 2014). More specifically, Germany since 2005 has been the world leader in installed solar power with over 36GW which contributes to roughly 6% of the countries demand for electricity. China is currently a distant second place with 18GW of capacity although with the growth rate at which China is developing solar power, they will likely catch up to and even surpass Germany in the near future (3).

The high density of electricity consumption found in urban environments along with attractive government incentives installing rooftop solar power are shifting the focus of solar power development towards cities and the location of electricity consumption (Gharakhani Siraki, A. and P. Pillay (2012). Incentive programs in many markets around the world continue encourage the construction of smaller scale solar projects. Individual homes and business owners can now purchase and install solar panel technology on their own buildings and expect a reasonable rate of return on their investment [3-4-5].
There are many advantages of installing solar panels on individual rooftops over traditional point source power generation stations such as coal, hydro-electric or nuclear. Rooftop solar essentially places a small scale source of electricity generation at the source of electricity consumption. There are a number of advantages to this setup. The need to construct large scale power stations commonly outside the urban center is greatly reduced or eliminated. In many locations, power generation systems place all or most of the focus on the few dozen sources of electricity production. Hydro-electric stations are limited to sources of fast moving water, nuclear stations need to be next to water sources to cool spent uranium and fossil fuel stations are typically located far from residents because of the emissions they produce. Rooftop solar disperses power generation across the existing grid infrastructure. This dispersion not only reduces or eliminates the need to construct or upgrade existing infrastructure to these large power plants, the many smaller generation stations in a sense reinforce the electrical network by not putting the onus on a handful of power sources (Sovacool, B. K., 2008).

IV.STUDY AREA OPTIMAL SECONDARY DISTRIBUTION SYSTEMS

The City of India was chosen for this research. India is 64.10 square kilometers in size, has a population of 98,780 (Statistics Canada, 2013) and is located approximately 100km west of the City of Toronto.

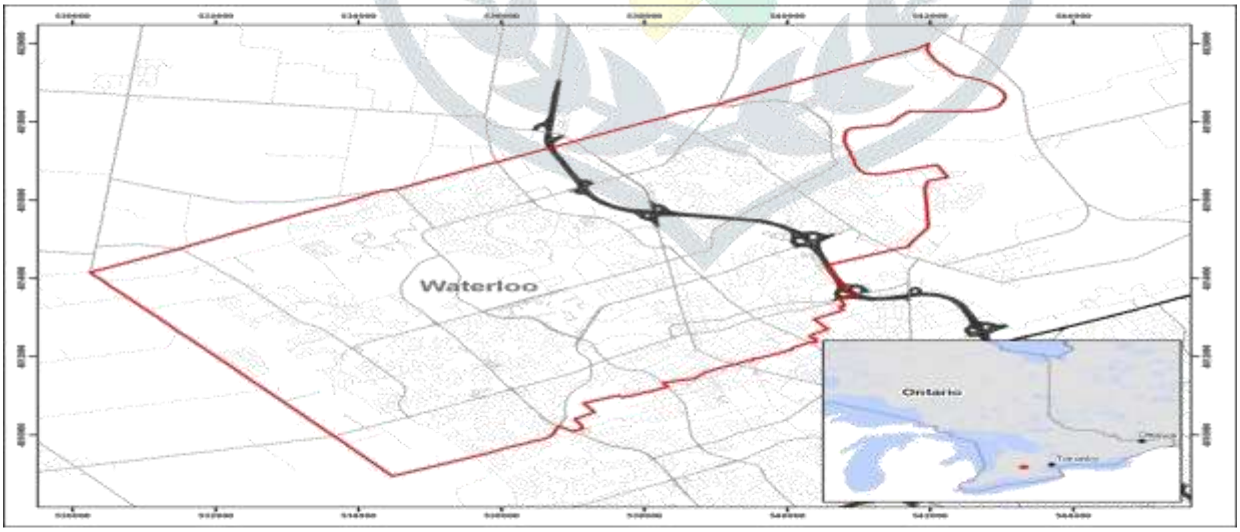

Figure (1) Geographical location.

The City of India is home to two major Ontario Universities (University of India and Wilfrid Laurier University) as well as Conestoga College. The computer science programs and graduating students from these schools have spurred several large technology companies. Blackberry, Open Text, and Google along with a host of other technology companies have flocked to Kitchener-India. In doing so, these companies have transformed the City of India and its surroundings into a major technology hub of North America. This transformation is evident to me every day since India is where I live, work and attend school. India's potential to generate electricity from rooftop solar is fascinating to me because it will impact me directly [7-8].

Solar arrays located in large open spaces such as a farm field do not have to contend with shadow from nearby objects such as trees. Many neighborhoods within an urban center can be limited by trees, buildings and other objects casting a shadow at some point during the day. Tooke et al. (2011) used LiDAR remote sensing technology to examine the seasonal effects that shadow from trees can have on the effectiveness of rooftop solar power. After studying a subset of buildings and vegetation in the City of North Vancouver, they determined that vegetation played a significant role in amount of radiation received at the rooftop level of a building. For residential buildings they found roughly a 38% reduction in incoming solar radiation to rooftop solar arrays and a strong correlation between tree structure and the amount of radiation intercepted. By avoiding areas influenced by vegetation cover, rooftop space and solar panel arrays can be used more efficiently to generate the maximum amount of electricity for the space available [8].

The proper classification of some rooftop types (Flat or Pitched) led to some noticeable errors in the data during this error checking process. In one or two cases, missing buildings that were not originally drawn in the building footprint layer from the City were added to the data.

Additionally, any changes to land use classification of existing building footprint polygons was based on several sources of information. In many cases, the incorrect data were obvious through visual examination of the air photo. Incorrect buildings were easily identified based on examining adjacent buildings and their size, shape or classification. Field checks and Google Street View were used to determine some buildings with missing or incorrect attribute information. Knowing where new commercial and residential projects have been taking place throughout the City also helped identify some of these problem areas. Some specific locations within the downtown core (Figure 4.5) and along University Avenue and King Street where several residential and commercial developments have been constructed in recent years were noted. In rare cases where the land use type of a building was not apparent, it was assumed that the land use type of a building within that same area was the correct land use type. This was the case in the Davenport and Northfield area where there are large sections of Resource and Industrial classed buildings. By zooming into each air photo tile at a scale of roughly 1:2000 meters, a clear level of detail could be achieved while still making the data manageable for error checking and other analysis.

V.PROPOSED MARKOV CHAIN MONTE CARLO (MCMC)

This chapter discusses the proposed *Markov chain Monte Carlo (MCMC)* simulation methodology for investigating digital elevation model (DEM) uncertainties in *GIS-based solar radiation models*.

The methodological framework proposed in the thesis is given in Figure1. It consists of four phases. Phase I: Identification and classification of solar radiation model inputs, Phase Stochastic (*MCMC*) simulation and convergence analysis for DEM, Phase III: Check for variogram reproduction, and Phase IV: Execution of solar radiation models and uncertainty assessment. Sections 4.2.1 - 4.2.4 discusses these phases in details. This study considers only two *GIS-based solar radiation models,* that is, *Solar Analyst* (Rich et al. 1995) - a commercial software developed for ArcGIS, and *r.sun* model (Hofierka and Šúri, 2002), an Open Source GIS software developed for GRASS. The versions of the software used in this research are; ArcGIS 9.3 and GRASSS 6.4.0.

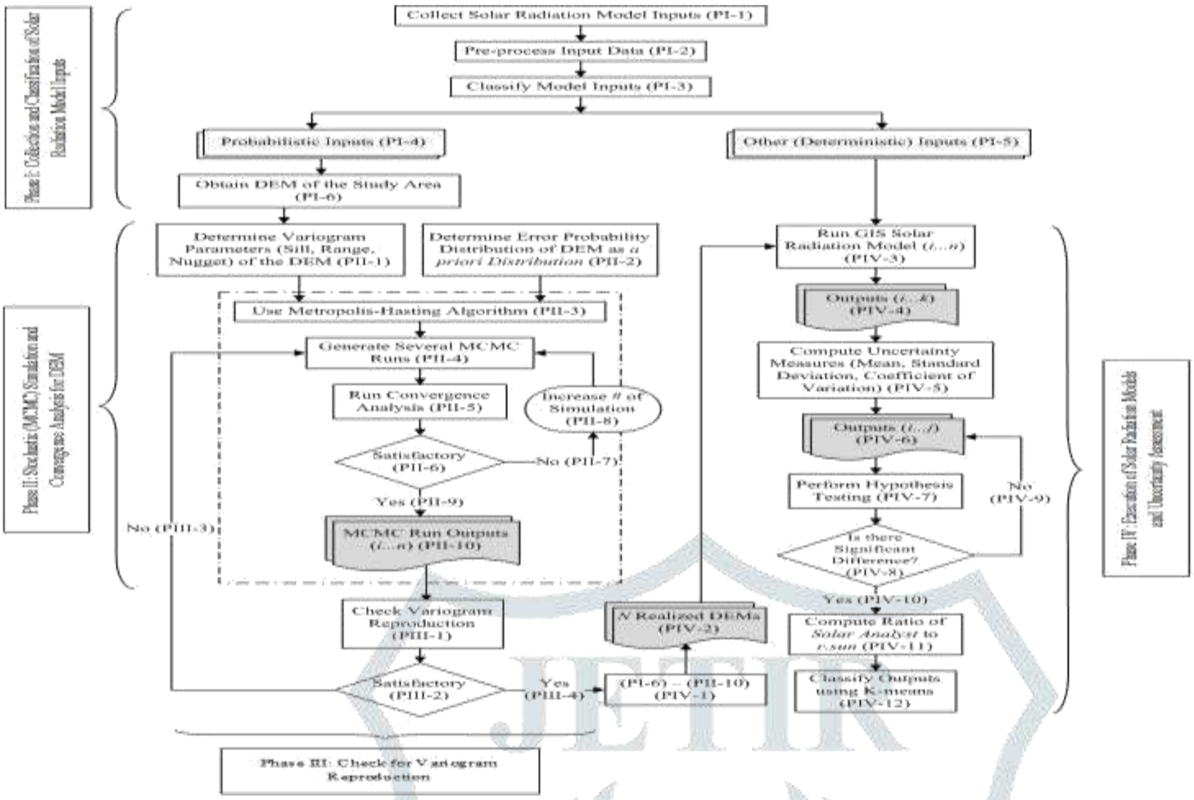

Figure 4.1. Flow chart of the proposed methodological framework.

PHASE I: COLLECTION AND CLASSIFICATION OF SOLAR RADIATION MODELS INPUTS:

The first stage in this phase involves the collection of *Solar Analyst* and *r.sun* models inputs (Figure 6: PI-1). These inputs are given in for *Solar Analyst* and *r.sun*, respectively. Then followed by pre-processing which deals with processing of both digital and analog data collected to required data format for the respective models, e.g., conversion of analogue to digital data format, conversion from one file format to another and spatial formats, transformation from one projection to another (Figure 4: PI-2). The third stage is the classification of model inputs into probabilistic and deterministic (Figure 6.1: PI-3, PI-4, PI-5). Probabilistic (stochastic) inputs are those in which random events and effects play an important role (Edwards and Hamson, 1989). In contrast, the deterministic inputs are those variables that whenever given to a model the outputs will be same (World Health Organization, 2005). DEM, slope, aspect, linke turbidity factor ( ), and ground albedo has the characteristics of being considered as probabilistic inputs. However, in this study and ground albedo are considered as deterministic inputs. The remaining inputs exhibit deterministic characteristics. As the aim of this study is to investigate the DEM uncertainty on *GIS-based solar radiation models*, therefore, Shuttle Radar Topography Mission (SRTM) DEM of the study area is obtained (Figure 6: PI-6) for utilization in the analysis. However, it is important to note that the proposed methodological framework is applicable to any kind of DEM data available.

PHASE II: STOCHASTIC (MCMC) SIMULATION AND CONVERGENCE ANALYSIS FOR DEM:

This phase deals with formulating and implementing the *MCMC* simulation, and then assessing its convergence (Figure 6). The first stage (Figure 4: PII-1 and PII-2) provides the necessary inputs for the *MCMC* simulation by determining the;
(1) DEM variogram characteristics or spatial dependence (autocorrelation) of the study area.
(2) DEM error distribution.
Spatial autocorrelation can best be explained by the first law of geography which is expressed by variogram/semivariogram of the DEM. Equation (1.1) (Journel and Huijbregts, 1978) is used to compute the semivariogram. The obtained variogram model and its parameters are then used in conditioning the *MCMC* simulation such that it generates several equiprobable realizations that provide the same spatial dependence (autocorrelation) structure of the original DEM.
The DEM error distribution (Figure 4: PII-2) deals with identification of error probability distribution function (pdf) of the SRTM DEM data and its parameters (mean and standard deviation). Generally, this can either be obtained from referenced data set with higher accuracy (Bolstad and Stowe, 1994; Fisher and Tate, 2006) or from the literature. This information serves as *a priori* pdf when formulating and implementing the *MCMC* simulation. In this study, SRTM DEM is utilized and as such DEM error distribution is extracted from Rodríguez et al. (2006) and then analyzed using distribution fitting software. Rodríguez et al. (2006) reported that the SRTM performance observed by comparing against the ground-truth (kinematic GPS transects) met/exceeded its performance requirements, often by a factor of 2.
The second stage deals with stochastic simulation, i.e., *MCMC* based on *Metropolis-Hasting (MH) algorithm* (Figure 4: PII-3). There are several *MCMC algorithms*: *Metropolis-Hastings algorithm* (Metropolis et al. 1953), *Gibbs sampler* (Geman and Geman, 1984), *Slice sampler* (Neal, 2003) as explained in Chapter 3. However, in this study, the *MH algorithm* is adopted because of its generality, simplicity and powerfulness (Robert and Casella, 2010). To formulate the proposed stochastic *MCMC*

algorithm for this study, the DEM error pdf obtained in the previous stage is utilized as *a priori* pdf while the variogram model is used to generate the spatial autocorrelation or covariance matrix.

INTRODUCTION OF MARKOV CHAIN MONTE CARLO:

Our goal is to introduce some of the tools useful for analyzing the output of a Markov chain Monte Carlo (MCMC) simulation. In particular, we focus on methods which allow the practitioner (and others!) to have con dence in the claims put forward. The following are the main issues we will address: (1) initial graphical assessment of MCMC output; (2) using the output for estimation; (3) assessing the Monte Carlo error of estimation; and (4) terminating the simulation.

Let be a density function with support X R^d about which we wish to make an inference. This inference often is based on some feature of . For example, if g : X ! R a common goal is the calculation of

$$E\ g = \ g(x)\ (x)dx : \quad (1.1.1)$$

We will typically want the value of several features such as mean and variance parameters along with quantiles and so on. As a result, the features of interest form a p-dimensional vector which we call . Unfortunately, in practically relevant settings we often cannot calculate any of the components of analytically or even numerically. Thus we are faced with a classical statistical problem; given a density we want to estimate several xed, unknown features of it. For ease of exposition we focus on the case where is univariate but we will come back to the general case at various points throughout.

Consider estimating an expectation as in (1.1.1). The basic MCMC method entails con-structing a Markov chain X = fX_0; X_1; X_2; : : :g on X having as its invariant distribution. (See Geyer (2010) for an introduction to MCMC algorithms.) Then we simulate X for a nite number of steps, say n, and use the observed values to estimate E g with a sample average

$$g_n := \frac{1}{n} g(x_i) : \quad n\ _x\ 1 \quad =0 \qquad (1.1.2)$$

The use of this estimator is justi ed through the Markov chain strong law of large numbers (SLLN)[1]: If E jgj < 1, then g_n ! E g almost surely as n ! 1. From a practical point of view this means we can obtain an accurate estimate of E g with a su ciently long simulation.

Outside of toy examples, no matter how long our simulation, there will be an unknown Monte Carlo error, g_n E g. While it is impossible to assess this error directly, we can obtain its approximate sampling distribution if a Markov chain central limit theorem (CLT) holds. That is, if

$$p\ \overline{\ }\ n(g_n \ \ E\ g)\ !^{d}\ N(0;\ _g^{\ 2}) \qquad (1.1.3)$$

as n ! 1 where $_g^2$ 2 (0; 1). It is important to note that due to the correlation present in a Markov chain $_g^2$ 6= var g except in trivial cases. For now, suppose we have an estimator such that $^\wedge{}_n^2$! $_g^2$ almost surely as n ! 1 (see Section 1.4 for some suitable techniques).

Using this tool, the values for the City of India are presented below in two tables. In Table 4.3 the amount of kWh per kW of solar power capacity installed (PV Potential) is given for every month. Four columns are also presented which show what values are possible based on the angle the solar panel is tilted. The PV potential did not include the Horizontal (tilt=0°) angle:

India, Ontario

Geographic location -> -80.51E, 43.47N

VI.RESULT AND SIMULATION

We consider the optimal economic dispatch of power generators in a smart electric grid for allocating power between generators to meet load requirements at a minimum total cost. The first algorithm presented, is a distributed algorithm for frequency control and optimal dispatch, where, each generator independently adjusts its power-frequency set-point to erase power imbalance and load fluctuations by using the aggregate power imbalance in the grid, observed by local measurements of the frequency deviation. We also present a second decentralized consensus based algorithm where, we assume each generator, in addition to the measured frequency deviation in the grid, has minimal information exchange with its neighbors. Existing algorithms assume that frequency deviation is proportional to the load imbalance. In practice this is seldom exactly correct. We assume in both cases, that the only thing known about this relationship is that it is an unknown, odd, strictly increasing function. By simulations and mathematical proof of convergence, we provide verification of the efficiency of the algorithm.

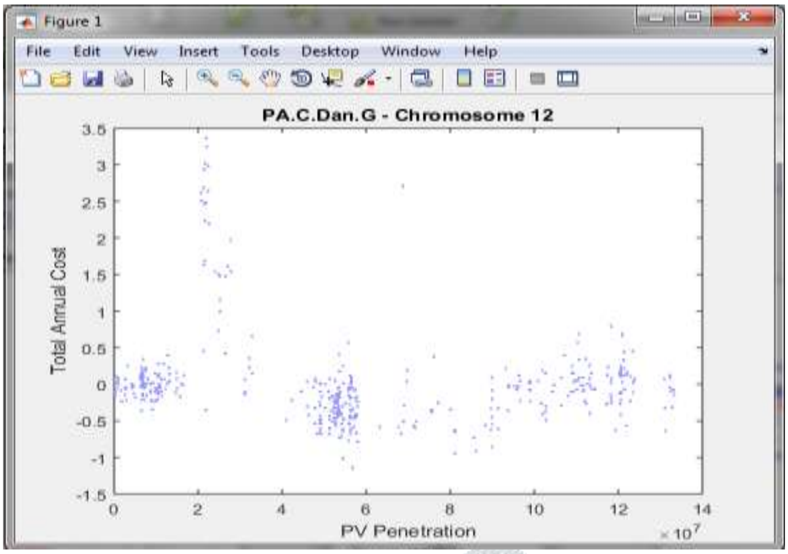

Figure 6.1: MCMC based Chromosome dot representation.

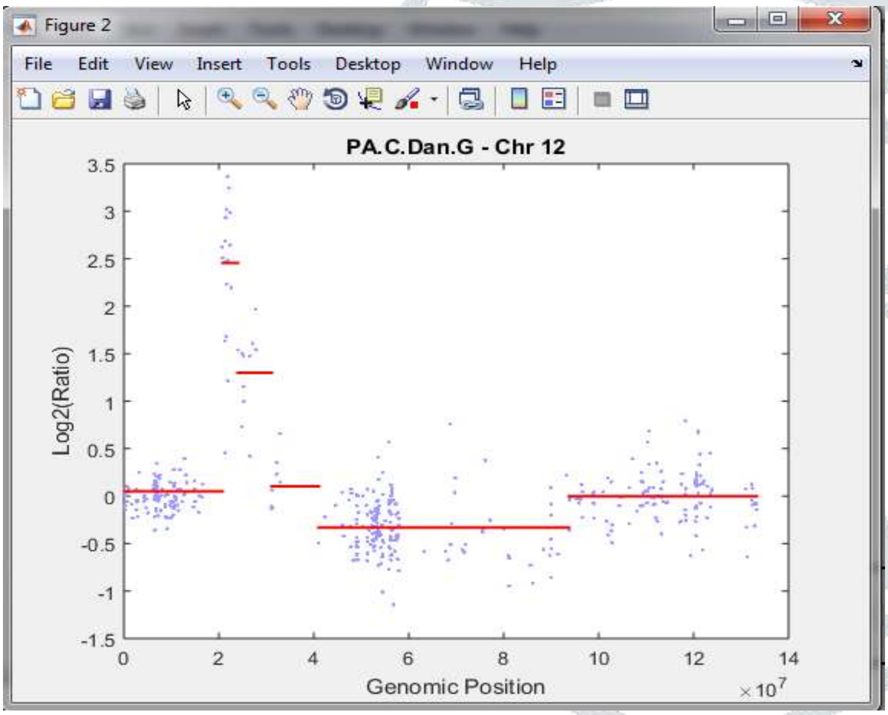

Figure 6.2: MCMC based Chromosome Lavel representation.

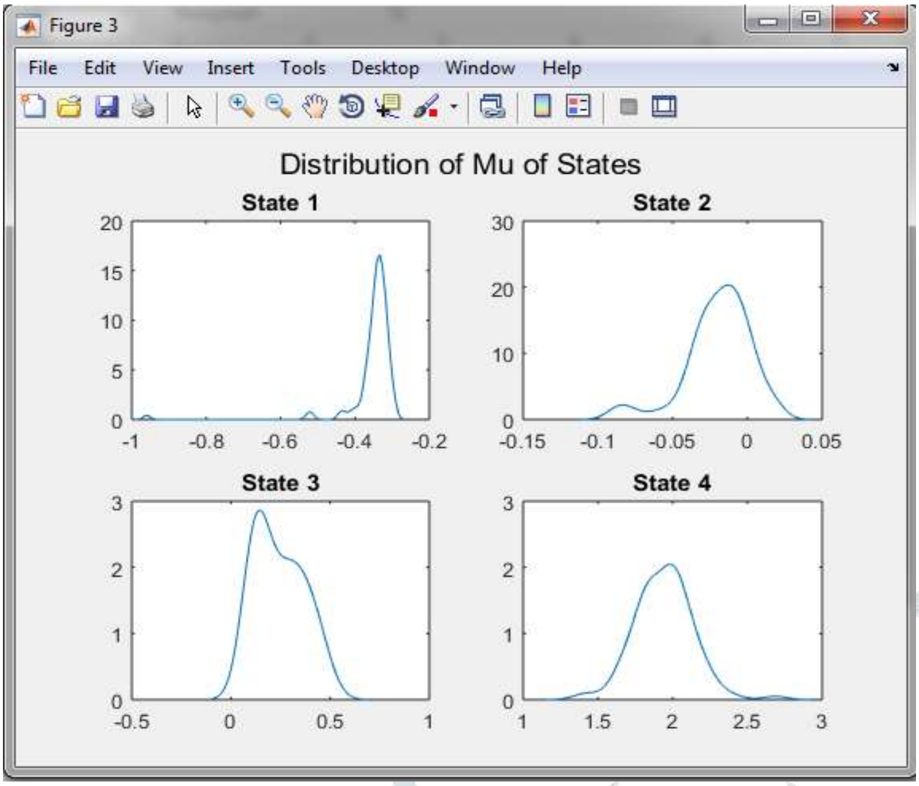

Figure 6.3Disribution of Mu of state.

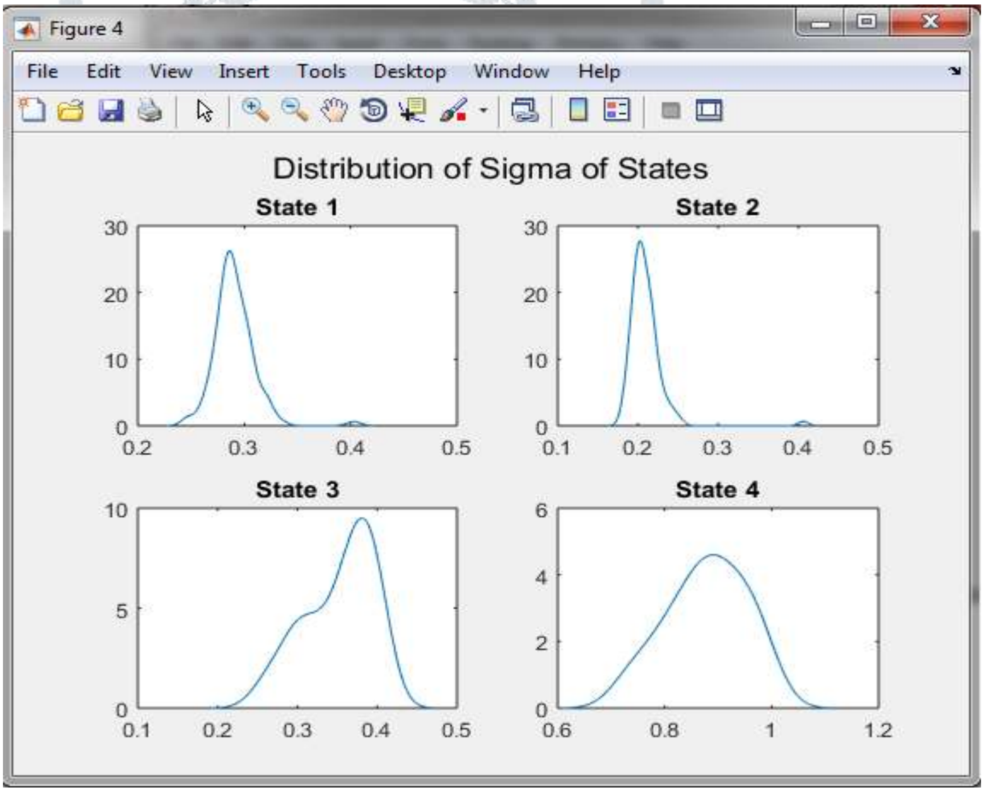

Figure 6.4 Distribution of Mu of state 2.

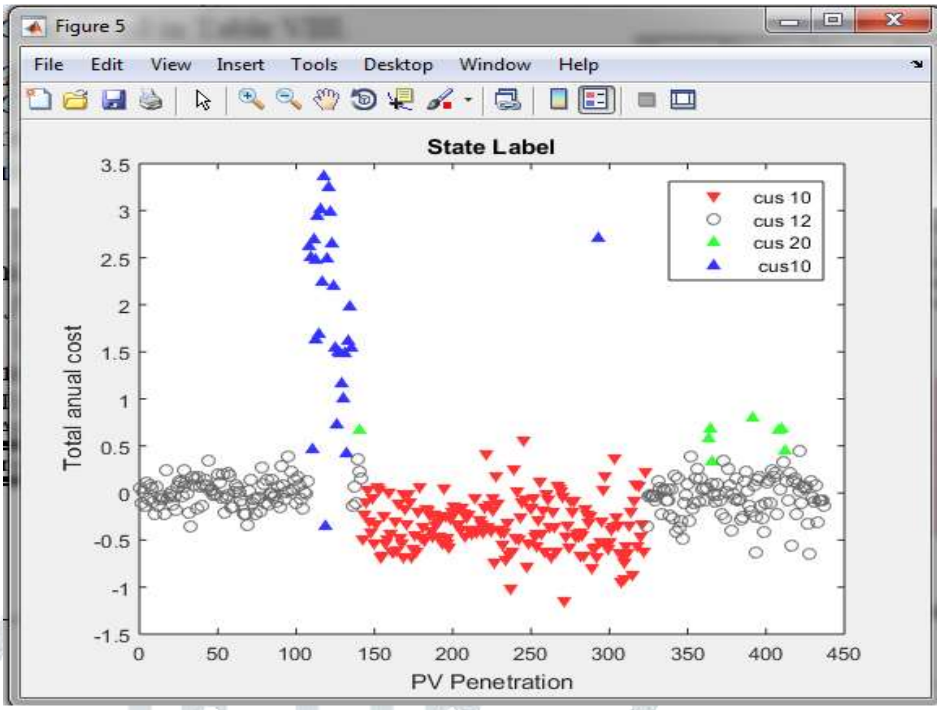

Figure 6.5 Different Customer different Total annual cost.

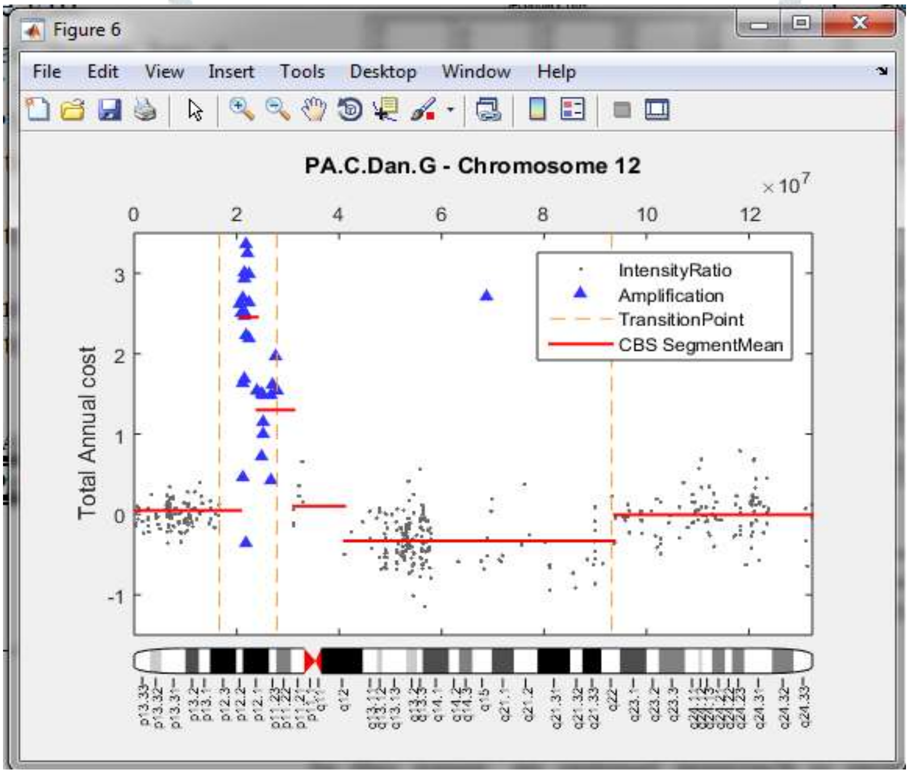

Figure 6.6Chromosome Level Total Annual cost with PVs based power generation and load flow.

VII. CONCLUSION

The objective of this research was to estimate rooftop solar power potential for the City of India. A range in values was produced beginning with liberal “best case scenario” results which were refined to more conservative “worst cases scenario” estimations after factoring in a number of variables.

The first objective of this research was to estimate how much electricity could be generated in the City of India if all suitable buildings installed a rooftop solar power generator. This estimate was achieved by using base values from the Natural Resource Canada solar mapping tool which were then refined. These values were presented as kWh/year and MWh/year for flat and pitched rooftops. These overall values were further broken down into best and worst case scenario totals for each of the 5 land use types found throughout the city.

The identification of which land use types, roof types and locations in the city hold the most promise for rooftop solar power was the second objective for this research. This question was answered by breaking down the results into their various land use and building type categories. Values specific to land use type can be found in the appendices. These results were also compared to locations and characteristics of existing rooftop solar generators. This comparison helped to further answer the above objective. Simply put, residential buildings hold the most promise for rooftop solar given they are the most commonly found land use type across the City.

Several limiting factors to rooftop solar power were examined using studies from the literature. Suitable array size, influences of weather and solar panel efficiency were areas not examined using examples from the literature but rather examined in terms of their sensitivity, variability, and importance in the Discussion section. These variables were indented to be addressed in this research however each of these topics are large and complex enough on their own to warrant individual examination as they relate to rooftop solar power potential. These topics should be examined in future studies.

VIII. OPPORTUNITIES FOR FUTURE WORK

There are a number of opportunities to study the topic of solar power and rooftop solar power further. Many authors have studied a single specific aspect of rooftop solar power on a small scale and then extrapolated those results to a much larger scale therefore creating the possibility of introducing errors in the results. Other examples have taken a more general approach to quantifying rooftop solar power in the attempt to understand the potential for a large area without focusing much detail on the many different aspects that influence an accurate assessment of that potential. Further research on this topic could attempt to marry these two approaches by studying the many aspects of quantifying rooftop solar power at the small scale and then increasing the study area size to better understand the potential of a larger area. There are many unique circumstances (e.g. shadow from trees/buildings and different building types/sizes) across large urban area that can lead to highly variable results. These variables and situations could perhaps be studied at the small scale throughout many different pockets of an urban area and then extrapolated or generalized for the rest of the study area. Conversely, larger areas such as a city could be broken up into more manageable sections, examined closely and then combined to calculate an overall result. Regions of a city could be divided up based on building type, land use type, political boundaries, or population density. Deciding how to subdivide such a large study area based on which factors would be a topic for debate.

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