

# A Land Mobile Channel Modeling in LabVIEW

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**Abstract**— This paper presents a case study implementation of a fading channel model for a recently introduced Global Positioning System (GPS) simulator from National Instruments. Existing models are discussed and implementation aspects are presented for a model which combines statistical properties of different multipath channels. The NI's GPS simulator is implemented in an open development environment, LabVIEW, which allows an incorporation of user-defined models. Computational optimization issues are also discussed.

## I. INTRODUCTION

During recent years location technologies have emerged as a research area with many possible applications in wireless communications, surveillance, military equipment, etc. In particular, wireless operators around the world develop Location Based Services (LBS) which are identified as an excellent growth niche. Currently Global Positioning System (GPS) has an established a reputation of a robust global technology allowing users to determine their locations using receivers incorporated in various devices including cell-phones, PDAs, watches etc. [1].

Initially GPS was designed to function in open areas with a clear view of the sky, but emerging applications in urban and indoor areas need receiver functionality in degraded signal environments. Cities are challenging environments for positioning using GPS. Signal is distorted because of signal reflections and diffractions, and the direct path signal may or may not be present (see Fig. 1). This phenomenon is generally known as multipath, and reflected components may enhance or cancel the signal depending on various delayed replica paths which is known as fading. While many other distortion effects can be compensated by e.g. differential or assisted techniques multipath phenomena is a challenge for the state-of-the-art receivers. There are many multipath mitigation techniques such as narrow correlators, strobe and edge correlators, gated correlators etc. [1]. Real world testing presents very unquantifiable and un-repeatable multipath environments which is not efficient for early algorithm development stages. Simulators and simulation channel models may provide typical multipath signals for convenient study of different mitigation techniques. This paper shortly reviews existing simulation concepts and describes a case study of a user-defined models for the GPS simulator from National Instruments. Existing models include conventional methods which are a generalization of common adapted wireless channel models, modeling of pseudorange measurement distortions due to multipath, geometric approaches, and other techniques.

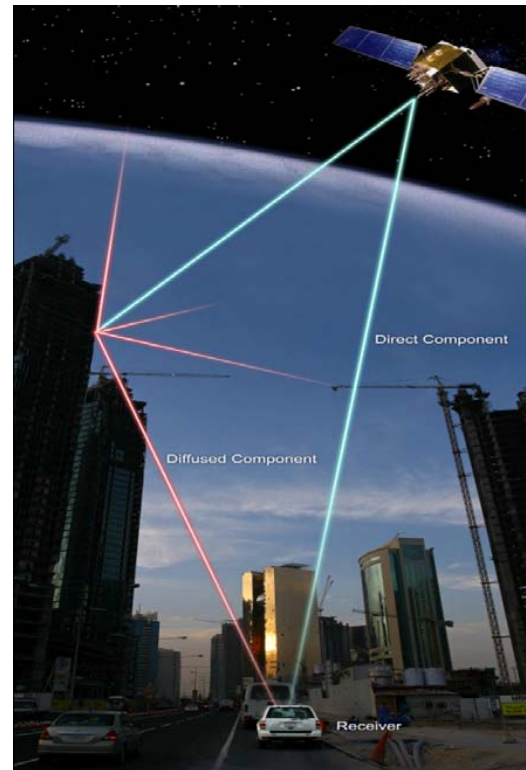


Figure 1 Multipath illustration using direct and reflected propagation paths between satellite transmitter and a receiver.

## II. A REVIEW OF GPS MULTIPATH PROPAGATION MODELS

In general terms existing models for GPS signal propagation fall into the following major categories: (1) conventional wireless propagation models which are adapted for GPS signals; (2) modeling multipath phenomena on the level of GPS measurements (pseudoranges); (3) physical and geometric approaches which model the distortions based on the propagation and reflection phenomena; (4) hybrid methods.

An example of conventional and geometric multipath simulation environment is presented in [2,3]. Several simulation modes are reported. In “fixed-offset” mode the simulator combines Line-of-Sight (LOS) signal with an “echo” signal with a constant user-defined delay and power (conventional). In “ground-reflection” mode the multipath simulator computes the echo parameters based on signal

arrival angle and antenna height (geometric). This model also introduces Doppler offsets for multipath components in a user-defined constant way or randomized. The Land Mobile Multipath (LMM) model in [2,3] simulates conventional statistical models commonly used in simulating wireless communication channels. This includes direct LOS signals with Rician fading, reflections (echoes) with Rayleigh fading and power decays, Doppler offset etc. Typical parameters for different environments are tabulated for rural, suburban, urban and highway environments [4].

The three state fade model which falls into conventional statistical modeling category is presented in [5]. A GPS satellite signal profile is considered as a result of a statistical combination of three possible phenomena (a) clear line-of-sight signal; (b) shadowed signal e.g. observed during the signal propagation through tree canopies; (c) blocked environments without LOS signal. The model is similar to the conventional LMM model with a difference that all the environments are considered as a mixture of these three and signal amplitude variations are modeled as using linear combination of three probability density functions, i.e. Rician, Rayleigh and Loo [6]. This model is implemented as an implementation case study using NI's GPS simulator and LabVIEW development software [7].

When considering position computation in a GPS receiver then multipath phenomena impacts measurements which are called pseudoranges. These measurements are satellite-to-user range estimations biased by a common value due to clock inaccuracies. Instead of modeling multipath signals one can directly model the pseudorange errors (see e.g. [8]).

More complicated models are using physical propagation theories for more accurate simulations. Examples are [9],[10]. [9] is based on parabolic equation (PE) technique to solve GPS propagation models. It also includes the effects of the backscatter and provides time-domain representation of the propagated GPS signal. [10] integrates city models with GPS observables in order to predict both satellite availability and the level of signal degradation due to the multipath effect on pseudorange measurements. In [10] authors address a fundamental problem of rapid and efficient assessment of urban environment data. The ratio of the number of surfaces that cause multipath effects compared to the total number of surfaces in an entire city model is extremely low. The method finds surfaces which may cause reflections. [11] describes the simulator that uses a ray-tracing technique to determine paths that a GPS transmitted signal can take. The model uses Geometrical Theory of Diffraction (GTD) to model signal reflection and diffraction from surfaces, edges, corners. The multipath environments generally modeled as a finite number of surfaces whose dimensions, relative locations, and orientations, as well as their electromagnetic properties are specified.

The model presented in [12] has elements of both statistical and geometrical models. It considers three types of objects (a) house fronts; (b) trees; (c) lampposts. In contrast with ray-tracing algorithms specific scenery is not modeled. Rather reflections are statistically distributed in the space and they are

also statistically generated. Based on the receiver motion the model generates artificial scenery which is then used for the fade model design

### III. AN IMPLEMENTATION CASE STUDY OF A THREE-STATE FADE MODEL

One of the goals of this paper is to demonstrate the feasibility of applying channel models in a user-defined setting for NI's GPS simulator. The simulator is implemented using NI's open development tool – LabVIEW. The combined Urban Three-State Fade Model (UTSFM) has been selected for the case study [5,13]. The fading model is based on the combination of three types of distributions—Rayleigh, Loo, and Rician. Different combinations of distributions are used depending on the satellite elevation angles and user-defined environments such as urban, rural, etc.

Considering a randomly moving receiver, the surroundings and related reflection patterns will always change due to obstructed and shadowed places that block the signal path. Fig. 1 exemplifies this by illustrating the arrival of radio frequency (RF) signal through a few different paths resulting in multipath phenomena.

Signal variations according to the Rayleigh distribution are observed in the absence of the LOS signal and the signal arrives through reflected paths only. The probability density function (PDF) can be defined as follows:

$$f(v) = 2Kve^{-Kv^2} \quad (1)$$

where  $K$  is the ratio of the direct power received to the multipath,  $v$  is the received voltage relative to the voltage of the clear path [6].

Loo distribution is observed mainly in shadowed environments. It is the combination of the lognormal and Rayleigh distributions. The PDF of Loo distribution is as follows [6]

$$f(v) = 8.686 \sqrt{\frac{2}{\pi}} \frac{Kv}{\sigma} \int_0^{\infty} \left( \frac{1}{v} e^{-\frac{(20 \log(v) - m)^2}{2\sigma^2} - K(v^2 + z^2)} \right) * I_0(2Kvz) dz \quad (2)$$

where  $\sigma$  and  $m$  are standard deviation and mean value of  $\log(v)$ .

Rician fading is observed in a multipath environment with LOS reception. The PDF is as follows: [6]

$$f(v) = 2Kve^{-K(v^2+1)} I_0(2Kv) \quad (3)$$

The total combined model for the urban canyon is formed using the combination of these three distributions [13]:

$$f(v) = C \cdot f_{Rician}(v) + S \cdot f_{Loo}(v) + B \cdot f_{Rayleigh}(v) \quad (4)$$

where  $C+S+B=1$ ,  $C$ ,  $S$ , and  $B$  are coefficients which depend on the satellite elevation angles and environments.

A. Simulations

Based on reported measurement campaigns the coefficients ( $C$ ,  $S$ ,  $B$ ) are tabulated as a function of satellite elevation angles and environment [13]. In general the simulator generates signals based on the user location and time. Thus elevation angles can be computed and used for the model implementation as required by the model. An experiment using user-defined number of samples for the statistical evaluation (10,000 samples by default) is used to generate simulated datasets and evaluate statistical distributions, i.e. their probability density functions (PDF). Figures 2 to 5 provide examples of PDFs for various elevation angles. They also provide signal variations resulting from the simulation. The signal profiles are applied individually to the various satellite signals using an interface provided by NI. One can observe one to three signal fragments with various statistical behaviors. In these simulations the combination of various distributions is achieved by selecting signal intervals which are proportional to the distributions coefficients. Fig.2 illustrates the case with all three distributions, while Fig. 3 exemplifies a case with two distributions only. All three distributions are simulated using random Gaussian signal generators which is a common approach which can be found e.g. in [6].

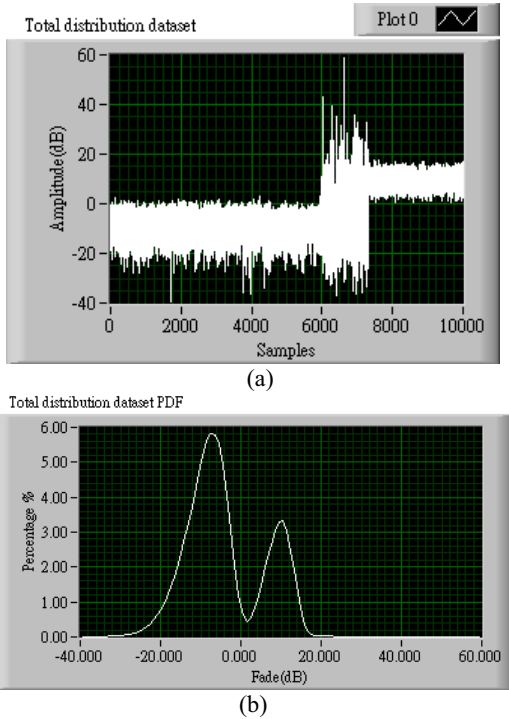
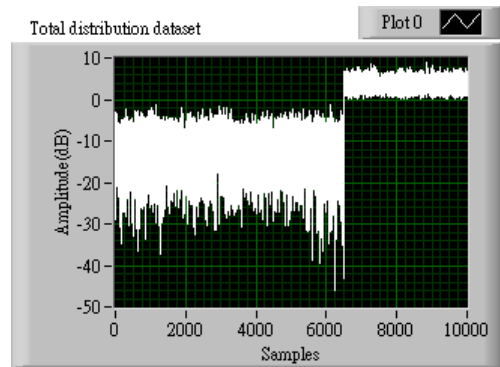
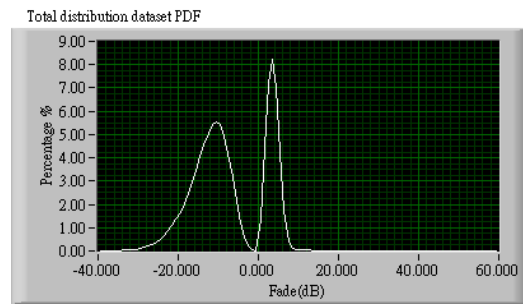


Figure 2 (San Francisco urban canyon: elevation angle 0°~20°) (a) Signal variations; (b) Histogram of the signal profile for the combined model.

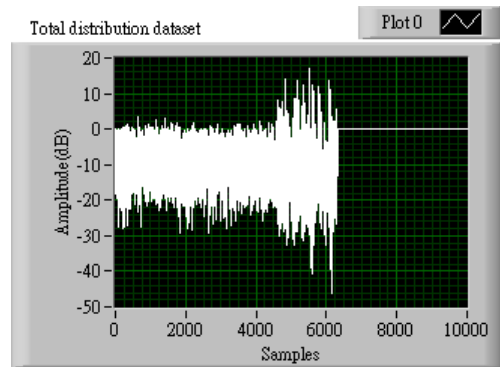


(a)

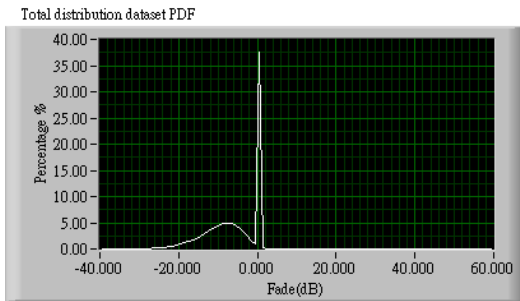


(b)

Figure 3 (San Francisco urban canyon: elevation angle 20°~40°). (a) Signal variations; (b) Histogram of the signal profile for the combined model.

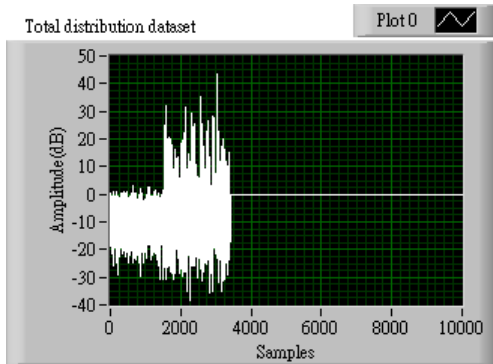


(a)

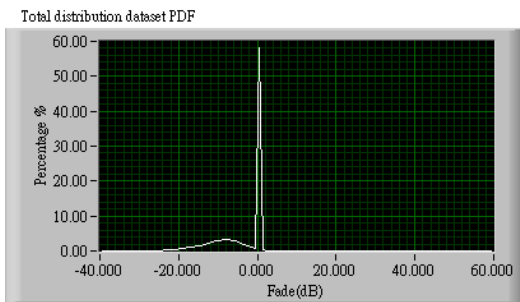


(b)

Figure 4 (San Francisco urban canyon: elevation angle 40°~65°). (a) Signal variations; (b) Histogram of the signal profile for the combined model.



(a)



(b)

Figure 5 (San Francisco urban canyon: elevation angle 65°~90°) (a) Signal variations; (b) Histogram of the signal profile for the combined model.

In general, when simulating random user movements and time-varying environments one should implement random signal intervals. Our implementation uses dynamic switches which activate random generators corresponding to three possible states. Dynamic switches preserve the average proportion of different environments as required by coefficients ( $C, S, B$ ). Fig. 6 illustrates the idea of dynamic switches. Depending on the environment the system alternates properly the random generators, their operation times and signal strengths.

### Switch options

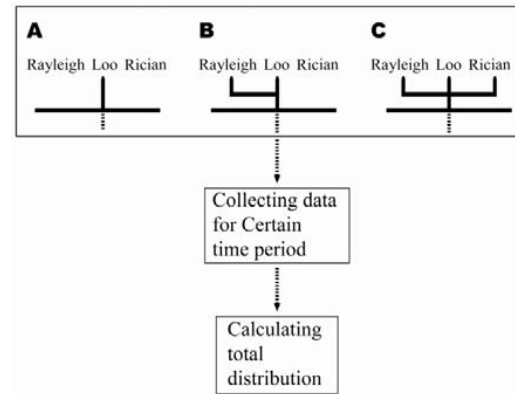


Figure 6 Schematic illustrations of dynamic switches with separated random generators.

If the observation period is long enough, the histogram of the dynamically switching system is similar to the results obtained with constant interval setting which is described earlier. Figures 7 to 10 show the results for the proposed smart switch. 10,000 samples and 100 observing time intervals were used to generate simulated datasets.

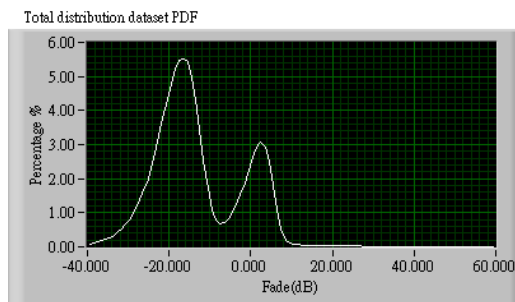


Figure 7 (San Francisco urban canyon: elevation angle 0°~20°) Histogram of the signal profile for the combined model.

### B. Simulation Complexity Reduction Using Shared Gaussian Random Generator

As it was mentioned earlier all three distributions are generated using random Gaussian signal generators [6]. As NI's GPS simulator does not use hardware accelerators one should minimize costs associated with the implementation which runs three different signal generators depending on the state. The LabVIEW environment implements signal flow and launching or suspending generators requires additional conditioning loops. To simplify the signal generation our implementation runs all three generators in parallel (Rayleigh, Rician, Loo) and they are all enabled by the same random Gaussian generator. To decorrelate all the signals generators random delays are added so signal for all three states are not correlated. This setup is shown in Figure 11. The samples and

observing time intervals are the same as for dynamic switches with separated random generators.

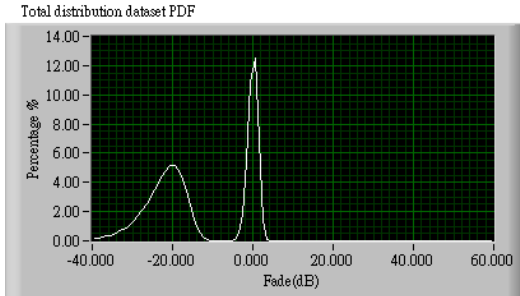


Figure 8 (San Francisco urban canyon: elevation angle 20°~40°) Histogram of the signal profiles for the combined model.

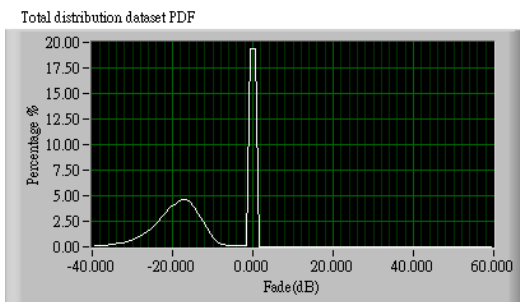


Figure 9 (San Francisco urban canyon: elevation angle 40°~65°) Histogram of the signal profiles for the combined model.

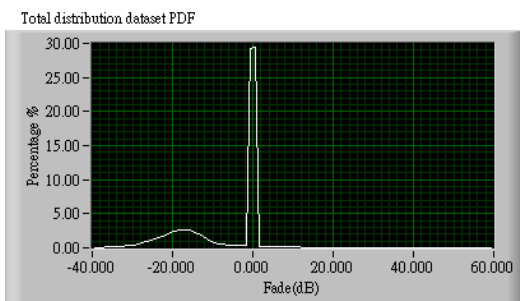


Figure 10 (San Francisco urban canyon: elevation angle 65°~90°): Histogram of the signal profiles for the combined model.

### Switch options

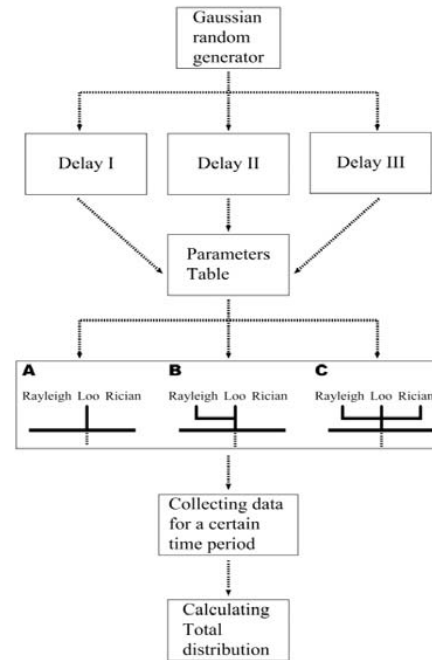


Figure 11 Illustration of the shared random generator switches.

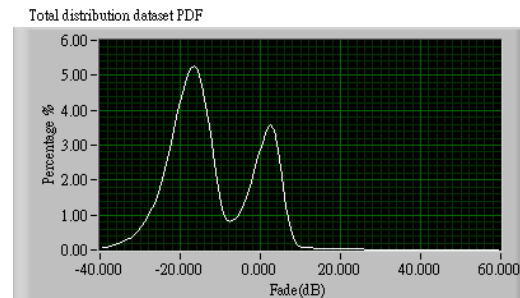


Figure 12 (San Francisco urban canyon: elevation angle 0°~20°) Shared random generator switches: (a) Combined model dataset. (b) Histogram of the model.

Figures 12 to 15 illustrate signal distributions for the optimized LabVIEW implementation using shared random generator. The simulation results demonstrate that a shared Gaussian generator does preserve the signal distribution as if the signals are enabled by separate Gaussian generators. As a result the implementation costs are optimized by excluding extra generators or avoiding conditional loops. Figure 16 shows the CPU time consumed in both scenarios. Table I shows the statistics obtained from the LabVIEW's profiler screen (see Figure 16). One can apparently observe reduced load with shared generator.

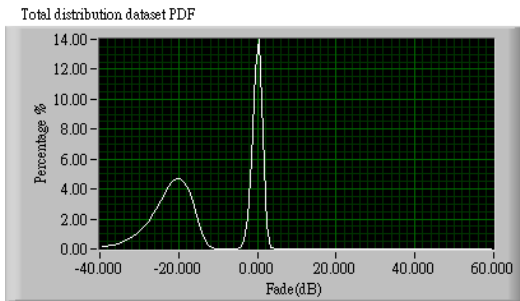


Figure 13 (San Francisco urban canyon: elevation angle 20°-40°): Histogram of the signal generated by the model.

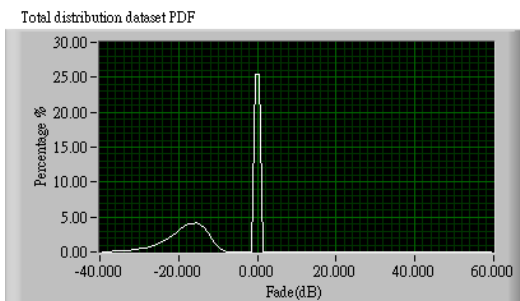


Figure 14 (San Francisco urban canyon: elevation angle 40°-65°): Histogram of the signal generated by the model.

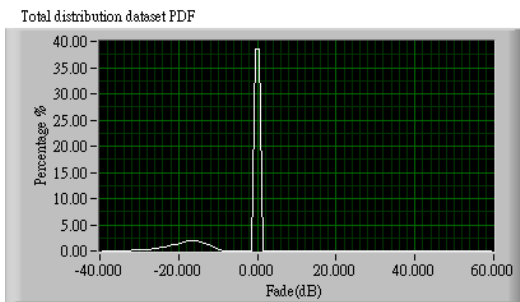


Figure 15 (San Francisco urban canyon: elevation angle 65°-90°): Histogram of the signal generated by the model.

Profile Data	VI Time	Sub VI Time	Total Time	# Runs	Average	Short
Separated_Dynamic_Switches.vi	580.896	108.0625	688.9531	1	580.896	580.1
Sharing_Random_Generator_Switches.vi	476.7187	101.0625	577.7812	1	476.7187	476.7
mbHistogram.vi	126.5781	0.5156	127.0937	5762	0.0220	0.0000
Create Histogram for sharing random generator switch (Sharing_Random_Generator_Switches.vi)	15.8281	62.8437	78.6719	731	0.0217	0.0000
Create Histogram for smart switch (Separated_Dynamic_Switches.vi)	15.2656	61.1719	76.4375	708	0.0216	0.0000
NI_Growth_Vis-Normal Random.vi	0.2969	17.6406	17.9375	7362	0.0000	0.0000
NI_AAI_Elem_Vis-Create White Noise.vi	17.6406	0.0000	17.6406	7362	0.0024	0.0000
Convert to Dynamic Data4 (Sharing_Random_Generator_Switches.vi)	14.2187	0.0312	14.2500	731	0.0195	0.0000
Convert to Dynamic Data4 (Separated_Dynamic_Switches.vi)	13.2344	0.0000	13.2344	708	0.0187	0.0000
Lognormal_V03.vi	1.1562	2.7031	3.8594	958	0.0012	0.0000
mbDelayValues.vi	1.5781	0.1250	1.7031	1464	0.0011	0.0000
Plotter Value (Sharing_Random_Generator_Switches.vi)	0.0000	1.0000	1.0000	735	0.0000	0.0000

Figure 16 CPU Time consumed by both switches

Switch Type	CPU Time (sec.)
Separate Gaussian generators	688.9531
Shared Gaussian generator	577.7812

#### IV. CONCLUSIONS

In this paper we reviewed existing GPS multipath channel modeling techniques and as a case study implemented a three-state model which accounts for signal variations for the moving user. It is demonstrated that NI's LabVIEW environment can be efficiently used to incorporate user-defined channel models to enhance NI's GPS simulator. We also proposed a computational cost optimization approach based on a shared random Gaussian signal generator when generating signals for different environments

#### REFERENCES

- [1] P. Misra, P. Enge. Global Positioning System. Signals, Measurements, and Performance. Ganga-Jamuna Press, Lincoln, MA. 2001.
- [2] Spirent Communications. Simulating multipath. Application Note DAN004-TM, Issue 1-00.
- [3] Peter B. (2002), A. Read, G. MacGougan, R. Klukas, M. E. Cannon, G. Lachapelle. Proposed Models and Methodologies for Verification Testing of AGPS-Equipped Cellular Mobile Phones in the Laboratory. Proceedings of the Institute of Navigation GPS2002. Portland, OR, September 24-27, pp. 200-212.
- [4] Spirent Communications. The role of RF constellation simulators in accelerating certification testing. J. Pottle, S. Smith, C. Beatty (CBi Ltd), April 24, 2007, Braunschweig.
- [5] C. Ma, G.-I. Jee, G. MacGougan, G. Lachapelle, S. Bloebaum, G. Cox, L. Garin, J. Shewfelt, "GPS signal degradation modeling," ION GPS 2001, Sep 11-14, Salt Lake City, UT.
- [6] F. Perez Fontan, P. Marino Espineira, Modeling the Wireless Propagation Channel: A Simulation Approach with MATLAB, John Wiley & Sons Ltd, 2008.
- [7] National Instruments. LabVIEW and GPS Simulator. www.ni.com.
- [8] M. S. Braasch, "GPS multipath model validation," IEEE PLANS'1996 Conference.
- [9] B.M. Hannah, K. Kubik, R.A. Walker, "Propagation modeling of GPS signals," University of Stuttgart, Technical Report, 1999.
- [10] J. Bradbury, M. Ziebart, P.A. Cross, "Code multipath modeling in the urban environment using large virtual reality city models: determining the local environment," Journal of Navigation, vol. 60, pp. 95-105, 2007.
- [11] S.H. Byun, G. A. Hajj, L.E. Young, "Development and application of GPS signal multipath simulator," Radio Science, paper #0048-6604, 2002.
- [12] A. Lehner, A. Steingass, "A novel channel model for land mobile satellite navigation," Proceedings of ION GNSS 18<sup>th</sup> International Technical Meeting of the Satellite Division, Sep. 13-16, 2005, Long Beach, CA, pp. 2132-2138.
- [13] Klukas, R., Lachapelle, G., Ma, C., Jee, G.-I., GPS Signal Fading Model for Urban Center, IEE Proceedings - Microwaves, Antennas and Propagation, Vol. 150. No.4 August 2003.
- [14] Chun Loo, A statistical model for a land mobile satellite link, IEE transactions on Vehicular Technonogy, Vol. VT-34. No.3 ,August 1985.
- [15] Charles W. Therrien, Murali Tummala, Probability for Electrical and Computer Engineers, CRC Press, 2004.
- [16] Hu, T, G. Lachapelle, R. Klukas, Indoor GPS Signal Replication Using a Hardware Simulator, ION GNSS 2005.

TABLE I. COMPUTATION GAINS WITH THE SHARED GENERATOR