Noise characterization in a stochastic neural communication network

Amir Jabbari\textsuperscript{a,}\textsuperscript{*}, Ilangko Balasingham\textsuperscript{a,b,c}

\textsuperscript{a} Department of Electronics and Telecommunications, Norwegian University of Science and Technology (NTNU), 7491 Trondheim, Norway
\textsuperscript{b} Intervention Center, Oslo University Hospital, Norway
\textsuperscript{c} Institute of Clinical Medicine, University of Oslo, Norway

\textbf{A B S T R A C T}

Recent advances in nanotechnology lead to designs for a new generation of communication systems using nano-scale elements. Researchers in nanocommunication networks propose novel engineering solutions for various application areas such as biological neural systems. In a neural communication network, the signals are encoded, propagated through synaptic channels, and decoded in a noise-free network. The desired performance of the nanocommunication network would be influenced by either internal or external disturbances, i.e. the spiking irregularities, history of firing in the neural cell, and the randomness in release of the neurotransmitters depending on the operating conditions. In this paper, a noise-free biological communication network is stochastically modeled. The internal and external disturbance sources are characterized considering the in-body communications and a comprehensive stochastic model is developed to verify the effects of various noise sources. The proposed model is comprised of a signal dependent encoding noise and signal independent synaptic/ionic disturbances. An effective probabilistic algorithm is given to model the firing rate of the neurons, while the noise sources are coupled. The proposed model is numerically studied and simulated, when various noise sources are applied simultaneously on the neural communication network.

\textcopyright{} 2013 Elsevier Ltd. All rights reserved.

1. Introduction

The contribution of nanotechnology to designing nanocommunication networks is the invention of novel engineering solutions using the communicating objects at the scale of a few nanometers. The so-called tiny nanomachines are used to sense, process, and communicate efficiently in a nanocommunication network. An application area is the human biological system which consists of a hundred billion of neural cells. Each neural cell has three main elements including the dendrites, soma, and an axon in order to receive, process, and transmit the signals from presynaptic neurons to the postsynaptic connections. In a nano-scale network, the communication would be either molecular, by transmission of signals through molecular diffusion, or electromagnetic using electromagnetic transceivers (i.e. carbon nanotube antennas) [1]. In a biological neuron, the nanomachines communicate through a fluidic environment which is called wet-communication through the living organism. The other difference between the wet- and dry-communication is the channel. In the neural nanocommunication network, the channel is comprised of two main characteristics including electrical and chemical parts. The electrical properties denote the process of generation and transmission of the action po-
tential to the postsynaptic connections which stimulates chemical transmitters. The chemical feature of the channel relates to the release of neurotransmitters at the presynaptic point of the next connecting neuron. The membrane is to absorb and reject the ions through inter- and extracellular fluids. Each neuron might be excited either internally through presynaptic connections or externally by an external current source. Modeling the biological neurons includes classical and modern algorithms [2]. The deterministic model studies the biological neuron physically and mathematically, in order to extract rules out of the parametric variations [4]. The leaky integrate and fire, FitzHugh–Nagumo, Hodgkin–Huxley, Morris–Lecar, Hindmarsh, and Izhikevich are the main examples [6]. The models are derived deterministically to relate various elements of a neural cell in a regular manner. The leaky integrate and fire is a deterministic modeling algorithm which represents the diffusion of ions in a neuron, known as leak. The Hodgkin–Huxley algorithm is established on the neural characteristics that was later simplified and improved by FitzHugh and Nagumo. The Morris–Lecar and Hindmarsh–Rose are the optimized form of the proposed Hodgkin–Huxley and FitzHugh–Nagumo techniques. The latest research on the neural modeling to control fluctuations of the membrane potential was presented by Izhikevich.

The disturbance sources and input variations reflect on the performances of the neural cells. Therefore, random ionic effects, oscillations, and firing probabilities are described by stochastic modeling. This is the main advantage of stochastic modeling over the classical techniques. Gerstner proposed a spike response model for stochastic neurons [3]. The reliability of signal transmission in a neural cell depends on the in-body disturbances and environmental noise conditions. Various types of noise have been already explored such as thermal, ionic conductance, ion channel shot noise, synaptic release noise, static connectivity, and slow neuromodular noise [11, 7]. The deviation would be due to the shot noise which reflects on the firing frequency of the neurons [12, 8]. These generated fluctuations were studied statistically to be implemented on the membrane potential [14]. Synaptic release noise is a class of disturbances which was studied by Koch considering the firing rates and the synaptic strength [10]. There are a group of noise sources such as thermal noise and synaptic bombardment which adds uncertainty to the model [16]. The neural model is expected to be robust in the presence of bursting and refractoriness [5, 13]. The noise coupling reflects on the signal transmission either directly or indirectly [15]. Therefore, it is essential to be characterized in order to increase the reliability of the neural nanocommunication network.

The new idea of this paper is to model and characterize the noise in a nanocommunication network considering the reliability of data transmission. Although various noise sources have already been discussed in neuroscience, the simultaneous effects of noise sources are not considered in terms of communications of neurons. The term, simultaneous noise, in this paper denotes coupling of various noise sources at the same time on the proposed stochastically modeled network. Moreover, the behavior of the noisy neuron needs to be simulated and statistically analyzed for noise characterization.

In Section 2, a noise-free neuron is modeled deterministically and stochastically. Then, three types of the disturbance sources are elaborated including encoding noise, shot noise, and synaptic release noise. The encoding noise refers to the coupled noise on the input current, before transmission through a neural presynaptic connection to stimulate the neuron. The shot noise is generated from random ionic release which alters the membrane potential directly. Finally, the synaptic release noise changes the firing rates and the synaptic strength due to the environmental disturbances. In Section 3, a new generalized stochastic network including various disturbance sources is proposed for a noisy neuron in a nanocommunication network. The new idea is to couple a signal dependent and two signal independent noise sources simultaneously on various parts of the neuron. Later, a generalized model is proposed. In Section 4 the numerical results for the derived stochastic model is presented. The noise-free and noisy neuron models are compared mathematically, in the time and frequency domain, respectively. Finally, Section 5 concludes the paper.

2. System modeling

Once the response of a neuron is represented by the following form, the model is called deterministic, where $S$ denotes the input vector, and $X$ is the state vector:

$$\frac{dX}{dt} = f(X, S).$$

(1)

The schematic of the “leaky integrate and fire” (LIF) model is shown in Fig. 1. The channel in a noise-free neuron is divided into synaptic, leaky, and electrical channels, where $g_c$ and $e_l$ are the conductance and equilibrium voltage of the leaky channel, respectively. In addition, $g_v$ and $e_v$ are the conductance and equilibrium voltage of the membrane, and $g_s$ and $e_s$ denote the conductance and equilibrium voltage of the synaptic channel, respectively.

The leaky channel denotes any change in membrane due to diffusion of ions. Furthermore, the synaptic channel models the transmission of neurotransmitters. The membrane potential $v$, capacitance $C$, and the applied current $I$, generate a time-dependent equation:

$$C \frac{dv}{dt} = (e_l - v)g_l + I.$$

(2)
In addition, $v_T$ is the voltage threshold which leads to spiking, $v_R$ is the reset voltage after spiking, and $\tau_F$ denotes firing period, where $v_R \leq e_L \leq v_T$.

$$\tau_F = \frac{C}{g_L} \log \left( \frac{(v_R - v_L) - \frac{I_{g_L}}{g_L}}{(v_T - v_L) - \frac{I_{g_L}}{g_L}} \right).$$  \hfill (3)

Although the deterministic model effectively demonstrates the main characteristics of a neuron, coupling the random input and noise would increase the modeling uncertainty. Therefore, a stochastic algorithm is suggested to model the neural activities\[14\]. The degree of randomness, correlation between noise values, and the structural effects on the neuron are essential to be investigated in a biological system. The neural noise reflects on the transmission and propagation of signals between neighboring neural cells and alters the firings of the neurons. There are different noise sources which distort the shape and quality of the signal. The “shot noise” represents the random release of the neurotransmitters at synapses which leads to the random spiking of neurons. The “synaptic release noise” depends on the history of firings at the pre- and post-synaptic neurons. Moreover, the strength of synapses can be modified by spiking time-dependent plasticity. The “thermal noise” exists in any system operating in nature above absolute zero temperature. The “synaptic bombardment” investigates charging of the cells after spiking. The randomness in the cellular parameters is mathematically explained considering the “static connectivity noise”. The intrinsic noise sources, such as thermal and shot noise, cause faster fluctuations than the neural response. The probability of such noise is mainly presented in a distributed form, i.e. Gaussian white noise. The synaptic inputs have an irregular form depending on the frequency and the power of the noise. Due to the irregularity of spiking times, either from presynaptic events or interspike intervals, a stochastic modeling is applied to model neurons using a Poisson process. The neural response function $\nu(t)$, is given as

$$\nu(t) = d \sum_{i=1}^{k} \delta(t - t_i),$$  \hfill (4)

where $k$ shows the number of spikes, $\delta$ is the spike generator, $t_i$ represents the time of the $i$th event, and $d$ is a discrete function to track changes of the membrane potential. Using $\nu(t)$ over the spiking time $\Delta t$, we can compute the instantaneous firing rate $r$, at each instance

$$r = \frac{1}{\Delta t} \int_0^{\Delta t} \nu(t) dt.$$  \hfill (5)

Once the firing rate is calculated within a time slot $\Delta t$, then the probability of firing a spike $P$, is calculated as

$$P = r \Delta t.$$  \hfill (6)

Consequently, using the Poisson probability density function (PDF), the probability of spikes over the time interval is given where “exp” denotes the exponential function and $c$ is the non-zero spike count

$$P = \exp(-r \Delta t) \frac{(r \Delta t)^c}{c!}.$$  \hfill (7)

In a noise-free neuron, the probability to generate the next spike is calculated over the spiking period $\tau$,

$$P(\tau) = \frac{d}{dt} \left( 1 - \exp(-rt) \right) = r \exp(-r \tau).$$  \hfill (8)

3. Noise characterization in a stochastic neural communication network

There are various techniques to study noise sources in a stochastic neuron. The so-called Wiener process is a well-known algorithm to model the random noise in the system. Moreover, Poisson distribution is an alternative to model the coupled noise which is used in this paper. According to the described model for a stochastic neural network, encoding, channel shot, and synaptic noise sources are considered. Fig. 2 shows the block diagram of the comprehensive noise characterization in a neural cell in the presence of the noise sources. To model a neuron in a nanocommunication network, input current, channels, and postsynaptic connections are the key elements. The channel includes electrical and chemical characteristics. The encoding noise $N_1$, shot noise $N_2$, and the synaptic noise $N_3$ are simultaneously applied on various parts of the system.

Firstly, the input is encoded and the signal dependent encoding noise is applied. The noisy encoded noise is
propagated to the neuron through the transmitter TX. Then, the shot noise is applied on the membrane potential, and the action potential is generated. After passing through the electrical channel, the synaptic noise is applied and the neurotransmitters are randomly generated. At the end, the signal is received at the connection point to the postsynaptic neuron. In this section, the noise sources are described and characterized for a noisy stochastically modeled neuron:

3.1. Encoding noise

The encoding noise refers to coupling disturbances on the input current in a signal dependent form, before transmission through channels. The neurons are stimulated by presynaptic inputs. Ideally, the signal is expected to be encoded and transmitted successfully without any distortion, while coupling the environmental noise would change the shape of the signal which is discussed in this section. For this purpose, the following “spiking response model” is applied for a noise-free neuron:

$$u(t) = v(t - \tau_{exc}) + \int_{0}^{\infty} I(t - s) L(t - \tau_{exc}, s) ds,$$

(9)

where $u$ is the firing rate, $v$ represents a form of the action potential, $L$ shows the linear response to an input pulse from the previous neuron, and $I$ is the stimulating current. Furthermore, a threshold value can be selected for the firing of the neuron. If the threshold is exceeded, the time $\tau_{exc}$ is recorded and updated. The encoding noise mainly reflects on the input current according to the model which is given as

$$I_N(t) = I(t) + N_{SD}(t) + N_{env}(t),$$

(10)

where $I_N$ is the noisy current, $I$ denotes the applied current, $N_{SD}$ is the signal dependent noise, and $N_{env}$ shows the environmental effect on input. The noisy current includes a signal dependent part $N_{SD}$, which is derived from an autoregressive random process $w(t)$. The convolution of input and the autoregressive random process is given as

$$N_{SD}(t) = I(t)^* w(t).$$

(11)

Considering the variation of signal rates and due to the frequency constraints for low pass filtering, an autoregressive random process is chosen in this paper [9]. Later, the presented autoregressive random process can be discretized as $w(z) = a_0 + a_1 z^{-1} + a_2 z^{-2} + a_3 z^{-3} + \cdots + a_{n-1} z^{-n+1}$, where $a_0, a_1, a_2, \ldots, a_{n-1}$ are the $n$-th order discretization coefficients. The spike response model shown in (9) is rewritten as

$$u(t) = v(t - \tau_{exc}) + \int_{0}^{\infty} (I(t - s) + I(t - s)^* w(t - s))$$

$$+ N_{env}(t - s) L(t - \tau_{exc}, s) ds.$$

(12)

3.2. Shot noise

The shot noise is obtained by adding a signal independent noise function $N$, as

$$N(t) = N_0 \exp(-\gamma \cdot t),$$

(13)

where $\gamma$ represents the relaxation rate, and $N_0$ relates to the initial value of the noise function. The Fourier transform of the signal $F$, and the spectral density $S$, over $k$ samples is given as

$$N(f) = \int N(t) \exp(-j2\pi \cdot ft) dt,$$

(14)

where $\gamma$ represents the relaxation rate, and $f$ is the operating frequency.

3.3. Synaptic noise

Before, a homogeneous Poisson process was explained to model the stochastic neural architecture. Due to the non-static behavior of the neuron, the firing rate $r$ will be dynamic. There are more characteristics to practically establish an accurate model. The “refractory period” prevents the spiking process and the bursting causes more irregularities to the model. The recovery within the “relative refractory period” returns the firing to the initial value at a predetermined rate. In this paper, an exponential rate is chosen for recovery purposes. There are some alternatives to add bursting to a Poisson process. An option is to produce a random value which denotes the bursting to replace a spike at each instance with more spikes. This issue will be addressed in Section 4 for numerical simulations.

The overall probability is characterized by a total PDF. Then, the integral of the PDF generates the cumulative distribution function (CDF) showing the probability of producing output less than or equal to the specified numbers or limits. Due to refractoriness and the history of firing, the neural behavior is altered. Let us define a density function $f_d$, for interspike intervals (ISI). Therefore, the probability of a spike between $t_1$ and $t_2$ is $P(t)$, and $P'(t)$ denotes the probability of “no spike” within the time slot, given as

$$P(t) = \int_{t_1}^{t_2} f_d(t) dt,$$

$$P'(t) = 1 - \int_{t_1}^{t_2} f_d(t) dt.$$

(15)

According to (4), if $d$ is not history-dependent, the output is a homogeneous Poisson function. In this paper, $d$ will be a history dependent function which is

$$d = r(t, \phi),$$

(16)

where $\phi$ shows the period of recovery from the latest generated spike. Then, (8) is rewritten as follows

$$P = \exp(-r(t, \phi) \Delta t) \cdot \frac{(r(t, \phi) \Delta t)^c}{c!}.$$

(17)

Then, the probability density function is revised and computed accordingly, over a period of $r$

$$P(\tau, \phi) = \frac{d}{dt}(1 - \exp(-r(t, \phi) t)).$$

(18)

Moreover, the standard deviation $\sigma_{r,\phi}$, over the spiking period $\tau$, is computed where the spiking interval is sampled from the Poisson process

$$\sigma_{r,\phi}^2 = r(t, \phi) \exp(-r \tau).$$

(19)

4. Results and comprehensive noise analysis in a stochastic neural model

The noise sources reflect on various parts of the system and the following stochastic model is derived according to
(12), (13), and (18):

\[ u_P(t) = v_N(t - t_{\text{exc}}) \int_0^\infty \left( l(t - s) + N_{SD}(t - s) + N_{\text{env}}(t - s) \right) L(t - t_{\text{exc}}, s) ds, \]

where \( u_P \) is the Poisson firing rate, \( v_N \) represents a form of the noisy action potential, \( l \) shows the linear response to the noisy input pulse from the previous neuron, and \( l \) denotes the applied current. In addition, \( N_{SD} \) is the signal dependent noise, and \( N_{\text{env}} \) shows the environmental effect on input current.

The individual effects of the noise sources were modeled according to (12), (13), and (18). Considering the interactions between the noise sources on timing and intensity of firing, the simultaneous effect of the proposed noise sources is studied using (20). Therefore, the proposed model is a generalized model to study the simultaneous effects of the encoding, shot, and synaptic noise. In this section, the proposed noise model is numerically simulated and characterized in Matlab. The mathematical model has been derived according to the experimental noise studies reported in neuroscience [11,7] and the proposed noise characterization model is validated using the values of real experiments. The noise coupling effects are studied numerically using the proposed bio-inspired model to establish a theoretical basis.

For numerical simulation, a uniform white noise was implemented in Matlab to present the environmental effects on the input signal, given in (10). In this example, the last five discretized autoregressive process coefficients were generated randomly, where the order of \( n \) is equal to 5. The coefficients were updated using the least squares technique, and the convolution of input and the generated function was calculated. To couple the shot noise, the voltage difference was added based on the operating frequency to the amplitude of the noisy membrane voltage \( v_N \) using (20). In this paper, the noise relaxation function \( N(f) \) for shot noise is selected exponentially which is highly dependent on the relaxation rate \( \gamma_{RS} \):

\[ N(f) = \int N_0 \exp(-\gamma_{RS} t) \exp(-j2\pi ft) dt, \]

where \( N(f) \) denotes the Fourier transformation of the shot noise and \( N_0 \) relates to the initial value of the noise function, that is equal to 0.5 in this paper. Moreover, the membrane voltage of the noisy neuron is given as

\[ v_N(t) = f_S(t) + v(t), \]

where \( v(t) \) is the noise-free membrane voltage, \( v_N(t) \) is the noisy membrane potential, and \( f_S(t) \) is the shot noise function. For numerical simulation, the relaxation rate \( \gamma_{RS} \), was set to 2. The encoding noise reflects on the input current; the shot noise is applied on the membrane potential, and the synaptic noise adjusts the probability of firing rate.

To characterize the synaptic noise, the interspike intervals are randomly selected from the described Poisson process. The default value is 1 ms which is affected by noise and is randomly reset by an updated interspike interval density function using (20). The neuron will randomly fire within 100 ms and the spiking count will be adjusted randomly using a Poisson distribution. In addition, the noise will be coupled and the generated spikes will be varied by noise. The noise will alter the spike numbers and timing. Moreover, the refractoriness and bursting will distort the neural output. Consequently, the distribution and probability of interspike intervals will be changed. Before presenting the numerical results of noise-free and noisy neurons, a special recovery refractoriness is given here. According to the dynamical behavior in the neuron, the firing rate is time-variant. Considering the irregularities caused by the "refractory period", the firing rate needs to be recovered to a minimum threshold exponentially, in this paper. As mentioned before, the probability density function is calculated by (18). Then, the refractory period adjusts the firing rate, where \( \phi \) gives the period of recovery, and \( r_0 \) is the initial firing rate which is equal to 1 in this paper

\[ r(t) = r_0 \left( 1 - \exp \left( -\frac{t}{\phi} \right) \right). \]

Fig. 3 compares three potential alternatives for modeling the recovery firing function, where \( T_1 \), \( T_2 \), and \( T_3 \) are equal to 2, 10, and 50, respectively. These three values are selected similar to the actual neurons in order to simulate the recovery firing of cells [11,7]. There is a trade-off between speed and accuracy of the recovery function. \( T_1 \) increases the firing rate dramatically over time according to Fig. 3. This is illustrated by instantaneous differences between the actual firing and the initial firing rate which is equal
to “one”. The firing functions of $T_2$ and $T_3$ increase slightly over time and take a longer time to reach “one”. According to the results, $T_2$ was selected to model the recovery firing function in a noisy neuron which is recovered more accurately than $T_1$ and responds more quickly than $T_3$.

Then, the probability density function will be calculated where $\phi$ shows the period of recovery, over a firing period of $\tau$, and $P$ is the probability function

$$P(\tau, \phi) = \frac{d}{dt} \left( 1 - \exp \left( -r_0 \left( 1 - \exp \left( -\frac{t}{\phi} \right) \right) \right) \Delta t \right).$$ (24)

To add bursting on a Poisson process, the randomly generated bursts replace the regular firing rate at each instance. For simulation, each spike is presented by a spiking function $\delta$, according to (4). The bursting value is limited to $2\delta$ at each instance. The spike number for each bursting is consequently reproduced after noise coupling. Once various noise sources are applied simultaneously on $I$, the membrane potential, the synaptic channel, and the firing distribution are altered through bursting and refractoriness.

The output of the stochastic spiking neuron is shown in Fig. 4, in the noise-free and the noisy conditions. According to Fig. 4 (top), the noise-free stochastic neuron fires randomly and the spiking rate and probabilities are selected accordingly using Poisson distributions in (8). The maximum value of the spike, for the spiking function $\delta$, is equal to 1. In the presence of the noise, shown in Fig. 4 (bottom), the firing rate is altered depending on the amplitude of noise and the neuron will not be able to fire as planned at a few time slots. Even a minor drop of the action potential will stop spiking for a while. The other possible event would be undesired bursting which takes place with more than a spike per time instance, shown with a double amplitude $2\delta$, compared to the ordinary spikes in the noise-free neuron. On the other occasions, the derived neural firings will be according to the expected noise-free conditions in Fig. 4 (bottom).

The overall bursting and noise is demonstrated in the frequency domain over the normalized frequency variable $\pi$, and the noisy output is seen in Fig. 5, where Fig. 5 (top) shows the frequency response of the noise-free spiking neuron. As discussed earlier, the frequency domain response is altered accordingly due to variations of the firing rates in the noisy neuron, as illustrated in Fig. 5 (bottom). The noise leads to intrinsic fluctuations in frequency domain depending on the noise coupling time and amplitude.

Fig. 6 compares the histogram of the noise-free stochastic neuron with the probability of resultant interspikes in the noisy neuron over a similar spiking range, once all described noise sources are applied simultaneously on the neuron. The probability distribution of interspike intervals between every two consecutive spikes is displayed in Fig. 6 (top), for a noise-free stochastic neuron. It represents the probability of spikes over the number of firings within the spiking distribution. The probability of spikes...
Fig. 6. Top: comparison of probability density functions in the noise-free stochastic neuron, bottom: comparison of probability density functions in the noisy stochastic neuron.

for the noise-free neuron has a Poisson distribution according to (8). Moreover, the resultant probability distribution of the noisy neuron is shown in Fig. 6 (bottom), where noise sources are applied simultaneously according to (20). According to Fig. 6 (bottom), the firing rates are varied by noise and the probability distributions of the spikes are altered. It represents the impact of noise on changing the probability distribution weights compared to the noise-free neuron. An alternative to evaluate the effect of the noise is observing the variance ratio of the signal train with the coupled noise.

According to (20), the encoding noise mainly reflects on the input current including the signal dependent part which relates to the described autoregressive random process and its coefficients, given in (12). In the described stochastic model, ideally the signal is expected to be greater than the noise, to let the neuron fire regularly. If the input signal to the encoding noise ratio is high, and the environmental noise is negligible compared to the input, the encoding process will be noise free.

The shot noise reflects on the membrane potential and mainly varies the firings based on the structure of the neuron. To minimize the probability of the shot noise, the value of the firing threshold, generated potential, and the functioning frequency are three key elements to evaluate the reliability of the proposed model, once the shot noise is coupled according to (21) and (22).

The synaptic noise mainly alters the firings and distribution of spikes and it is assumed as a signal independent noise. The synaptic noise is highly related to the refractoriness, bursting, and irregularities caused by the cellular environment. Therefore, the following conditions would guarantee the reliable signal transmission through the synaptic channel according to (23) and (24):

- The refractoriness period is desired to be less than the firing period.
- The bursting numbers over the firing period is essentially limited.
- The cellular environmental effects are expected to be negligible.

The comprehensive noise analysis is an important issue in neural communication network design and the reliability of the proposed stochastic model will be further studied in the near future.

5. Conclusion

In this paper, a new stochastic model was presented for a biological neuron including the internal and external noise sources. Firstly, a noise-free model was presented considering the main deterministic and stochastic features of a biological neuron. Then, the noise coupling was investigated and three types of noise sources were further elaborated and characterized including the encoding, channel shot, and synaptic release noise.

The encoding noise denotes the signal dependent distortion of the applied input signal to the neuron due to the environmental effects and the structure of the presynaptic connection. The shot noise relates to the structural behavior which changes the membrane potential considering the threshold values. Finally, the synaptic noise was modeled using the probability density function of neural firings.
The described noise sources were simultaneously coupled on the stochastic neuron and a new model was derived. Later, the noise-free and noisy responses were numerically simulated. Finally, the noise effects on the firing rate and period was presented both in the time and frequency domain, for the proposed mathematical model.

Acknowledgments

This work was supported by the ERCIM “Alain Bensoussan” fellowship program at the Norwegian University of Science and Technology (NTNU) and is part of the MELODY project of the Research Council of Norway (contract number 187857/s10).

References


Amir Jabbari received his B.Sc. degree in electrical engineering (2004), M.Sc. degree in Mechatronics (2006) in Iran, and his Ph.D. degree in electrical engineering from the University of Bremen, Germany (2009). For his research on “Application of Autonomous Fault Detection and Isolation in Measurement Systems”, he received an ERCIM “Alain Bensoussan” fellowship. From September 2009, he started working at the Institute for Microsensors, Actuators and Systems, Germany as a research associate. Currently, he is a senior researcher at the Department of Electronics and Telecommunications in the Norwegian University of Science and Technology. His current research activities are in signal processing, autonomous control, system modeling, fault diagnosis, and noise characterization in communication networks and embedded systems.

Ilangko Balasingham received the M.Sc. and Ph.D. degrees from the Department of Telecommunications, Norwegian University of Science and Technology (NTNU), Trondheim, Norway, in 1993 and 1998, respectively, both in signal processing. He performed his Master’s degree thesis at the Department of Electrical and Computer Engineering, University of California Santa Barbara, USA. From 1998 to 2002, he worked as a Research Scientist developing image and video streaming solutions for mobile handheld devices at Fast Search & Transfer ASA, Oslo, Norway, which is now part of Microsoft Inc. Since 2002 he has been with the Intervention Center, Oslo University Hospital, Oslo, Norway as a Senior Research Scientist, where he heads the Wireless Sensor Network Research Group. He was appointed as a Professor in Signal Processing in Medical Applications at NTNU in 2006. His research interests include super robust short range communications for both in-body and on-body sensors, body area sensor network, microwave short range sensing of vital signs, and short range localization and tracking sensors, catheters, and micro robots. He has authored or co-authored 140 papers and has been active in organizing special sessions and workshops on wireless medical technology at major conferences and symposiums. He was the General Chair of the 2012 Bodynets conference and serves as Area Editor of Elsevier NanoCommunication Networks. He is a Senior IEEE member.