Noise Profile of Wireless Channels in High Voltage Substations

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***Abstract*--In this survey, some measuring metrics are identified to study the average noise power variations in typical outdoor power substations. Power substations generally have metallic structures and despite the insulation considerations have high electric fields. The physical size of a substation does not allow a completely controlled experiment. A setup plan was arranged to study the noise floor variation in a few substation switchyards in residential, industrial, isolated and sparsely populated subdivisions. The empirical data sets were collected, processed and compared with the known noise constituents that were cited in the literature. A two-week measuring window was chosen to encounter any possible factors that might affect results at several substations. Several field measurements were executed to enable the comparative analysis of the recorded data. By collecting the weather data during the survey, it was illustrated that the average noise floor in the spectrum of interest (i.e. 2.4 GHz), does not correlate or has week correlations with the real time weather condition changes, such as humidity, pressure and precipitations. The analysis suggests that the noise floor variation (and hence the link quality) is time-dependent and has an underlying dominant semi-deterministic constituent in addition to the classical random distribution. This semi-deterministic component is associated with the location of the substation switchyard (e.g. residential or industrial), and its dynamic range is significant and should be identified. The methodology, which is adopted in this study has applications in the analysis of static outdoor environments. Several practical considerations have been discussed in this paper for future implementations in high electromagnetic field environments.**

***Index Terms*-- Electromagnetic interference, Estimation, Data communication, HF radio propagation, Impulse noise, Noise measurement, Power system communication, Pseudonoise coded communication, Random noise, Substations.**

I. Introduction

Wireless networks have several features that make them an attractive communication solution in the harsh industrial environment such as electrical distribution or transmission networks. Since wireless networks do not use expensive signal and control cables for data transmission, they are easier to install and use, and hence provide a cost effective solution for industrial and power system applications. The utilization of the existing wireless technologies should be closely investigated to better understand the detrimental impacts of switching transient fields on the radio band channels [1]-[5]. An accurate analysis for comparing different wireless implementations requires measurement and inspection of a wide spectrum of modulation, coding and implementation techniques. Metallic structure, electric impulses from the corona effect or switching operations of power apparatus, and electromagnetic interferences and weather variations are among the discriminative features in this particular industrial environment. From theoretical standpoint, the wireless receivers are often designed based upon certain assumptions about noise [6]. Most of them assume that noise is IID (Independent Identically Distributed) and has some form of exponential-family distribution such as Guassian or Rayleigh. Some others consider correlated noise but with specific autocorrelation properties. Some noise distributions contribute to the noise floor. Other noise profiles may produce impulsive disruptions of links, for instance the Poisson-Gauss model [3].

The validity of the scientific conclusions becomes intrinsically linked to the validity of these underlying assumptions. In practice, since some of the assumptions are unknown or untested for specific applications, the scientific conclusions become arbitrary. A good estimate of the noise pattern is the target of this study. If there is a good estimate of the noise pattern, then we can calculate the error rate under a given channel-coding scheme. We prefer not to do the reverse, i.e. estimate the noise profile by just observing the resulting calculated and processed error rates, in particular when an estimate of the noise profile is directly obtainable.

To assess the characteristics of the wireless network, field experiments were conducted with spread spectrum radios operating at 2.4 GHz. A special attention was paid to long term observations. For instance, long period measurement runs allows us to observe the variation of average noise power during the weekdays. In some applications, the impact on wireless devices needs to be attributed to portable structures as opposed to constantly moving (or mobile) objects (e.g. cellular phones). In this approach, measurements were made for a period of fourteen days, with both moving transceivers (on a wheel-cart to facilitate repositioning) and fixed location transceivers in critical locations, for example, in the vicinity of a circuit breaker.

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There are some recommendation practices in the literature for the site surveys, which are primarily based on the Bayesian probability assumptions of the noise. In the observation of such recommendations (e.g. in [7]), field surveys, tests and cross-validations were performed and reported in [8]. It is shown that despite the soundness of the recommended Kolmogorov-Smirnov Test (KS test) based on the Bayesian assumption, the average noise power variation at 900MHz Industrial, Scientific and Medical frequency bands (ISM [9]) has typically stronger time-series constituent and can therefore be approximated by an Auto-Regressive Moving Average (ARMA) model. This finding has some implications in the design of wireless systems. For instance in CDMA applications [10], to avoid the capacity degradation, power control schemes are used to improve power efficiency and the connectivity by addressing the near-far problem. The semi-deterministic nature of the noise floor which is further addressed in the present study, relates to the dynamic range of the power control schemes.

Admittedly, due to the large physical size of the test environment, the measurement was not a controlled test process (i.e. controlled experiment [11]) in which one could acquire and record all the relevant environmental and electrical parameters (e.g. delay profile). In this study, as much information about the test and as much analysis as possible is gathered to supplement anecdotal evidence used in the past.

In the first part, the probable impacts of the industrial environment on the wireless channel are investigated considering the observation windows based on previously published measurements, analyses and pertinent assumptions found in the standards and technical literature ([4], [6], [12], [13]). The data recording plan and disposition of test devices is discussed next. Description of how the data was conditioned and pre-processed to enable an accurate analysis is given in a follow up section. Subsequently, statistical data analysis and comparison of the performance of different analyses approaches are presented. The simulation results and the conclusion are given at the end.

II. Noise Pattern Constituents

One particularly detrimental characteristic of the (wireless) channel of interest is the presence of ambient electromagnetic interference (EMI) produced by power lines and power apparatus used for switching the substation configuration. The electromagnetic fields radiated by these interfering sources may occur as spurious signals and, hence, are a source of noise [12]. In radio transmission we are especially concerned about the electromagnetic noises which are non-stationary in nature. There are two main types of radiated radio noise sources in substations: gap breakdown and line conductor corona [4].

Gap discharge radio-noise is produced by a rapid flow of electric current in the air gap between two points of unequal potential occurring on electric power switching equipment. The current-surge accompanying avalanche ion production is of very brief duration, consisting of one or several impulses persisting for a few nanoseconds. These noises are strongly impulsive in nature. The statistics of this phenomenon are directly related to the electrical incidents, and result in opening or closing of switching elements commonly called circuit breakers.

Corona discharge is also a threshold transition process that requires a critical potential gradient in the vicinity of a charged object be exceeded before the effect is manifested. The charged object needs not be an electrical conductor.

Either source may be comparable or exceed the noise power levels of other man-made noise sources. A noise source might create impulsive noise in one system and a random noise in a different system (for instance as in Frequency Hopping Spread Spectrum systems versus Direct Sequence Spread Spectrum [14]). A strong impulsive noise may create a uniform disturbance over the frequency spectrum of interest. The radio noise produced by these phenomena exhibit RF components of substantial magnitude in the UHF-TV band (470-806 MHz) [3].

This study does not suggest the importance of the impact of the gap breakdown (e.g. circuit breaker operations) on the wireless channel due to the scarcity of the phenomenon, nor does it probe the absolute value of the corona discharge. In normal operations, the corona discharge is the discriminatory phenomenon between the power substations environment and other industrial environments, which are already studied in the literature. This survey was to investigate whether the variation of the corona discharge has an effective impact on the variation of the noise power. In general, we expect to observe three types of noises in substation applications: background noise, incidental impulsive noise and unwanted signals. In this study, the background noise is defined as the total sources of disturbances in the link and the measurement system, independent of the presence of the signal. For instance the Trichel streamers and glow corona contribute to this background noise. The incidental impulsive noise is due to the gap breakdown discharge phenomena (often caused by circuit breaker opening). The ideal method of tracking these phenomena is to apply fast response measuring devices (i.e., peak detectors) for long runs and record the receptions during breaker opening, as well as investigating the seasonal effects and climate impacts. In power-line applications, random noise (often considered Gaussian) is a component of the total noise caused by the discharge [13]. Hence the average noise level indicates the level of background noise and interference at the measurement site. It is worth noting that there is little or no (slow or fast) fading due to the stationariness of the devices in substations. The testing periods were chosen to be long enough to include atmospheric cycle extremes, and probable diurnal and weekly patterns.

III. Test Setup Plan

The measurement setup was designed by using readily

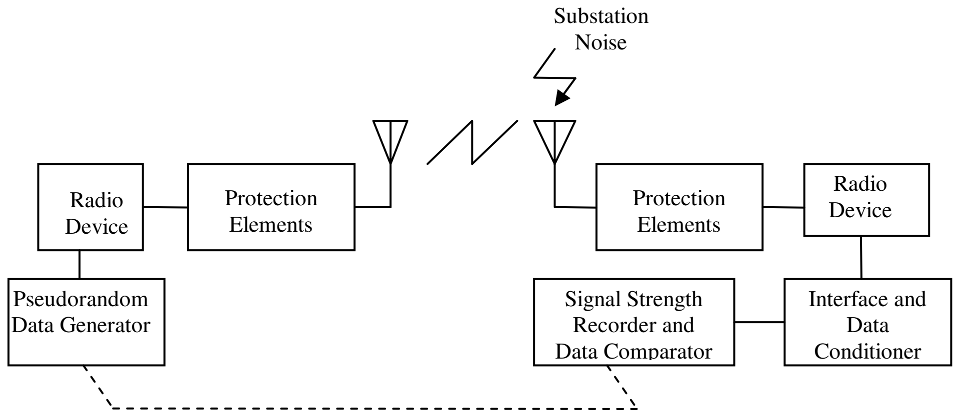

Fig. 1. Measurement Block Diagram

available instruments while considering the size of substation yards and the presence of high power signals. Surges initiated by the power system and ground leakage currents can damage the measuring devices, therefore appropriate grounding and protection have been incorporated in the setup design.

The main methods of high voltage surge protection are the *series* and the *shunt* approaches. Series devices are typically designed or plugged directly into the Radio Frequency (RF) line between the antenna and the RF circuitry attempting to block the incoming surges before they reach the RF amplifier. In the shunt approach, the surge is guided away from the RF input by providing a better path to ground.

The use of Quarter-wave stubs is a popular method among the RF design engineers which could be realized in series or shunt configurations. A quarter wave stub protector creates a band-pass filter focused at the center frequency of the wireless device. Notwithstanding the low-frequency attenuation of the stubs, a detrimental portion of the energy could still enter the equipment input (Note that the voltage and energy levels are too high for sensitive RF front-end even given significant attenuation).

Gas-Tubes and Non-Gas Tubes protection devices are among other elements which limit the let-through voltage into the sensitive RF circuitry by exhibiting a Zener-like breakdown phenomenon. These devices are seldom built-in and need to be attached externally.

In this survey, a setup plan is conducted for the 2.4 GHz frequency band using IEEE802.11 compatible radios. In the preliminary test implementations, none of the aforementioned methods exclusively secured the setup against the detrimental surges in the substations, ultimately causing some equipment damage and failures. Our conjecture is that the impulsive noise in the substations is too fast to be contained with DC-blocks alone and is too strong over the time to be contained solely by the Quarter-wave stubs. Hence a combination of the protection methods is used in the final setup and is suggested for future implementations.

The linearity of these protection provisions needs to be considered to avoid skewing the recorded data within the frequency spectrum.

The setup consists of wireless modems (acting as access units and base units), data acquisition devices and a processing unit. The access unit was placed next to the control room (where the base unit is more likely to be located) with an omni-directional antenna attached to it. Note that the physical structure of a typical substation or an industrial environment may not allow the use of directional antennas. The subscriber unit was placed at the far end of the substation, attached to a metallic structure (i.e. the circuit breaker panel). The device disposition was such that there was no *line of sight* communication. The power control feature in the communication device is inhibited and the signal power is maintained constant during the trial. The processing unit fetches the wireless quality parameters from the modems. The data are then automatically recorded on a laptop machine for post-processing. Two laptops were deployed and programmed to emulate the continuous data communication to the virtual circuit breaker receiver and to handle the logging and background processing. Fig. 3 shows typical dispositions of the radio transceivers. The in-yard radio was installed 1.2m above the ground level and electrically attached and grounded to the metallic structures of the circuit breaker (Since the wireless communication analysis is aimed at monitoring operation of circuit breakers, free-body metering suggested in [7] would be inappropriate in this case).

The survey duration of the measurement run was about 14 days in each yard (i.e., the 34.5 KV, 138 KV and 345 KV yards) to include weather cycle extremes, and probable diurnal and weekly patterns.

IV. DATA RECORDING AND PRE-PROCESSING

The main objective of this survey is studying the variations of the noise floor levels rather than the absolute magnitudes of the measured parameter. In most wireless design quality analysis, the magnitude of the Signal to Noise ratio (S/N) and Signal to Interference ratio (S/I) are of more importance than the absolute values of signal, interference and noise levels individually.

The results presented in this paper have been generated using the observed data collectively. There was no electrical

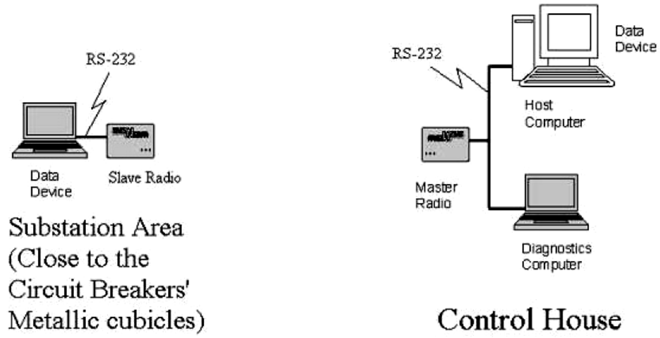

Fig. 2. 2.4 GHz field measurement setup

Fig. 3. None-line-of-sight (NLOS) disposition of the instruments in a power substation

incident or breaker operation during this survey, and hence there is no major gap-breakdown noise (i.e. as mentioned before these incidents are rare in nature). Other than that, the wireless devices seemed to receive no disturbing high power noise impulses due to the high voltage (HV) corona effect, which could cause major link disruption. The higher the voltage level, the higher average noise was observed.

The polled signal levels from the radios are in Receiver Signal Strength Indicator (RSSI) format, which are often in linear or in logarithmic format. RSSI is used in the control loop of the firmware of the radio. Manufacturers do not usually calibrate the RSSI of their radios to dBm values, and often instead provide an approximate conversion table for the mapping between these values. Since RSSI is a relative index, the device works regardless of RSSI calibration to dBm values and hence it was assumed that the measurement setup was subject to the offset (calibration) error. This error has been ignored as the general methodology adopted is invariant to this offset error and the background noise may anyway induce offset in different locations. The level calculations are implemented by utilizing the conversion table and then converting the dBm values to the desired voltage levels. The recorded data from this experiment have been utilized for the 2.4 GHz analyses. Each reading takes approximately one second which contains the exact timing information. The average noise power, in this survey, is calculated as the average noise level in the transmission spectrum and is recorded in one-minute intervals as a moving average of 60 readings (i.e. window size). The radios use 79 channels in the 2400 to 2483.5 MHz frequency range using 9 hopping sequences per each hopping set. A program has been designed to continuously poke the link quality data from the radios, seeing that this feature was not a built-in function in the device. Specific provisions were made to avoid data congestion while polling the data from the radios. In this regard there were just two wireless devices at each measurement run in the substation yard and the baud rate of the dummy data generator is set constant and low. The processing unit also handled the data logging. As test duration was fourteen days, there were more than 20,000 observations per each data set.

It is reported that the weather conditions drastically affect the noise generation in high voltage outdoor environments [13]. To include the environmental impacts on the wireless channel, dew point, dry bulb and wet bulb temperatures, station and sea level pressures, and the relative humidity and the presence of any precipitation during the observation window have been incorporated in the analysis on an hourly basis. These surface weather data have been recorded on hourly basis through the three nearest weather stations, which have at most 12.4 miles aerial distance to the test site. Note that the rates of changes of environmental data are typically low and the variations (and not the mean) of the surface data in these closely spaced weather stations are almost similar. This data resolution is accurate enough due to the tardiness of the atmospheric changes. To relate the weather parameters to the average SNR variation, pre-processing of data was done such that the data sets have similar timings (i.e. observation windows). The resulting weather data has less timing resolution than the electrical data (e.g. the load pattern of the transformers in the substation and the recorded SNR values).

To calculate an approximate estimate for the (higher resolution) electrical data coinciding with the weather hourly data, Parzen window [15] with smoothing parameter of h=60 (minutes) has been used. We define the Parzen Kernel function $\varphi(u)$ such that:

$$\varphi(u)=\begin{cases} 1 & |u|<\frac{1}{2} \\ 0 & \text{otherwise} \end{cases} \qquad (1)$$

then the estimated values at the hourly grid points, x_H, would be:

$$x_H=\frac{1}{Nh}\sum_{m=1}^{N} x_m \varphi\left(\frac{H-m}{h}\right) \qquad (2)$$

where N is the total number of samples with higher resolution (i.e. observations with one-minute precision), x_m is the magnitude of the m^{th} sample, and x_H is the new generated sample with lower resolution (i.e. one-hour precision). Thus the resulting size of the data set becomes 340 samples. We can use other types of Kernels such a Gaussian [15], but we found little variations in our final result to justify the use of more complex Kernels.

Table I lists the observed parameters and the experiment settings. The dynamic range of the noise variation has particular significance, when a wireless *Power Control* scheme is considered, the dynamic range together with the wireless *circuit design constraints* prescribe the step-size and the granularity of the power control. Without loss of generality, it is assumed that the wireless devices have five *power steps* within their dynamic range and hence five classes are assigned for this survey.

TABLE I
THE OBSERVED PARAMETERS AND THE SETTINGS

Observation parameters	Setting
SNR Dew point temperature Relative humidity Sea level pressure Station pressure Wet bulb temperature Dry bulb temperature Dew point temperature Presence of precipitation Transformer load patterns Time	Observation size= 333 samples, Training percent =13/14 (Hold-Out Method) KNN neighbor = 1 5 noise classes

V. DATA ANALYSIS

The goal of this study is to probe the predictability of the noise floor level (note that the power control is disabled and since the signal levels are constant during the transmission, the SNR variations are proportional to noise variations). To this end, several classifiers have been considered given the observation parameters and then their classification rates have been gauged. The success of a classifier in having higher classification rate could reveal the underlying structure of the data. As mentioned before, the inertness of one observation parameter can be determined if the omission of that parameter does not substantially change the classification rate of the chosen "best classifier".

The data set is divided to the training set and the test set using the *hold-out* method [16]. 90% of the data is considered for the training and the remaining for the testing purpose. Quadratic and K-Nearest Neighbor (KNN) classifiers are used as pattern classifiers [17].

Some of the observation parameters may not affect the process or have less impact as they may act similar to random noise in our process. The issues regarding the correlation, causality, the common cause scenarios, and confounding and coincidental factors are also addressed in the analysis. Some observation parameters are inter-correlated. Given the actual station pressure and the wet bulb and the dry bulb temperatures, the dew point and relative humidity can be calculated. We did not know this underlying relation when we gathered the weather data. This is an apparent example of correlation, which may exist in the observation. We kept all the observation parameters and could investigate if the chosen "best classifier" is robust to these discrepancies in the observation data. (One can always compare the results to the case when these correlations are known a priori).

A. Feature extraction

In practice, there is a maximum number of features above which the performance of any classifier will degrade rather than improve. This phenomenon is due to the fact that blindly increasing the number of features (as also exemplified above with the weather data), may allow correlated features and the noise to incorporate in the classification process. To remedy the problem, feature extraction which transforms the existing features into a lower dimensional space that preserves most of the information in the original samples x has been performed.

$$f : x \in R^{\Omega} \longrightarrow y \in R^{\Pi} \ where\ \Pi < \Omega \qquad (3)$$

where f is the transform function, Ω is the dimension of our sample space, y is the vector of new features with reduced dimension Π, and R is the sample or the feature space. The optimal linear features are calculated for two objective functions in this paper.

The first objective criterion is to preserve as much randomness (or variance) in high dimensional space as possible using the Principal Component Analysis (PCA) or Karhunen-Loeve Transform (KL). The projection functions in PCA are defined by the first eigenvectors of the sample covariance matrix Σ_x [15].

Although there is no guarantee that the direction of maximum randomness contains good discrimination features, this method generally leads to good *signal* representations.

The second objective criterion is to preserve as much of class discriminatory information as possible using Fisher Linear Discriminant Analysis (LDA). The projected samples result more compact clusters. Let us consider that the projection results in J classes, where each of them contains N_j samples, then the center of the class Cj and the center of the complete set, C are:

$$\mu_j = \frac{1}{N_j} \sum_{x_i \in C_j} x_i \qquad (4)$$

$$\mu = \frac{1}{N} \sum_{x_i \in C} x_i = \frac{1}{N} \sum_{j=1}^{J} N_j \mu_j \qquad (5)$$

then, S_b is the *between classes scatter matrix*:

$$S_b = \sum_{j=1}^{J} N_j (\mu_j - \mu)(\mu_j - \mu)^T \qquad (6)$$

and S_w is the *within classes scatter matrix*:

$$S_w = \sum_{j=1}^{J} \sum_{x_i \in C_j} (x_i - \mu_j)(x_i - \mu_j)^T \qquad (7)$$

Then Fisher LDA projections are calculated by the first eigenvectors of the matrix $S_w^{-1} S_b$, maximizing the variance of the clusters while minimizing the variance of the projected sample points within each clusters [16]. As can be seen, if the discriminatory information is in the mean of the data, LDA generally results in better class separability.

These two feature extraction methods are not the only methods. We shall see whether they are accurate enough for our estimation problem. The results of these classification techniques are addressed in the next section.

VI. SIMULATION RESULTS AND DISCUSSIONS

Table 2 shows the classification rates achieved by the above-mentioned classifiers, when we do not consider time dependency of the observation parameters.

Table 3 indicates the result of the same classifiers, when the time labels are incorporated in the observation vector. There are other nonlinear classifiers which may result in better classification rates. Nevertheless, the achieved classification rate of 92% practically suffices noise level predictions. PCA indicates which of the observation parameters have the most prominent impact on the predictability of the variation of noise power. It is observed that noise power level has a strong time-series component, which has more impact on our signal than random noise (i.e. distributional part). Statistical cross-validations among different test sets were performed to inspect and verify the absence of over-fitting in our predictors. Optimal receiver design incorporating the time series analysis is still an open problem (Even for the processes that are known and are fully controlled there is still ongoing debate about an optimal design).

TABLE II
RESULTS WITH TIME INDEPENDENT OBSERVATIONS

Classifier	Reduced Dimension	Classification Rate
Quadratic	No	0.29
KNN	No	0.38
Quadratic	PCA	0.25
Quadratic	LDA	0.29
KNN	PCA	0.75
KNN	LDA	0.33

TABLE III
RESULTS WITH TIME DEPENDENT OBSERVATIONS

Classifier	Reduced Dimension	Classification Rate
Quadratic	No	0.25
KNN	No	0.54
Quadratic	PCA	0.75
Quadratic	LDA	0.38
KNN	PCA	0.92
KNN	LDA	0.38

The weather conditions may impact the telecommunication channel in two ways. If the precipitation causes the transmission line conductors to be wet, this may results in a drastic increase in corona noise generation. The climate condition also impacts the propagation constant. This analysis did not support further studying the strength of the association of these weather phenomena to the channel properties. The runtime snapshot comparison of the humid and rainy days to the sunny days indicate no major noise floor fluctuation with respect to the weather types and conditions, which anecdotally suggest that the noise floor variation is due to the Earth rotation, galactic sources or planetary atmosphere layers.

Fig. 4 shows the variation of the transformer load (in Volt-Amperes) versus the noise level (in Volts) and scatter plot of 138KV transformer loading versus the noise level at 2.4 GHz frequency band (taken from a typical data set which is in conformity with other data sets). The plots in Fig. 4 may prematurely suggest the presence of causality between these two parameters. Through confirmatory study of the data sets, it is observed that there is basically no causality between the load pattern and the noise level but they just share a *common cause*, i.e. “time”. Even though the load patterns of the transformers significantly differ in the residential subdivisions from the industrial regions, the recorded noise levels indicate identical patterns. Second, no significant changes in the classification rate were observed when we omitted the load pattern from the observation vector and deployed the best classifiers (This is due to the fact that the PCA de-correlates the data). In retrospective study, by juxtaposing the experiment results in different substations, it appears that the noise power floor is associated with the substation voltage levels (which is almost constant during normal operations) but is not affected by the load pattern of the transformers. The slow change in the load pattern and the impact of the voltage levels on the noise floor are consistent with the theoretical equation of the conductor corona noise [4]. The comparisons of different test sets confirm similar findings in different substations.

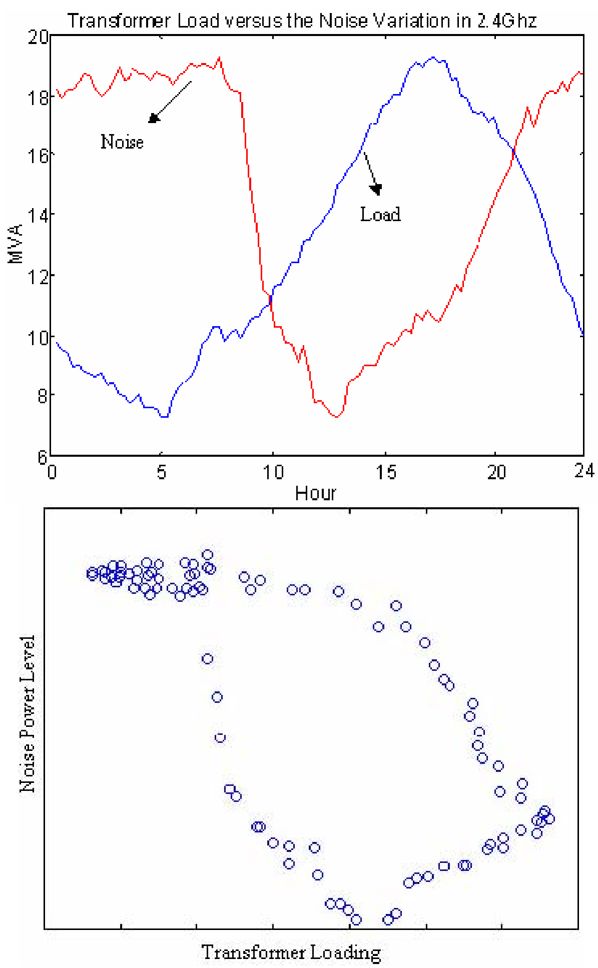

Fig. 4. Typical runtime and scatter plots of the transformer load versus the noise level

In Fig. 4 the absolute values of the noise voltage level and the transformer loadings are not of concern in this analysis so the units have been taken off from the axis.

In [14], it is shown that the noise variations over the time in a typical power-line substation are substantially different during the weekdays and weekends at 900MHz ISM frequency band (in particular in residential subdivisions). This observation may attribute to the interferences from other devices, e.g. cordless phones, government exclusive radios, etc., which operate at similar frequency band.

One can show with a simple calculation and using the simplified Friis equation that the path loss in 2.4 GHz is almost 8.5 dB higher than that of 900 MHz. This corresponds to less transmission range (and less interference range) at 2.4 GHz. By observing the collected data sets in this survey, it is confirmed that the data in the substations that were located in the residential subdivisions indicated no major behavioral differences from the industrial, isolated or sparsely populated subdivisions at 2.4GHz. This observation is coherent to the theoretical path loss result regarding the inertness of interferences of distant devices in 2.4 GHz (even in the residential regions).

Worth mentioning is that according to the regulations [9], the *primary* users of 2.4GHz spectrum are government systems and ISM users and the *secondary (license-free) users* are subject to strict output power in ISM frequency bands. Given the limited transmission range at 2.4 GHz and the consistency of the test results from several substation yards in different locations, it is suspected that the channel variations were due to the usage pattern of the *primary* users of this band. Nonetheless the interferences of the primary sources should be studied, which again demands for time-series analysis.

Moreover the deterministic variations of the noise floor have potential implications when no channel estimation and signal-level adjustments are performed. For instance in spread spectrum scenarios, the optimal performance of Direct Sequence Spread Spectrum (DSSS) systems often depends on the power control schemes in contrast with the Frequency Hopping Spread Spectrum (FHSS) schemes. By the same token in non-spread spectrum systems, amplitude dependant modulations such as QAM and ASK require more sophistication than the constant envelope career modulations such as CPFSK unless an adaptive power control scheme is applied, which incorporates the noise floor variation.

VII. CONCLUSION

The noise sources and their behavior in extreme electromagnetic environment such as a power substation have been investigated in this survey. An experiment has been designed to investigate the noise power variation and to cross-validate the probable confounding factors. Statistical analyses and confirmatory studies were done in attempts to ascertain the underlying associations. The underlying random and also semi-deterministic structure of the measured data suggests the inertness of the weather variations, ambient temperatures and load patterns. Using classification analyses, it is observed that the noise power had a strong time-series component, which had more impact on the channel than random noise (i.e. distributional part). Furthermore, it verifies the non-randomness of the noise floor and the possibility of noise floor estimation to some degree of certainty.

This suggests that the variation of the Signal to Noise Ratio (SNR) has a deterministic component, which optimally require more complex and adaptive schemes for certain types of modulations (e.g. QAM, ASK). The test methodology, measuring metrics selection and protection provisions adopted in this effort have applications in wireless design under high energy fields. It is also suggested that the field survey recommendation practices (e.g. [7]) be modified to include time series analysis.

Leaving aside the lack of extensive measurements and characterizations of wireless communication systems in high voltage substations in the literature, the experiments in this survey collectively support the applicability and the feasibility of wireless implementation in this environment.

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IX. Biographies

Alireza Shapoury (S'99) received his B.S. and M.S. degrees from Shahid Beheshti University and Iran University of Science and Technology both in electrical engineering, in 1994 and 1997 respectively. He is a Ph.D. candidate in Texas A&M University. His research interests include channel estimation, RF/mixed signal measurement techniques and antenna array processing. He is also a student member of IEEE Vehicular Technology Society and the International Society for Optical Engineering (SPIE).

Mladen Kezunovic (S'77, M'80, SM'85, F'99) received his Dipl. Ing. degree, the M.S. and Ph.D., all in electrical engineering, in 1974, 1977 and 1980, respectively. Dr. Kezunovic's industrial experience is with Westinghouse Electric Corporation in the USA, and the Energoinvest Company in Europe. He was a Visiting Associate Professor at Washington State University in 1986-1987. He has been with Texas A&M University since 1987 where he is the Eugene E. Webb Professor and Director of Electric Power and Power Electronics Institute. His main research interests are digital simulators and simulation methods for equipment evaluation and testing as well as application of intelligent methods to control, protection and power quality monitoring. Dr. Kezunovic is a registered professional engineer in Texas, and a Fellow of the IEEE