MME Approach for Cognitive Radio Systems Evaluation: Measurement, Modeling and Emulation

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Abstract

We present a vertically integrated approach to evaluate the performance of cognitive radio systems. The approach consists of three pillars: measurement, modeling and emulation. This integrated approach enables the reproduction of the radio environment in laboratory conditions, and aims to guarantee the same performance results as one would obtain in the field. The paper provides a detailed explanation for each pillar along with state-of-the-art overviews. Finally, a test-bed based on the MME approach is presented.

Introduction: MME approach

In today's wireless industry it is generally accepted that the spectrum scarcity faced by the operators can be significantly alleviated by employing cognitive radio (CR) technology [1]. However, CR technology is still not mature, and it creates many challenges which have so far prevented its wide commercial deployment. Thus it is critical that all stakeholders interested in CR, such as operators, device manufacturers and regulators, have a clear understanding of the limitations and possibilities of this technology. An accurate characterization of the radio environment is therefore an essential task, as it will aid in understanding the CR limitations.

In this paper we propose a new approach to bring realism into the technology assessment. The approach is based on three pillars: Measurement, Modeling and Emulation (MME) of the radio environment as shown in Figure 1. In general, the radio frequency (RF) scene is first measured over a range of frequencies, time instants and locations. The data collected can then be turned into a mathematical model which can further be emulated in a controlled environment either in software or in hardware. It should be noted that besides this sequence (flow #1) it is possible that models are built from the scratch and then confirmed or fined tuned through measurements, before finally being emulated (flow #2). Finally it is also possible that the modeling block is completely by-passed (flow #3). We will call the last sequence the deterministic case, where the measurement is immediately followed by emulation of the measured signals.

The timescale and target of flows #1 and #2 are different from the one from flow #3. In the first two cases, a system-level evaluation is targeted, and the aim is to evaluate the capacity of CR systems or the macro spectrum occupancy pattern. In particular, this methodology should assist the designers in evaluating the potential of CR system in various bands and locations. This activity will require measurements over multiple periods and may involve days or weeks. In the last case (flow #3), a link-level evaluation is targeted. Typically short radio scenes are captured and then directly replayed in the laboratory in order to evaluate, for example, the CR sensing algorithms. The timescale in this case can be considered to be in the order of fraction of seconds.

The MME integrated approach brings the real-world environment to the lab, and aims to offer to the various CR stakeholders fully trustable results. In the rest of the paper, we will expand on the three pillars of the MME approach along with a state-of-the-art overview.

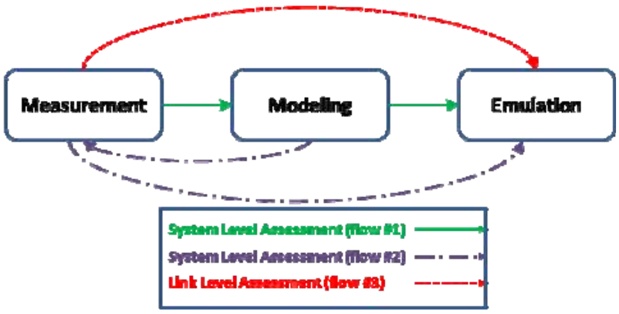

Figure 1 *MME integrated approach*

MME: Measurement

Since the CR concept emerged in 1999 [1], numerous measurement campaigns have been performed in diverse locations and for different scenarios. The measurements have typically covered a wide range of frequencies, from a few tens of MHz to a few GHz. Table 1 summarizes some of the recent campaigns. The main conclusions are always consistent. They show a low usage of the overall spectrum with vacant spectrum bands, spatially and temporally. This implies that CR technology has the potential to be able to significantly improve the spectrum usage by exploiting these spectrum "holes".

Location	Instigator	Type	Frequency range	Ref.
Denver, San Diego, Los Angeles	NTIA	Outdoor	108 MHz to 19.7 GHz	[2]
Singapore	Institute for Infocomm Research	Outdoor	80 MHz to 5.85 GHz	[3]
Auckland, New Zealand	University of Auckland	Indoor / outdoor	806 MHz to 2.75 GHz	[4]
Aachen, Germany	RWTH Aachen University	Indoor / outdoor	20 MHz to 6 GHz	[5]

Table 1 *Characteristics of some recent measurement campaigns for spectrum usage evaluation*

The most commonly used measurement method is the energy/power detection scheme. In [6] it was shown that depending on the selected parameters, such as the frequency span, measurement period, location, and antenna polarization, the measurements results can lead to a different conclusion about spectrum occupancy. However, the most significant parameter is the decision threshold, which may have a huge impact on perceived spectrum occupancy.

Figure 2 shows an example of a measurement result which compares the sensitivity of the signal occupancy in percentage to the decision threshold variation for the ISM-band in 2.4-2.4835 GHz frequency. The results are obtained at 2pm and 8am over an entire week, with the outcome for Wednesday afternoon at 2pm highlighted. These measurements were done by the University of Oulu in downtown Oulu, Finland in June 2011. The setup consisted of ISM-band antenna, ISM-band filter, a low-noise amplifier (LNA), and Agilent N6841A RF sensor. Frequency bin separation was set to 109.375 kHz. The figure shows that the average occupancy is typically low. Similar low occupancy results for ISM-bands have also been reported in [3] and [7]. The Figure 2 also shows a different occupancy result as the threshold is varied. Thus if the selected threshold is too high, it will lead to an underestimation on the spectrum occupancy, and to an overestimation if it is too low. The selection of the correct threshold value is therefore an important criterion. There are classically three ways to select a threshold [6]:

- **<u>Maximum noise criterion:</u>** This takes the maximum recorded noise level as threshold. Its main drawback is that it may underestimate the occupancy due to weak signal samples lying below the maximum noise level.
- **<u>Probability of False Alarm (PFA):</u>** The threshold is selected such that only a fraction of the noise samples are above the threshold. The PFA is classically set to 1%, which is considered to be the best trade-off.
- ***<u>m</u>*<u>-dB criterion:</u>** This adds *m* dB to the average noise floor.

The criterion for threshold selection is dependent on the application use-case. However the selected threshold value should result in the most accurate picture of the occupancy scenario.

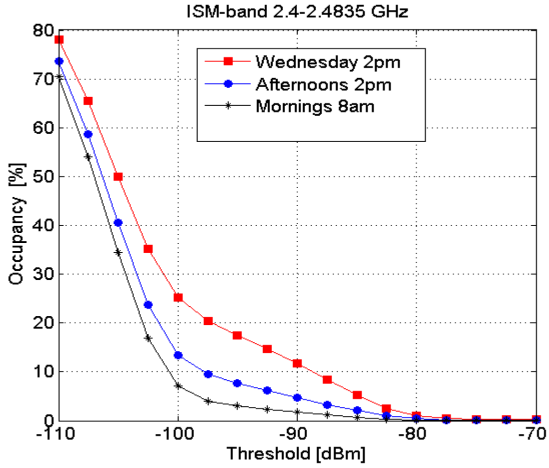

Figure 2 *Impact of the decision threshold on the spectrum occupancy for ISM-band*

In Figure 3 we compare the occupancy result based on power measurements with the access point (AP) logs taken from the public access network OULU (panOULU). This figure has been obtained after a one-week measurement at the Tellus library of the University of Oulu in January 2011. The power measurement results were obtained by an FFT-based spectrum analyzer that performs at least 200 measurements per second over 156 kHz frequency bin separation in 2.4-2.5 GHz ISM-band. The threshold is set to 20dB above the noise floor which is approximately -95dBm in this case. The high threshold value is selected so as to avoid any false alarm due to internal noise of the receiver. In the figure the log based traffic information has been scaled and shifted up according to a regression analysis. The comparison is made for only one WLAN channel with a close-by AP. The figure shows that there is a very good agreement with the actual WLAN activity logs. The slight deviation from the logs may be due to non-panOULU WLAN traffic, non-traffic beacon signals and other interferences.

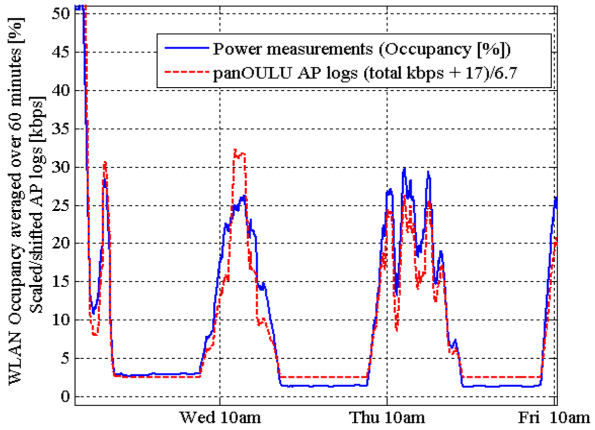

Figure 3 *Power measurement vs AP logs (time series), with a sliding window of 60 minutes.*

Similar occupancy results for GSM carriers over one working day were obtained at the University of Aveiro campus in Portugal [8]. Figure 4 shows the variation of the spectrum occupancy of a single 200 kHz GSM1800 channel consisting of 8 time-division multiple access (TDMA) slots. The measurement period is set equal to the GSM frame duration of 4.62 ms. The measurement here is continuous compared to the typically discontinuous wide-band measurements undertaken in Table 1. In the result a channel is considered occupied if at least one of the eight time slots in the frame is used. From the figure we see that during the business hours, the occupancy is at most 70%, whereas during the night hours there is considerably more availability of the spectrum.

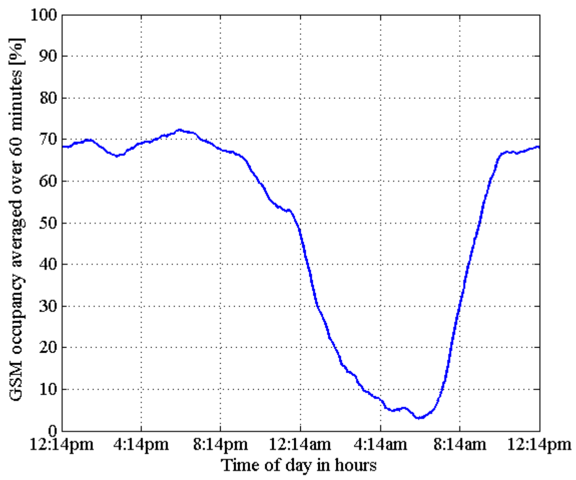

Figure 4 *A single 200 kHz GSM1800 channel occupancy measured over a single day at Aveiro, Portugal, with a sliding window of 60 minutes.*

So far we have considered only the spectrum occupancy criterion, but for certain radio access technologies, the spectral resource is used even when no user is actually transmitting, for example in downlink code division multiple access (CDMA) systems. Even with GSM systems a huge difference exists between spectrum occupancy and real traffic occupancy. This can be due to two factors:

- an increase in number of frequency channels used as Broadcast Channels (BCH); or,
- an increase in occupancy due to frequency-hopping functionality.

Thus the concept of "traffic occupancy" gives a much better image of how spectral resources are actually used. In the GSM case, it can be defined as the average occupancy over the TDMA time slots on each of the Traffic Channels (TCH) which can be potentially used by the user equipment (UE). To this end, a measurement campaign was undertaken by Thales Communications and Security in a business area in the suburbs of Paris in February 2011. The campaign was conducted to quantify the difference that exists between the spectrum and traffic occupancies on GSM900 bands. On each of the 124 channels of the band, a detection algorithm was implemented in order to detect and decode the BCHs, and detect the TCHs and estimate their time-slot occupancy.

Figure 5 illustrates the evolution of both occupancies during 24 hours for France Telecom (FT) Orange network operator. This figure emphasizes the existing difference between the spectrum occupancy and its actual usage on GSM bands. One can observe that the spectrum occupancy is much higher than the traffic occupancy. The results highlight that there is much more potential opportunity in the available spectrum space which can be exploited by the CR system.

It should be noted that Figures 3-5 provide the measurement results over 60 minute window period and mainly emphasize on system-level evaluation. The results from these measurements are first fed to the modeling block, and then based on statistical studies the emulation block plays the radio scene in order to evaluate, for example, the capacity of CR systems. This corresponds to flow #1 within the MME framework.

Similarly shorter measurement periods in the order of fraction of seconds or minutes can also be estimated. In this case, short radio scenes are captured and then directly fed to the emulation block in order to evaluate, for example, the CR sensing algorithms. This corresponds to flow #3 within the MME framework. The aim here is to evaluate and validate the link-level evaluation of the CR system. We may now consider the second item that is the modeling block in our three-pillar process.

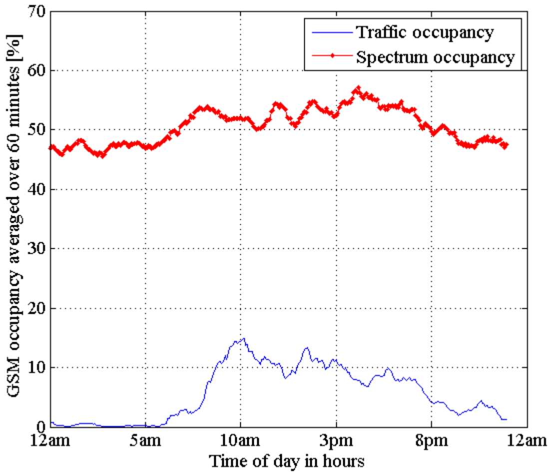

Figure 5 *Spectrum and traffic occupancies during a single day for a French Operator at Colombes in Paris, with a sliding window of 60 minutes.*

MME: Modeling

In order to enable spectrum-sharing techniques based on CR technology, it is also crucial to be able to understand and model incumbent user behavior. Therefore, we here provide an overview of modeling task within the MME framework. The approach is divided into statistical modeling, and database modeling. While the statistical approach models the dynamic behavior of the incumbents, on the other hand the database approach focuses on static environment such as the television white space (TVWS) bands.

Statistical modeling

The measurement results shown in the previous section cannot be extended directly to other locations, spectrum bands and time intervals, this is because of variations in the incumbent usage pattern; hence, in theory, separate measurements are needed at each time and place. In order to provide a representative usage of an incumbent, a statistical-based modeling approach can be considered as an attractive solution. Here the first-order and second-order statistical parameters are employed on the measurement results in order to develop the spectrum occupancy model of the incumbent users. The radio scene then corresponding to this occupancy model is finally played by the emulator for the system level evaluation. It should be noted that within the MME framework this corresponds to flow #1.

A quick survey of literature shows that the statistical modeling is a very active area in research. The different approaches that have been considered for modeling the incumbent usage pattern in time, frequency and space domain are as follows:

In the *time domain*, spectrum occupancy models are widely based on discrete or continuous time Markov chain schemes. The basic principle of Markov chain is that the spectrum usage in each channel can be modeled by two states; with one state indicating that the channel is occupied and therefore not available to the opportunistic user, while the other state indicates that the channel is free and available to the opportunistic users. In continuous time Markov chain (CTMC) model, the channel remains in one state for a random period of time. This state holding time can be modeled based on empirical results as a generalized Pareto, or as geometric or log-normal distributions [9]. In real systems (for example, cellular systems), occupancy of a channel is a consequence of a large number of random factors such as traffic load, resource management policies, specific location, mobile operator packages, and so on; and hence as a result channel usage is itself a complex stochastic process and still an open research question. Recently, Wang and Salous [10] analyzed the spectrum occupancy in GSM bands by applying time series models. In order to analyze the data an auto-regressive integrated moving average (ARIMA) model was fitted to the data in GSM bands in Durham, UK [10]. A time-varying spectrum occupancy model was also proposed in [11]. Here the statistical spectrum occupancy model is based on a combination of several different probability density functions (PDFs).

In the *frequency domain*, the statistical distribution of channel occupancy is shown to follow a Beta distribution [12]. The use of Poisson and Poisson-normal distributions for the characterization of channel occupancy has also been presented in [13].

In the *spatial domain*, the models characterize the spectrum occupancy patterns at different locations. Spatial distribution of the power spectral density of incumbent user signal has been studied in [14] using random field theory. Most recently a more sophisticated approach to model spectrum occupancy in a realistic urban environment (at a ground level, inside buildings, on rooftops) was presented in [15].

Based on the incumbent user's channel access dynamics for specific location and time, it is possible to also derive the statistical information such as the total number of spectrum opportunities in terms of the probability of each channel being free. In previous work [16], the exact and approximate probability distributions for the total number of free channels not being used by the incumbent users was derived. Figure 6 compares the exact and the various approximate probability distribution functions in a scenario when the channels are most likely occupied by the incumbent users. As seen from Figure 6 that Camp-Paulson approximation provides the most accurate curve.

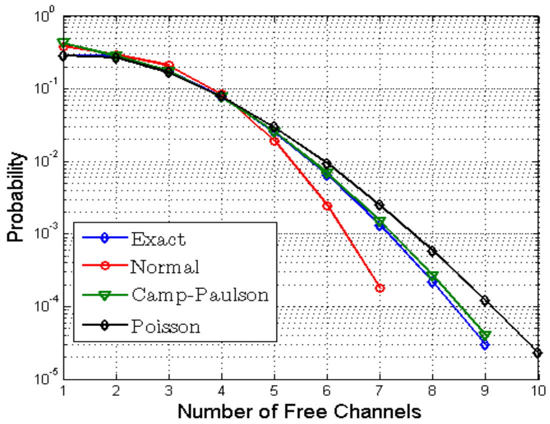

Figure 6 *Probability distribution function of total number of opportunities.*

Database modeling

In static radio environments, CR systems are envisaged to have access to a database of incumbent spectrum occupancy, in order to minimize the risk of interference and to reduce the sensing requirements. In TVWS bands such a database will contain signal strength information from TV transmitters, as well as possibly wireless microphone data. The computation of such a database is a large computational task. It needs two main inputs:

- A list of TV transmitter data, usually provided by national regulators.
- The terrain data required by propagation models. The propagation models used are often of the irregular terrain Longley-Rice type, which include empirical models of diffraction effects over hills.

Additionally a protocol is required for remote communication with the database; various proposals are currently being evaluated. Security will be a basic requirement here. Upon receipt of a query, the database will provide a channel (or channels) and an allowed power level, and register the channel as in use at the specified locations and for the specified period. In the UK, the Ofcom regulator has published consultation documents on design issues†. Such databases are starting to be offered as a commercial service‡. The next two figures show the typical database computation outputs for the UK. Figure 7 shows a square of size six degrees of longitude and six degrees of latitude covering most of England, with spectral colors indicating minimum channel occupancy (dark blue) to maximum (red). It will be seen that there is considerable spatial variation, proving that the database does provide useful information.

†http://stakeholders.ofcom.org.uk/binaries/consultations/geolocation/responses/Comsearch.pdf

‡ http://spectrumbridge.com/whitespaces.aspx

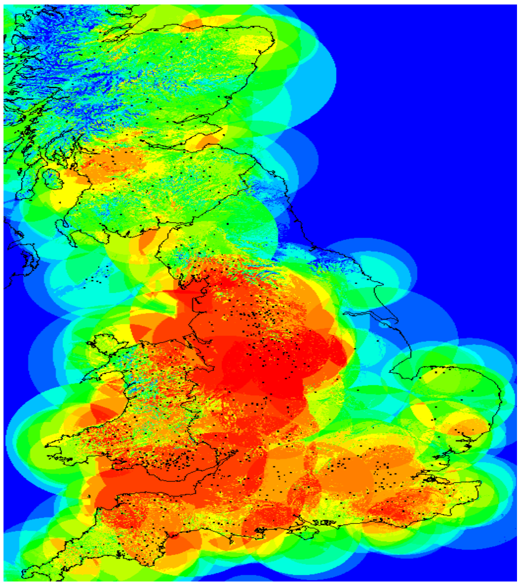

Figure 7 *TV band occupancy density for UK*

From the database, statistical summary information may also be computed. The most useful is population-density weighted, so that we gain estimates of the distribution of the amount of free spectrum per user. Figure 8 shows a typical cumulative distribution computed this way for the whole of the UK. It will be seen that 50% of the population has 6 channels available; that is, 48 MHz.

Within the MME framework, the database computations derived from TV transmitter and propagation data, can eventually be fed to the measurement block (flow #2) for further verification and refinement of the model. Once the verification is complete the computed data can then be fed to the emulation block.

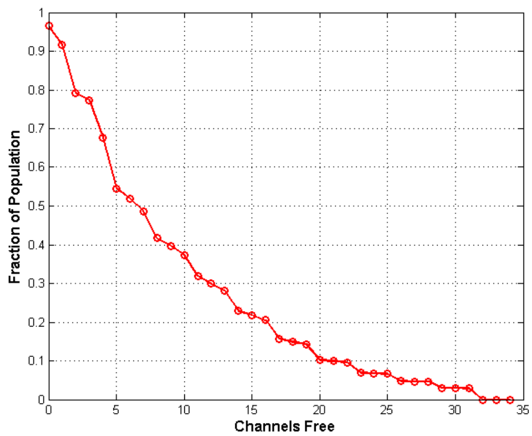

Figure 8 *TV band whitespace availability for the whole of the UK*

MME: Emulation

Emulation is the third pillar of the MME integrated approach. It is worth noting that this test-bed can be implemented either in hardware or in software. It is the core of the proposed cognitive radio test-bed as shown in Figure 9. The emulator consists of a wideband (WB) signal generator that stimulates the sensing engine of a CR device with a set of waveforms derived from the measurement-modeling (MM) stages of the MME approach. As discussed in the introductory section, the emulation involves two cases with different time scales: deterministic and model-based.

In the first *deterministic* case, the modeling block is skipped and the recorded sequences obtained from the measurement campaign are directly replayed on the emulator without any changes. The incumbent usage pattern (on/off) is emulated without the need for any channel emulation. This emulation scenario serves the link-level performance evaluation and in particular the sensing engine performance study.

In the second *model-based* case, both statistical and database approaches are considered. Here the incumbent usage pattern emulation is combined with the channel emulation in order to accurately reproduce the actual RF scene. This emulation scenario serves the system level performance evaluation.

The Figure 9 shows that in the test-bed the sensing estimates of the CR device can be compared with the source in order to evaluate the performance of the sensing engine. Metrics like the probabilities of detection, false alarm or the detection speed can be evaluated in this manner. On the other hand, the CR device can also make decisions about the available opportunities based on the sensing engine outputs. In this case the transmitter of the CR device (secondary) can start transmitting on the available spectrum holes. The output of the secondary transmitter is then added to the stimulus signal and later fed to CR device receiver as well as the incumbent systems receiver. Through BER measurements (as an example), both the quality of the secondary transmission and its impact on the incumbent systems can be evaluated. As depicted in the figure, a CR test-bed can also include channel emulation blocks. Adding these blocks between the receivers and the modeled (or emulated) transmit sources will enable the inclusion of fading and Doppler effects in the radio scene. A true radio scene experienced by the mobile device is then emulated, and hence both the static and the vehicular cases are appropriately tested.

The emulator should have the following three properties:

- **<u>Controllability</u>**: the user should be able to precisely control the emulation scenario;
- **<u>Repeatability</u>**: the user should be able to repeat any desired sequence of events in the emulation scenario;
- **<u>Representability</u>**: the emulated RF scene should represent as well as possible the real environment that the CR system will experience. This is guaranteed through the MME vertical approach.

Besides the above desirable properties, the emulator should also provide a deep enough memory for the deterministic case emulation whereas a wideband system is typically required for both the deterministic as well as the model-based cases.

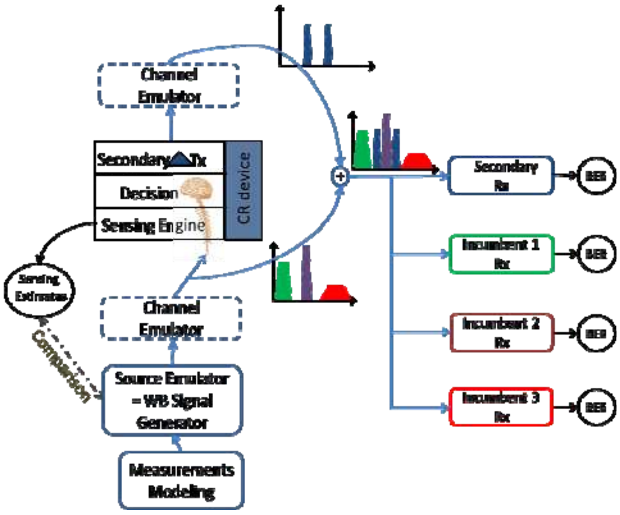

Figure 9 *MME-based cognitive radio test-bed*

Conclusions

We have presented an integrated vertical approach involving measurement, modeling and emulation. The vertical approach enables the reproduction of the radio environment in laboratory conditions, and offers to the various CR stakeholders fully trustable results.

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