# ICT Degradation Modelling

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**Abstract.** With the advent of Cyber-Physical Energy Systems (CPES) and their application on Smart Grids (SG), the integration of Communication Technologies (ICT) and Power Systems (PS) have been rooted deeply. ICTs and PS in such environments have heavy mutual interdependencies on one another. Failures in ICT can disrupt PS, while failures in PS could disrupt ICTs due to lack of energy, thus leading to cascading system failures. While the European Network of Transmission System Operators ESSC (ENTSO-E) provides classification systems for classifying PS operation states to determine PS degradation, such comparable systems are not available for ICTs. In this paper, we attempt to understand various components of an ICT system, and understand the various operation states of the ICT components. We attempt to survey the distribution network technologies as a part of the SG paradigm, and isolate components of interest. The essential properties such as availability and reliability are determined and used to map the states of components. Since distribution networks can be treated as Markov models, we attempt to design degradation models of the distribution networks using Markov chain analysis.

**Keywords:** Cyber-Physical Energy Systems · Information and Communication Technology · Degradation Modelling · Degradation Detection · PKIs · Markov Time Chains

## 1 Introduction

The ENTSO-ESSC is a system state classification that is implemented to determine the operational state of a Power System. ESSC however does not regard for the impact that the ICT system has on determining the operational state of a PS. ENSTO-E PS state classification defines five various states - Normal, Alert, Emergency, Blackout a Restoration. There is a change in the system state each time a failure may occur. For example, a certain failure may escalate the PS from a Normal state to an Alert state. In this paper, we shall attempt to understand if such a classification can be implemented on an ICT systems, and what components can be understood to achieve such a classification.

## 2 Background Work

In [1], there is an attempt to understand the bridge between the PS and ICT state classifications, and to isolate the elements, which could be used as properties to define system states. The study adopts from the ResiliNets project with the difference being a slight deviation in the definition of what an operation state is. While the ResiliNets project only considers the network and the service that it provides, the paper accounts for both the network infrastructure and the various services that it provides while defining the operational state. The three Key Performance Indicators (KPIs) considered are those of Availability, Accuracy and Latency. As such three states were defined as follows - Normal State, Limited State and Failed State.

In a similar study [5] on modelling communication technologies to find the Distribution Grid's reliability, the ICT components are considered to have some network states. The states range from an in-service state, observable state and an IED (intelligent Electronic Device) state. The KPIs in this particular study were component availability and latency requirements. The study similar to previous study emphasised on both the network infrastructure and the services provided to define operational states.

## 3 Network Degradation Modelling

### 3.1 Cellular Networks

As we focus on the ICT segment rather than the PS segment, we find that extensive work has been made on degradation detection in cellular network, there is currently not much work available for degradation modelling. However, we can study the degradation detection techniques and adopt from the same to formulate degradation models.

With the advent of 3G and newer generation cellular networks, SONs (Self-Organising Networks) have been integrated as a part of the 3GPP standard. SONs provide for easy network management and maintenance amidst the growing complexity of these newer generation networks, and can automate some functions such as network configurations, healing and also optimization. This ability is of certain interest to us as it enables a network to recover from a so defined degraded state to a normal state.

Research shown in [6] and [7] have detailed study on degradation detection in SON based networks. Both the researches work on understanding the degradation patterns in cells using various methods such as analysing cell metrics over a time period or by observing the interaction between two cells to determine a potentially degraded cell.

**LTE Network Structure and KPIs Identification**

The three main parts of a LTE network are:

– UE (User Equipment)
– E-UTRAN (Evolved UMTS Terrestrial Radio Access Network)
– EPC(Evolved Packet Core)

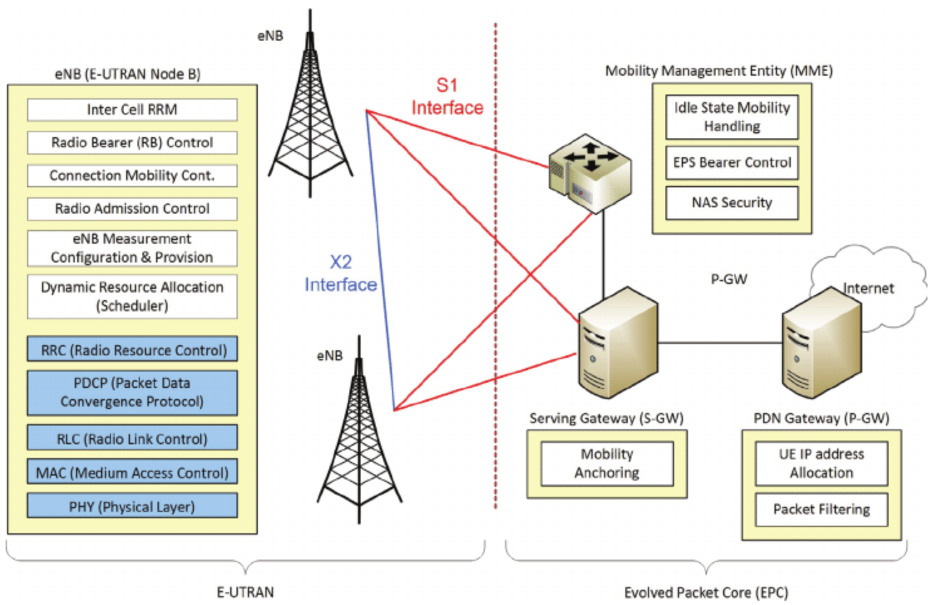


**Fig. 1.** LTE Network Structure (Image source :[8])

The user equipment is similar to the Mobile Equipment that is used in 2G-GSM networks. The E-UTRAN is responsible for managing the communication between the mobile (UE) and the evolved packet core (EPC). The EPC consists of the evolved base stations, called eNodeB, which is simply a base station that controls mobile devices in a given cell(s). EPC is analogous to the Core Network (CN) of the LTE system.

LTE cellular networks have 5 KPIs that are defined to monitor, optimise the network performance while detecting any performance problems. The KPIs are listed below with some possible test cases (see Table 1):

Hendrawi et al. [4] has demonstrated Accessibility based degradation prediction using the KPIs of RRC Setup Success Rate, ERAB Setup Success Rate and Connection Signaling Success Rate. The RRC (Radio Resource Control) Setup Success Rate is an index of the total count of successful RRC connections

**Table 1.** KPI index in LTE Networks

| KPIs | Test Cases |
|---|---|
| Accessibility | RRC setup success rate<br>ERAB setup success rate<br>Call Setup Success Rate |
| Retain-ability | Call drop rate<br>Service Call drop rate |
| Mobilty | Intra-Frequency Handover Out Success Rate<br>Inter-Frequency Handover Out Success Rate |
| Integrity | E-UTRAN IP Throughput<br>E-UTRAN IP Latency |
| Availability | E-UTRAN Cell Availability<br>Partial cell availability |

as opposed to the number of RRC connections attempted between the UE and eNodeB.

$$RRC - SSR = \frac{RRC\,Connection\,Success}{RRC\,Connection\,Attempts} * 100\% \tag{1}$$

E-RAB Setup Success Rate is the index of the success probability of the E-RAB accessing services in a given cell.

$$ERAB - SSR = \frac{ERAB\,Setup\,Success}{ERAB\,Setup\,Attempts} * 100\% \tag{2}$$

The Connection Signalling Success Rate KPI measures the success probability of sending *Initial_UE_Message* messages and getting it's response between the MME (Mobility Management Entity) and the eNodeB on the S1 interface.

$$ConnectionSignal_{SR} = \frac{S1\,ConnectionEstablish\,Connection\,Success}{S1ConnectionEstablish\,Connection\,Attempt} * 100\% \tag{3}$$

The paper proposes three states that a Self Organising Network (SON) may have, namely high, acceptable or low. A time series database was generated by collecting the measurement times for all three KPI indexes from an eNodeB (Evolved Node B) over a period of a month. The eNodeB consisted of three cells deployed over a LTE network. The collected data was used to calculate a representative value spanning over a larger period of time, such as a day. Since there were three KPI indexes considered, it was necessary for formulate a cumulative value to represent the system value.The system state was then found by evaluating the representative value against a predetermined threshold value. If the values were below the threshold, the the system was in a low state. If the values were above the threshold, then the system was in a high state. Else the system was in an acceptable state. The representative values were used to determine the transition of the system from one state at various time intervals. Based on collected data and transition of system between the three states, a state transition probability matrix was formed, and a model for Discrete Time Markov chain was then formulated to predict the long run accessibility conditions of the system.

**Availability State Identification** The KPI used for Availability is the E-UTRAN Cell Availability. This indicator is representative of the percentage of the time that a cell is available. The cell can be defined to be available when the eNodeB can provide the Evolutionary Radio Access Bearer (E-RAB) service. The E-RAB is a radio access bearer that functions on the S1 interface between the eNodeB in E-UTRAN and the Mobility Management Entity (MME) Control Plane in the EPC.

Thus:

$$Availability = \frac{Time\,that\,a\,cell\,is\,available}{Measurement\,time} * 100\% \tag{4}$$

## 4 Formulating Discrete Markov Time Chain

In order to model degradation of a network, we need some kind of a stochastic approach to said modelling. As opposed to a deterministic approach, stochastic approach accounts for a certain amount of randomness. Deterministic approaches produce same results or outputs for a particular input set. The material properties of the model are known and there is no scope for randomness. Stochastic approaches are better at predicting outcomes while accounting for some amount of unpredictability. There can be various reason as to why the system may degrade, ranging from software issues, hardware issues, wear and tear, malicious adversaries or natural disasters. There can even be a combination of factors. Thus we should account for certain level of uncertainty and still be able to predict if a system is able to maintain a given state and the amount of time that the system can maintain the said state.

The Markov process is said to be a stochastic process for $X_t : t \,\epsilon\, T$ such that for a point of observation $0 = t_0 < t_1 < .... < t_n < t_{n-1}$ for every state $s_i \epsilon\, S$, we have that the conditional probability distribution of $X(t_{n-1})$ depends only on $X(t_n)$ and not any previous values.

As such the Markov property will hold if:

$$P(X_{n+1} = S_{n+1}|X_n = S_n, X_{n-1}, ..., X_0 = S_0) = P(X_{n+1} = S_{n+1}|X_n = S_n) \tag{5}$$

Thus the conditional pmf for transition of the system from a state $s_i$ at time $n$ to $s_j$ at time *n+1* can be given by the equation:

$$P_{ij} = P(X_{n+1} = S_j|X_n = S_i) \tag{6}$$

We can also calculate the probability that the system, in some (unknown) state at current time, will be in a particular state $s_i$ after time $n$ ahead. This is know as the state probability, and can be calculated as:

$$\pi_i(n) = P(X_n = i) \tag{7}$$

For a Discrete Time Markov chain, the state probability can be calculated as follows:

$$\pi_i(n) = \sum_{j=0}^{\infty} P_{ji}^n \pi_j(0) \tag{8}$$

such that

$$P_{ji}^n = P(X_n = i | X_0 = j) \tag{9}$$

It is safe to assume that the LTE system or any network is an ergodic system, and thus ergodic markov chain rules apply. An ergodic Markov chain is a Markov chain in which it is possible to transition from one state to another with a positive probability always. That is, the system is able to transition from every state to every state. Thus, we can apply the Fundamental limits theorem and calculate the state-steady probability of the system. A state-steady probability determines how long will the system stay for in a certain state *j*.

$$\pi_j = \sum_{i=0}^{\infty} \pi_i P_{ij} \, for \, j = 0, 1, ... \, where \, \pi_j = lim_{n \to \infty} P_{ij}^n \tag{10}$$

Thus given an initial state of $s_0$ and some initial probability, we can easily find the state that the system will be in after 'n' steps.

## 5 State Identification and Analysis

It is possible to record measurement time of cell availability and record the same in an database. These measurements can be categorized into three states, namely *optimal, functional* and *degrading.* The three states shall give us an understanding of the current system performance:

- **Optimal State:** The system is performing under optimum conditions.
- **Admissible:** The system performs under acceptable conditions, but these are not optimum conditions.
- **Degrading:** In this state, the system is performing poorly and is facing certain problems. The system is in a sense degrading.

Each state can be assigned with a range of threshold values for category identification. A system is in Optimal state if our KPI values are in a range of above 99.5% . The system is in Admissible state if the values are between an lower threshold of 98% and upper threshold of 99.5%. The system is in the Degrading state if the KPI values for cell E-RAB service availability fall below 98%.

We need to be able to formulate the state transition matrix. The matrix will define the state probability, that is, the probability that a system moves from one state to another state in a given time frame. As such the transition from state Optimal to state Admissible can be written as

$$P(O, A) = probability\, that\, the\, system\, transitions\, from\, Optimal\, to\, Admissible \tag{11}$$

The matrix for the same can be formulated as:

$$\text{Transition Matrix (P)} = \begin{bmatrix} P(0,1)\; P(0,2)\; P(0,3) \\ P(1,1)\; P(1,2)\; P(1,3) \\ P(2,1)\; P(2,2)\; P(3,3) \end{bmatrix}$$

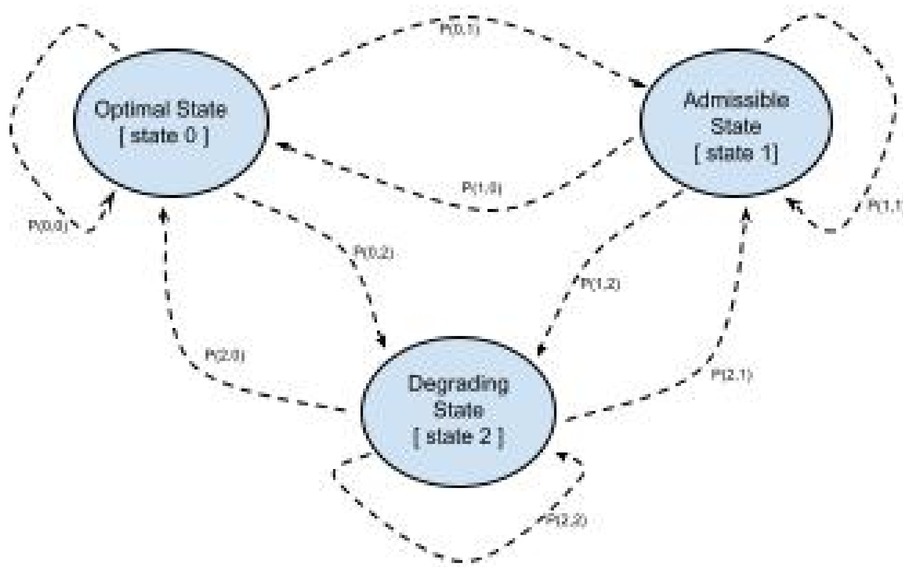


**Fig. 2.** State Transition

Based on the knowledge of the transition matrix, we can use equation (8) to calculate the state probability of the system after a certain time period, as well as the stationary probabilities.

### 5.1 Work to be done yet:

- Add definitions for state, operation state, etc in para 1 of background works.
- research on PLC degradation ideas.
- Look into getting data on how long cells are able to provide ERAB service, i.e eNodeB availability data. If data is available, can we adjust into equations and get values for state probability and stationary probability of system? if not, can this model be extended?

- complete reference list, improve information flow overall

## References

1. Klaes et al. Energy Informatics 2020, 3(Suppl 1):16 https://doi.org/10.1186/s42162-020-00119-3
2. Elnashar, A., El-saidny, M.A. & Sherif, M.R., Design, Deployment and Performance of 4G-LTE Networks a Practical Approach, John Wiley & Sons, 2014.
3. Khatib, E.J., Barco1, R. & Serrano, I., Degradation Detection Algorithm for LTE Root Cause Analysis, IEEE Wireless Communications, pp. 20- 28, June 2016.
4. Hendrawan, Accessibility Degradation Prediction on LTE/SAE Network Using Discrete Time Markov Chain (DTMC) Model https://doi.org/10.5614/itbj.ict.res.appl.2019.13.1.1
5. K. Kamps, F. Möhrke, M. Zdrallek, P. Awater and M. Schwan, "Modeling of Smart Grid Technologies for Reliability Calculations of Distribution Grids," 2018 Power Systems Computation Conference (PSCC), 2018, pp. 1-7, doi: 10.23919/PSCC.2018.8442727.
6. Asghar, M.Z., Fehlmann, R. & Ristaniemi, T., Correlation-based Cell Degradation Detection for Operational Fault Detection in Cellular Wireless Base-stations, in 5th International Conference on Mobile Networks and Management (MONAMI), pp. 83-93, 2013.
7. Pablo, M., Barco, R., Serrano, I. & Gomez-Andrades, A., Correlation-Based Time-series Analysis for Cell Degradation Detection in SON, IEEE Communications Letters, 20(2), pp. 396-399, 2016.
8. Antonopoulos, Angelos Kartsakli, Elli Alonso, Luis Verikoukis, Christos. (2011). Dealing with VoIP Calls During "Busy Hour" in LTE. 10.5772/20875.
9. V. Ramaswamy and J. T. Correia, "Enhancing Service Availability of LTE-in-a-Box Systems Using 3GPP-Compliant Strategies," MILCOM 2018 - 2018 IEEE Military Communications Conference (MILCOM), 2018, pp. 512-517, doi: 10.1109/MILCOM.2018.8599841.