Application of Probabilistic Modeling and Machine Learning to the Diagnosis of FTTH GPON Networks*

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*This paper highlights key outcomes of the PhD work of Serge Romaric Tembo, defended on January 23rd 2017: « Application de l'intelligence artificielle à la détection et l'isolation de pannes multiples dans un réseau de télécommunications »

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Fault diagnosis of FTTH networks

Fault diagnosis

- A fault is a failure explaining a set of symptoms (warnings, alarms, other faults)
- A fault degrades the QoS or leads to service unavailability
- Fault diagnosis correlates observed symptoms so as to determine their root cause(s)
  - ➢ It leverages on monitoring data collected by operator's hot line: counters, powers, temperatures, …

Diagnosis example on a Gigabit capable Passive Optical Network (GPON)

- An « upstream Loss of Signal » alarm at the OLT (Optical Line Termination) for ONT #3 (Optical Network Termination)
- Intermediate causes: low received power at the OLT, low transmitted power at ONT #3
- Root cause: faulty power supply of ONT #3

A tool typically used: the rule-based expert system (RBE)

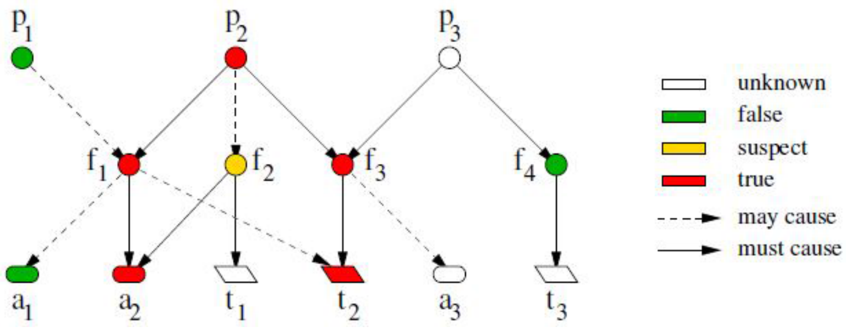
- Set of expert rules (IF <conditions> THEN <actions>) covering typical fault configurations (e.g. a few tens of rules for GPON)
- Efficient for known issues
- Specialized and deterministic rules: impossible to cover all fault configurations, difficult to maintain

Context and objectives of the work

Some alternative approaches to rule-based expert systems

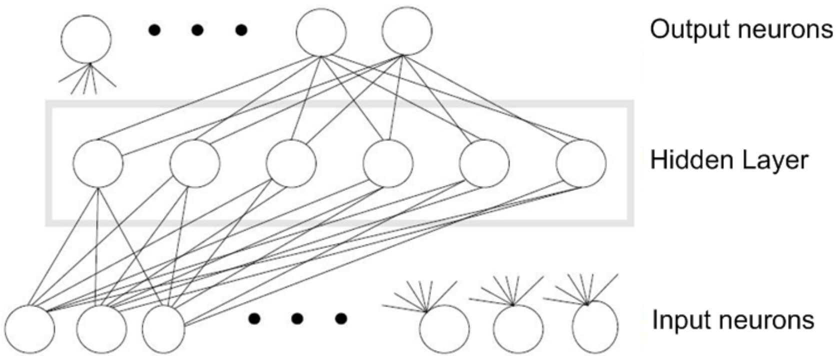
Model-based expert systems

- Explicit modeling of the network structure and behavior (alarm propagation and correlation)
- Example: dependency causal graph → deterministic reasoning algorithm
- ☺ Scalability, ability to deal with unknown issues, comprehensibility
- ☹ Modeling complexity, static model



Machine learning techniques

- Inductive capabilities derived from supervised or non-supervised training
- Example: multi-layer artificial neural networks
- ☺ Scalability, large induction capabilities
- ☹ Blind method, « black box »



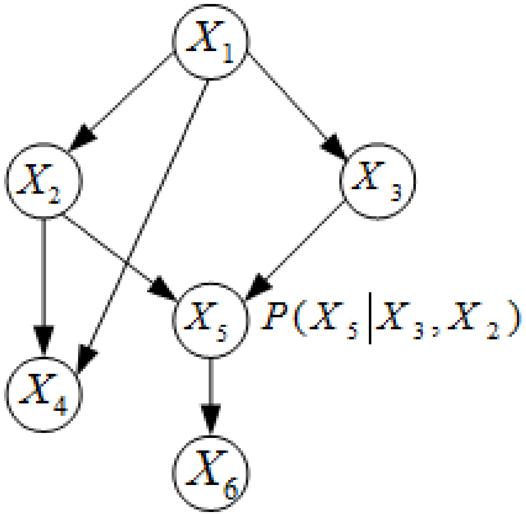
Objectives of this work

Improve performance of FTTH GPON fault diagnosis

- Allow easier maintenance of diagnosis tool
- Decrease the number of non-identified faults, even when some data is missing
- Maintain or increase diagnosis reliability

Diagnosis approach

- **Probabilistic** version of dependency causal graphs: Bayesian networks
- Handles non-deterministic fault propagation
- Robust to missing data
- Modular 3-layered model:
  - ➢ Layer 1 for modeling dependencies **between** components
  - ➢ Layer 2 for modeling dependencies **inside** components
  - ➢ Layer 3 for **Bayesian inference** of the whole system
- The model parameters can be tuned through **machine learning**



Bayesian network example

- X_i are random variables and edges represent dependencies $P(X_i = k \mid \text{parents}(X_i) = j)$
- Factorization of joint probability:

P(X1,X2,X3,X4,X5,X6) = P(X6 | X5) * P(X5 | X2,X3) * P(X4 | X1,X2) * P(X2 | X1) * P(X3 | X1) * P(X1)

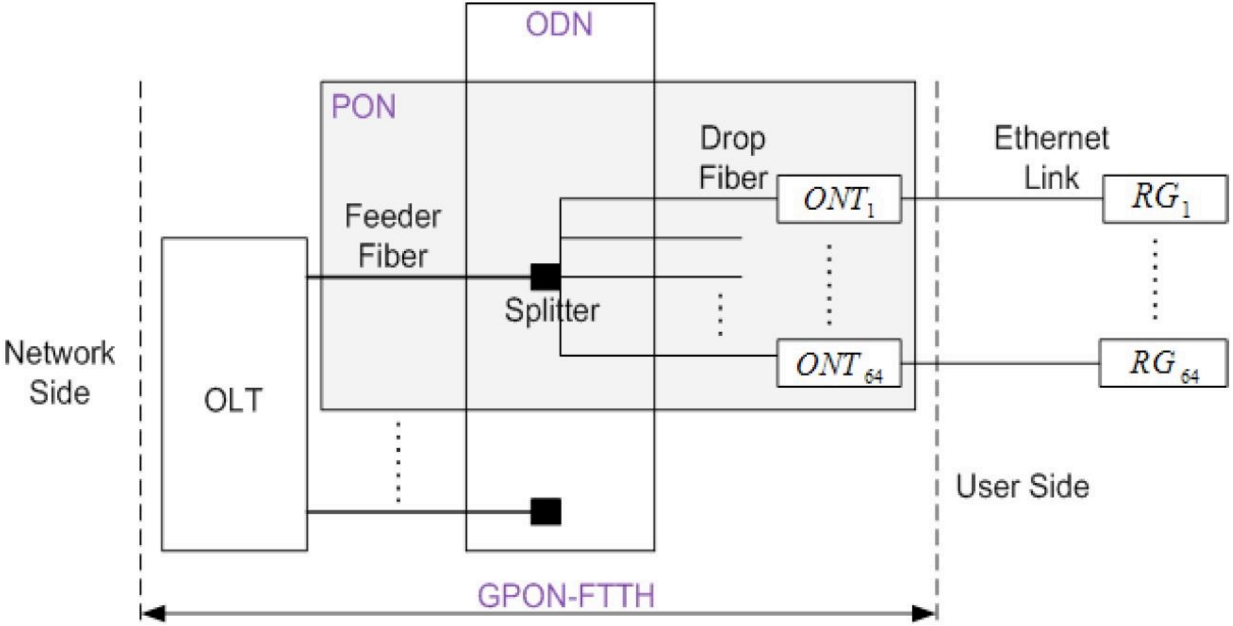
PANDA: Probabilistic tool for GPON-FTTH Access Network self-DiAgnosis

System under study: Gigabit capable Passive Optical Network (GPON)

FTTH infrastructure

- Optical Line Termination (OLT): Central office equipment
- Optical Network Unit / Termination (ONU or ONT): Customer side equipment
- Optical Distribution Network (ODN): distribute optical power from feeder fiber to drop fibers thanks to splitters

The ODN is typically composed of several splitter stages



*RG = Residential Gateways (not in this work's scope)

Example of the 3 layered generic model

Layer 3*

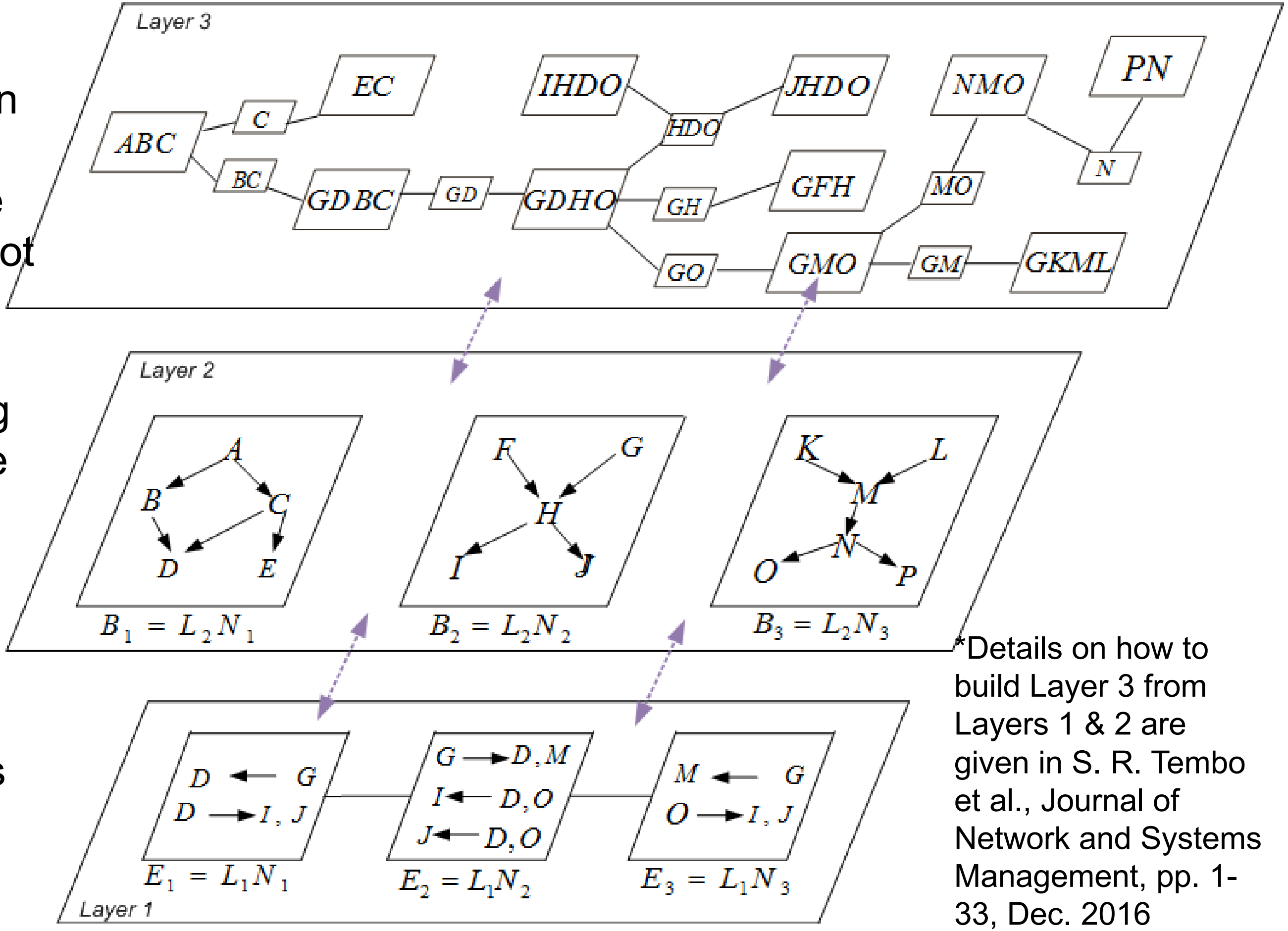
- Junction tree representation derived from the combination of layers 1 & 2
- Used for Bayesian inference leading to identification of root causes

Layer 2

- Bayesian networks modeling local fault propagation inside each component N_i (e.g. a given ONT)

Layer 1

- Network topology as well as distributed fault propagation **between** linked components (e.g. ONT-OLT)

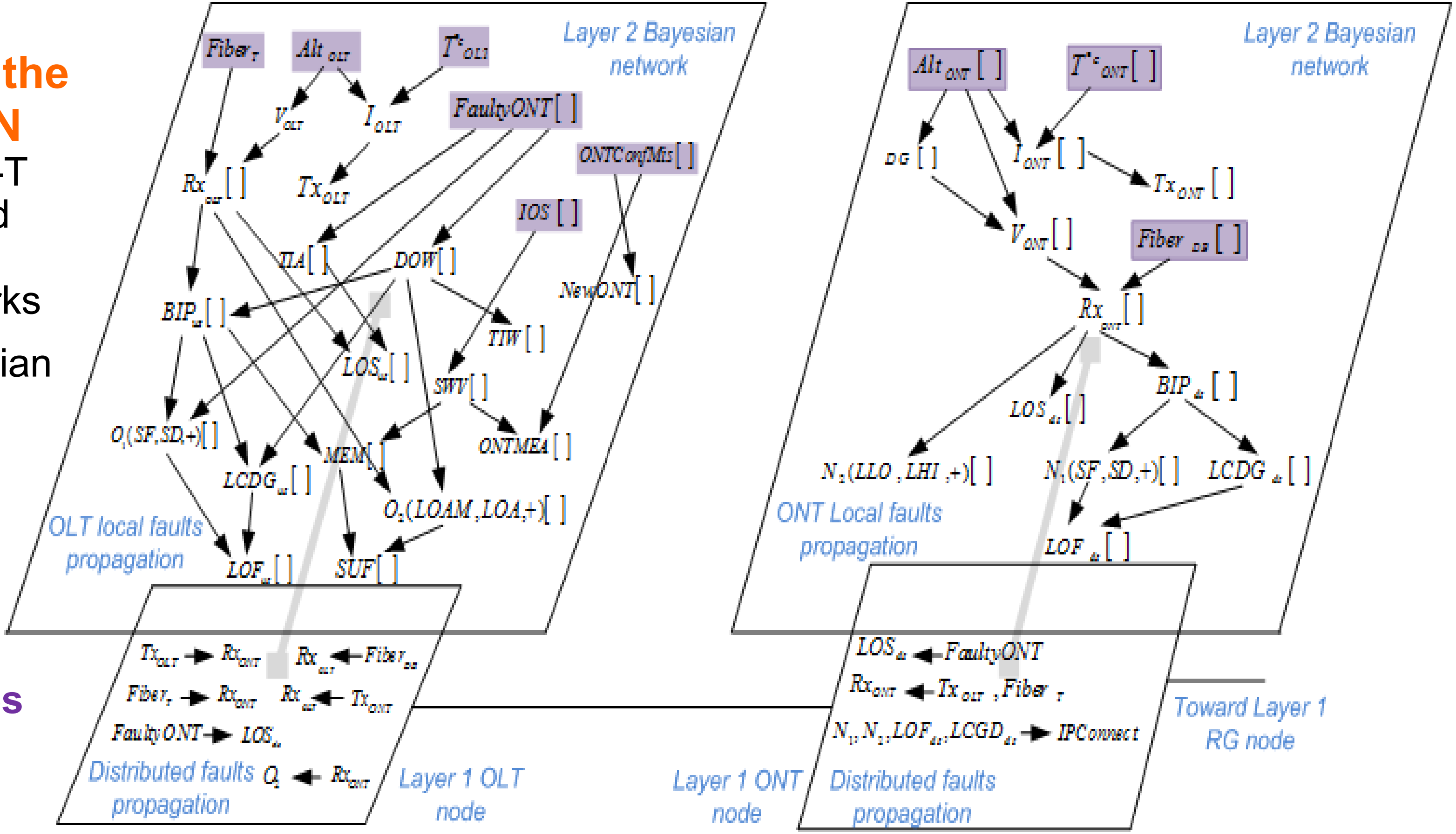


*Details on how to build Layer 3 from Layers 1 & 2 are given in S. R. Tembo et al., Journal of Network and Systems Management, pp. 1-33, Dec. 2016

PANDA: Probabilistic tool for GPON-FTTH Access Network self-DiAgnosis

Application of the model to GPON

- Based on ITU-T standards, and knowledge of current networks
- One L2 Bayesian network per component
- Nodes:
  - ➢ observed
  - ➢ computed
  - ➢ **root causes**



How PANDA works

Diagnosis computation

- Collected facts are injected in PANDA as evidence nodes
- Unobserved nodes are inferred based on model parameters
- Diagnosis → the most probable states of root nodes consistent with evidence nodes

Result example

- The root cause node « Feeder Fiber » shows a « AT » (Attenuation). The calculated belief = 97 %

Root causes	States	Beliefs
FiberT (feeder fiber)	[OK, AT, BR]	[0,02, 0.97, 0,01]

PANDA V1.0 – no training

PANDA V1.0: model parameters roughly guessed by the expert, no training
Confusion matrix between RBE (rows) and PANDA V1.0 (columns) over 10611 cases

Root causes	1	2	3	4	5	6	7	8	9
1. No default	7210		183	39			17		
2. Faulty ONT		3							
3. ONT configuration mistake			0						
4. Drop fiber attenuated				72			18		
5. Drop fiber broken					1463				
6. ONT power supply failure	2					780			
7. Feeder fiber attenuated							0		
8. Feeder fiber broken		1						57	
9. Unknown root cause	716	4		19		27			0

- ✓ PANDA always gives a conclusion
- ✓ When the RBE system gives a conclusion, both tools are aligned in 99% of the cases
- ✓ 24% of non-identified faults for RBE system
- ✓ BUT PANDA scope is smaller (FTTH only)

PANDA V2.0 – model parameters improved by machine learning

PANDA V1.0 → V2.0
Tuning of model parameters with machine learning

Principle

- in PANDA V1.0, dependencies $P(X_i = k \mid \text{parents}(X_i) = j)$ in the Bayesian networks have been roughly estimated by a human expert
- Dependencies are model parameters that can be estimated by maximizing the likelihood of a training dataset with respect to model parameters
- Maximum Likelihood Estimation has to be adapted in case of **incomplete** data, because the number of terms of the likelihood of observations is exponential with the number of missing variables → Expectation Maximization
- **Expectation Maximization** is an iterative algorithm composed of 2 steps per iteration:
  - ➢ E step: estimation of the expectation of the dataset likelihood under current model parameters, by inferring missing variables in the Bayesian networks
  - ➢ M step: maximization of this expectation to derive new model parameters

Implementation

- EM algorithm run on PANDA model parameters, starting from V1.0 parameters, based on a training data set of 5121 diagnosis cases. Convergence after ~7 iterations
- Details given in S. R. Tembo et al., IWCMC, Paphos, 2016, pp. 369-376

PANDA V2.0: machine learned model parameters (training data set of 5121 cases)
Confusion matrix between V1.0 (rows) and V2.0 (columns) over 5490 test cases

Root causes	1	2	3	4	5	6	7	8	9
1. No default	4030			6		7	9		
2. Faulty ONT		0							
3. ONT configuration mistake			183						
4. Drop fiber attenuated				56					
5. Drop fiber broken				14	602		1		
6. ONT power supply failure						402			
7. Feeder fiber attenuated		148					32		
8. Feeder fiber broken								0	
9. Unknown root cause									0

- ✓ Machine learning allows tuning of diagnosis decisions, but only in a few % of cases
- ✓ E.g. a « loss of frame » alarm results more consistently from an attenuated drop fiber than from a broken drop fiber
- ✓ Some cases lead to clearer decisions, although being uncertain from the expert viewpoint

Summary and final remarks

Summary and final remarks

Implementation of probabilistic modeling and machine learning for fault diagnosis in FTTH GPON networks

- Design and implementation of a 3-layer probabilistic model based on Bayesian networks
- Application to GPON fault diagnosis → PANDA tool
- Improvement of the model parameters through expectation maximization
- The PANDA approach handles unforeseen fault configurations, non-deterministic fault propagation and is robust to missing data

Artificial intelligence is no magic stick, but can be of great help for fault diagnosis

- Operational teams need easy-to-maintain tools, but also need to understand tool decisions
  - ➢ “Black box” approaches only-based on machine learning have to be avoided
- Model-based approaches tuned by machine learning are a promising intermediate path

Prospects

- Leverage on a **labelled** data set allowing detailed performance assessment compared with RBE system
- Investigate unsupervised approaches on non-labelled data sets (e.g. clustering of similar cases difficult to diagnose by a human expert) and semi-supervised learning on partly-labelled data sets

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