A Data-Driven Framework for Dynamic Trust Management

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International Conference on Computational Science ICCS2011

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Outline

- ✓ Trust and Reputation
- ✓ Reputation and trust-based models
- ✓ DDDAS inspired framework
- ✓ Case study/results
- ✓ Summary

Trust and Reputation

- ✓ **Trust**
- ✓ **Reputation**

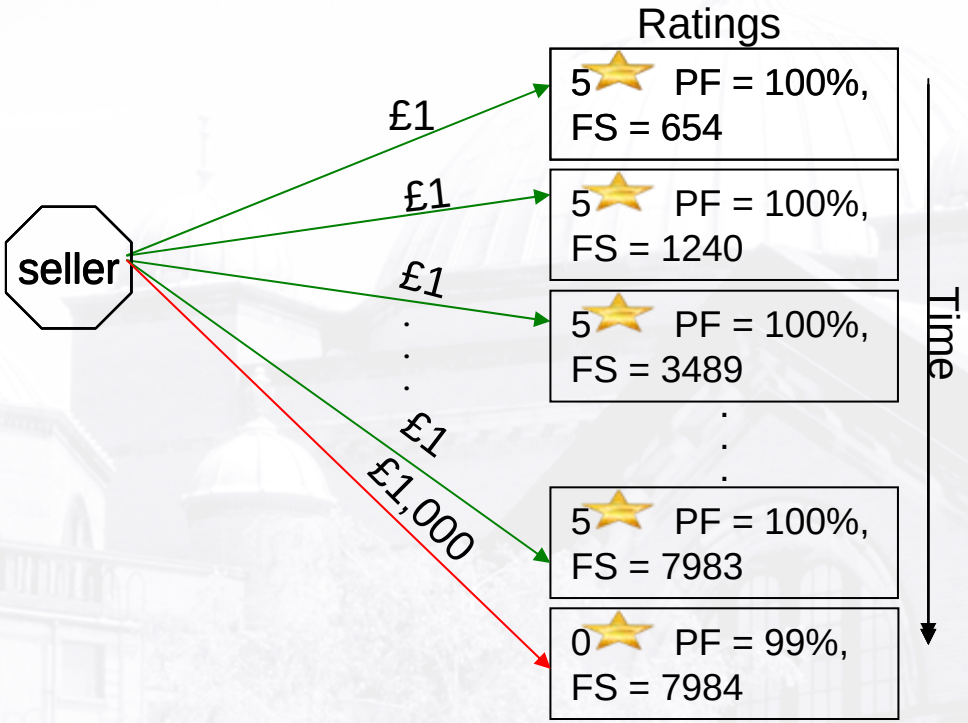
- ✓ **Trust management**

Reputation and trust-based models e.g
CORE, CONFIDANT, TrustGuard etc

- Domains
- Distinguish members
- Incentives / punishment
- Trust Values (TV)
- Watchdog (Collusion – trust decisions corrupted)
- Past histories (Intoxication)

Trust management: intoxication

- ✓ Assumption: predictive power depends on the supposition that past behaviour is an indication of future behaviour.
- ✓ Not true with *intoxication attacks.* Simple example, eBay.
- ✓ Difficult to identify - sudden misbehaviour.
- ✓ Effect of past good behaviour outweighs the effect of current actions on reputation.



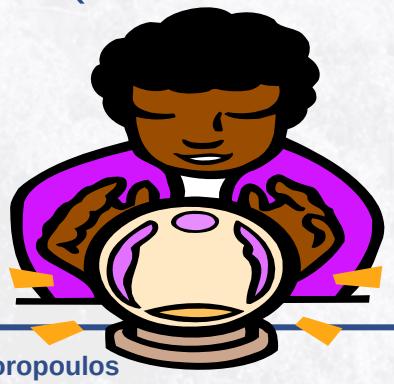
PF = Positive feedback ratings
FS = Feedback scores

Trust management: dynamic nature

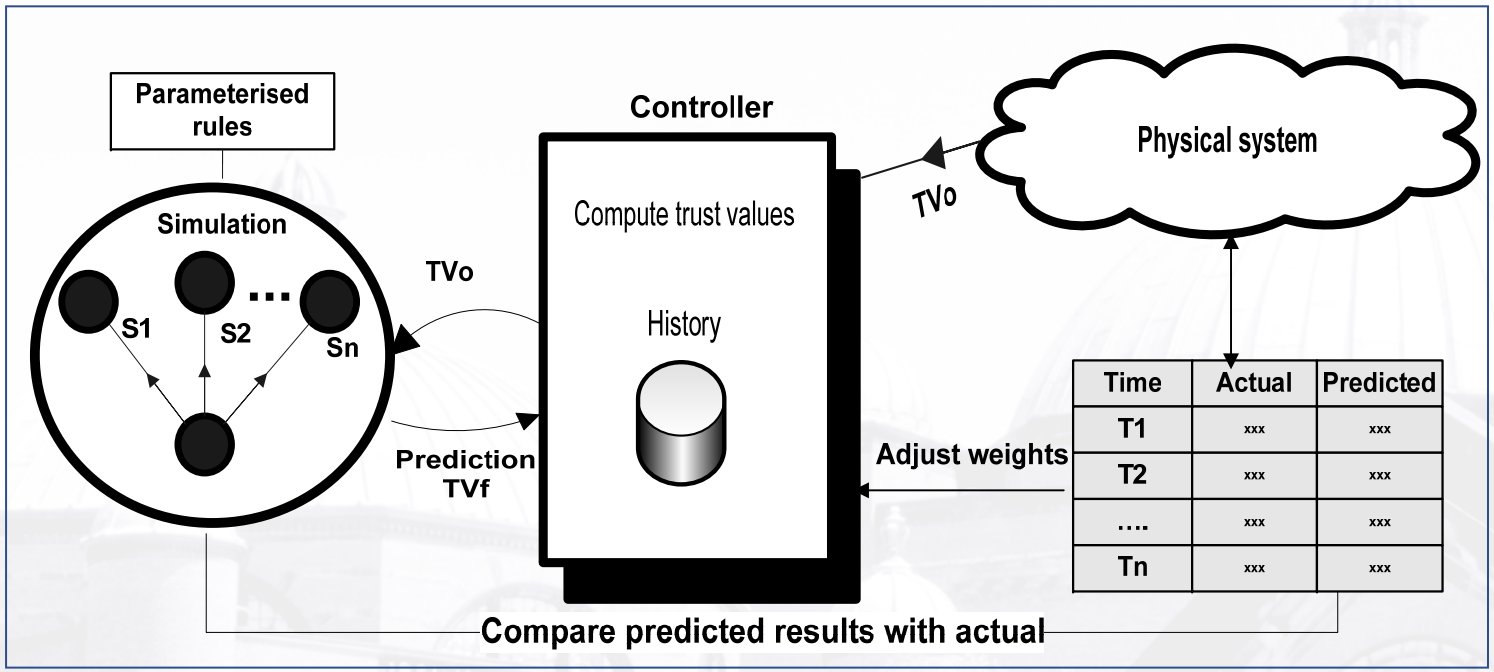
- ✓ Trust and reputation are not static but dynamic, computation of trust should be equally dynamic.
- ✓ Dynamic approach to identifying and isolating misbehaving (group of) members.

Requirements

- ✓ Dynamic online rating of members (data),
- ✓ Members' bias influencing trust decisions (as in the case watchdog) and
- ✓ Anticipate events and predict TVs.



Framework: components



Simulation

- ✓ Parameterised / behavioural rules
- ✓ Probabilities of collaboration / misbehaviour
- ✓ Scenario-based prediction of future ratings
- ✓ Focus of high risk members
- ✓ Compare with the real system and adjust weights (Feedback)

Real system

- ✓ Historical and recent online rating with weightings
- ✓ Qualitative data to quantitative value (Controller)
- ✓ Risk regions

Framework: trust values

$$tv^R = \mu_h tv_h^R + \mu_o tv_o^R$$

- ✓ Weights μ_h and μ_o - factors for the online and historical TVs.
- ✓ $[\mu_h, \mu_o] > 0$ and $\mu_o > \mu_h$, more emphasis on recent behaviour.

$$tv_f^S = \frac{(tv_o^S)\,S_1 + (tv_o^S)\,S_2 + (tv_o^S)\,S_3 + \cdots + (tv_o^S)\,S_n}{N}$$

$$TV = \mu_h tv_h^R + \mu_o tv_o^R + \mu_f tv_f^S$$

- ✓ tv_h^R, $tv^R{}_o$, $tv^S{}_o$ and $tv^S{}_f$ represent the historical, online TVs in the physical system, online TV in simulation and the predicted TV in simulation respectively.
- ✓ N is number of scenarios and $(S_1, S_2, \ldots Sn)$ are the scenarios.

Framework: trust table with level of risk

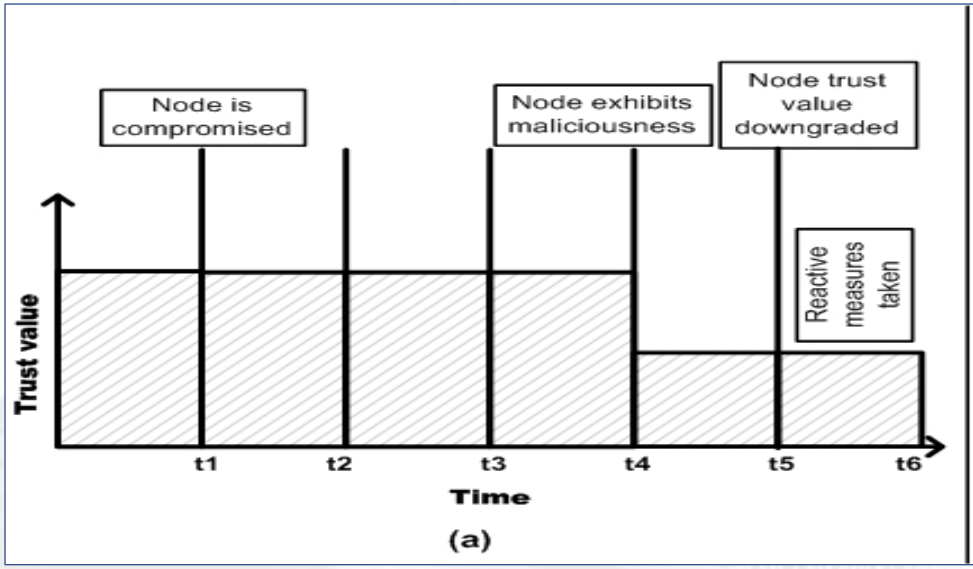
Trust table showing the degrees of trust and regions of risk

TV	Meaning	Description	Region
5	Complete trust	Trusted node with an excellent reputation	Low risk
4	Good trust level	Very reliable node	Low risk
3	Average trust level	Average value and somewhat reliable node	Medium risk
2	Average trust level	Average value but questionable node	Medium risk
1	Poor trust level	A questionable node	High risk
0	Complete distrust	Malicious node with a bad reputation	High risk

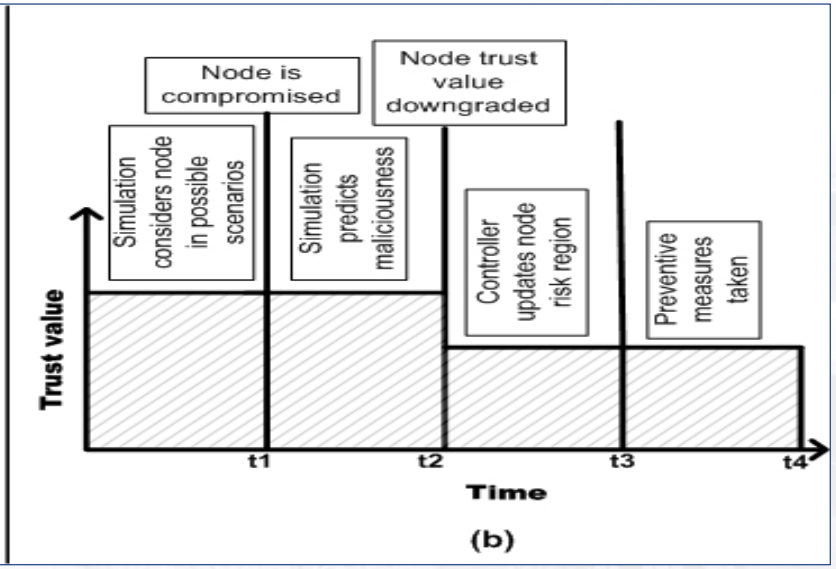
- ✓ Each value represents a degree of trust.
- ✓ Degrees of trust introduce flexibility into applications of our framework, as different behaviours correspond to different levels of trust.
- ✓ Region migration and reputation redemption takes longer.

Case study

Reactive



Proactive

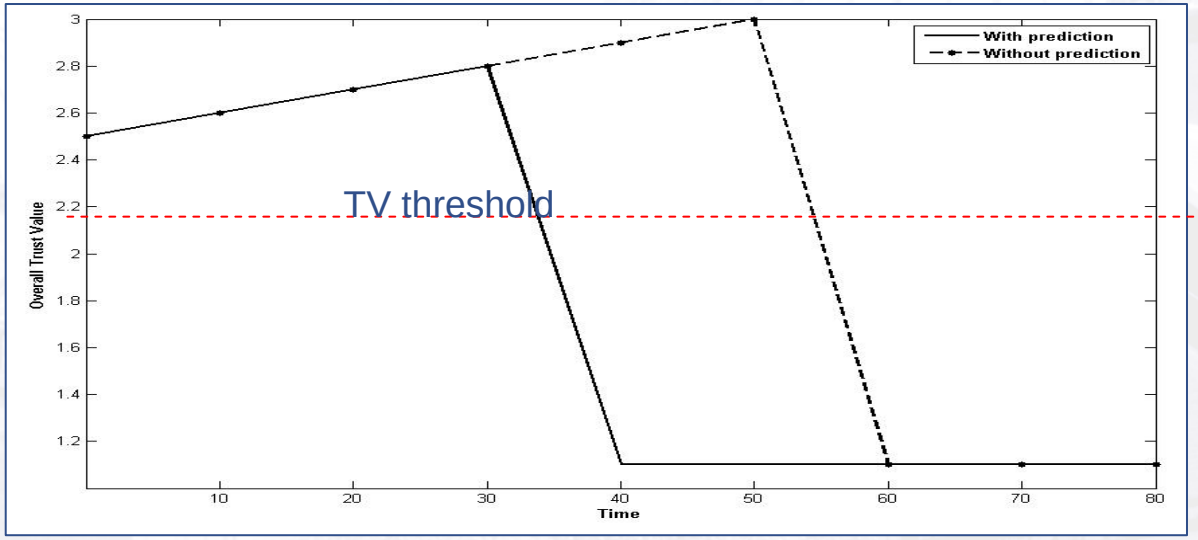


- ✓ Critical domains (P2P case study),
- ✓ The prediction gives the system enough time for preventive measures,
- ✓ Framework proactive compared to other models that are reactive in nature.

Case study

- ✓ Purpose: Test the performance the framework with and without prediction.
- ✓ Parameters: Maze p2p, 100 peers, 4% misbehave, 27 files transferred, μ_o = 0.5, μ_h = 0.3, μ_f = 0.2.
- ✓ Observation: Time difference of 20 ticks in identifying an intoxicating node.
- ✓ Lesson learnt: Framework has potential of better performance with prediction.

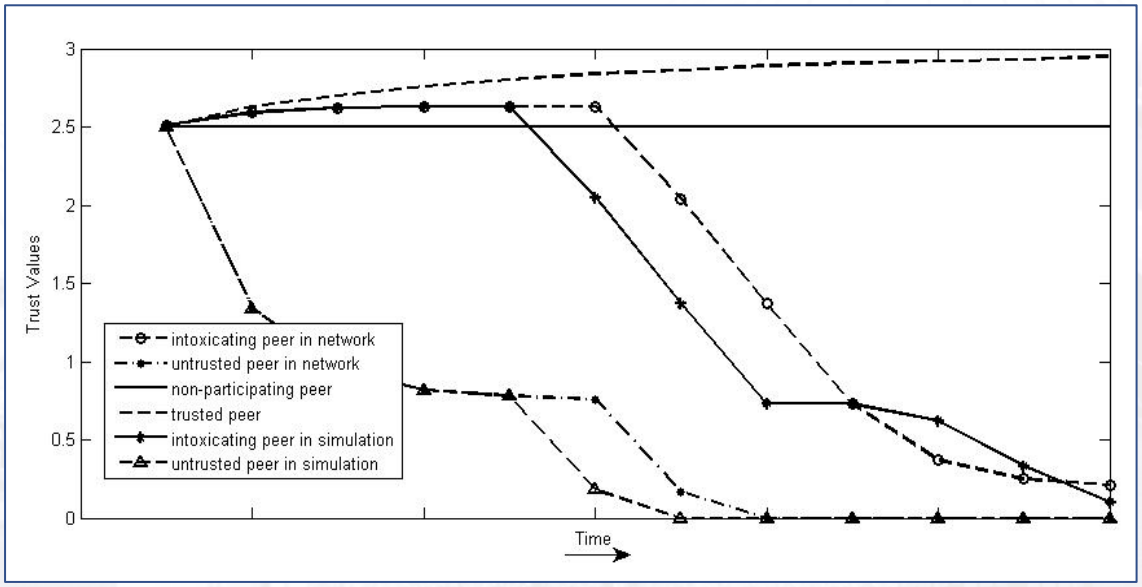
With prediction vs. without prediction



Case study

- ✓ Purpose: Compare real values with predicted values.
- ✓ Parameters: Maze p2p, 100 peers, 4% misbehave, 27 files transferred, μ_o = 0.5, μ_h = 0.3, μ_f = 0.2.
- ✓ Observation: Prediction not accurate but reflects reality.
- ✓ Lesson learnt: False positives and negatives.

Trust values of peers in the P2P network and simulation



Summary

- ✓ Framework has the potential of providing a high level of dynamism to trust and reputation systems allowing for a more realistic analysis of the system and enabling predictions.
- ✓ Results suggest that hypothesis is most likely correct based on the scenarios considered.
- ✓ Preventive mechanisms for avoiding collusion and intoxication attacks.
- ✓ Future challenges
  - Validation – accuracy of predictions, rate of false positives and negatives.
  - Evaluation of performance.
  - Emerging attacks.

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