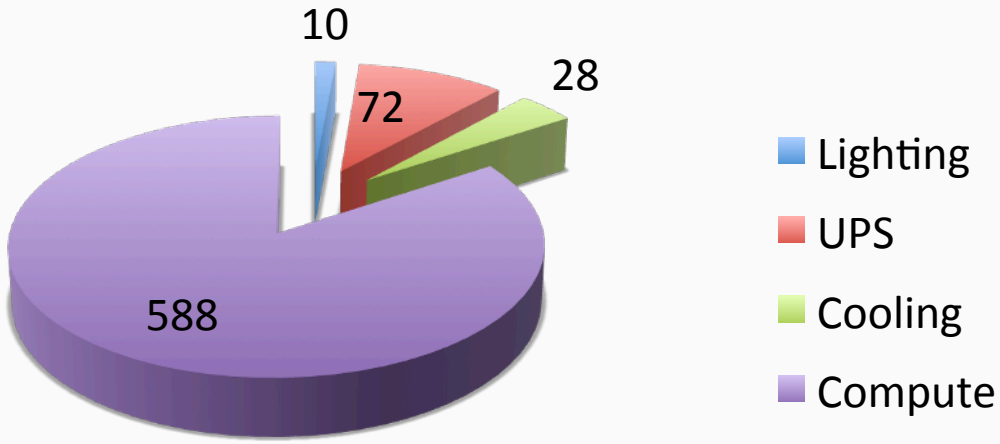
ENERGY EFFICIENT CONTROL OF VIRTUAL MACHINE CONSOLIDATION UNDER UNCERTAIN INPUT PARAMETERS FOR GREEN CLOUDS

ENERGY SAVING IN VIRTUALIZED DATACENTERS

- Assume small datacenter, 1064 Servers



  - Out of the 588 KW for Compute/Network
    - 44% are for processor, server power supply and other server components (in total 258 kW), → This is what we try to optimize
    - 4% for storage
    - 4% for communication equipment
  - Saving 1 W for processing saves additional 1.84 W for other components

ENERGY SAVING IN VIRTUALIZED DATACENTERS

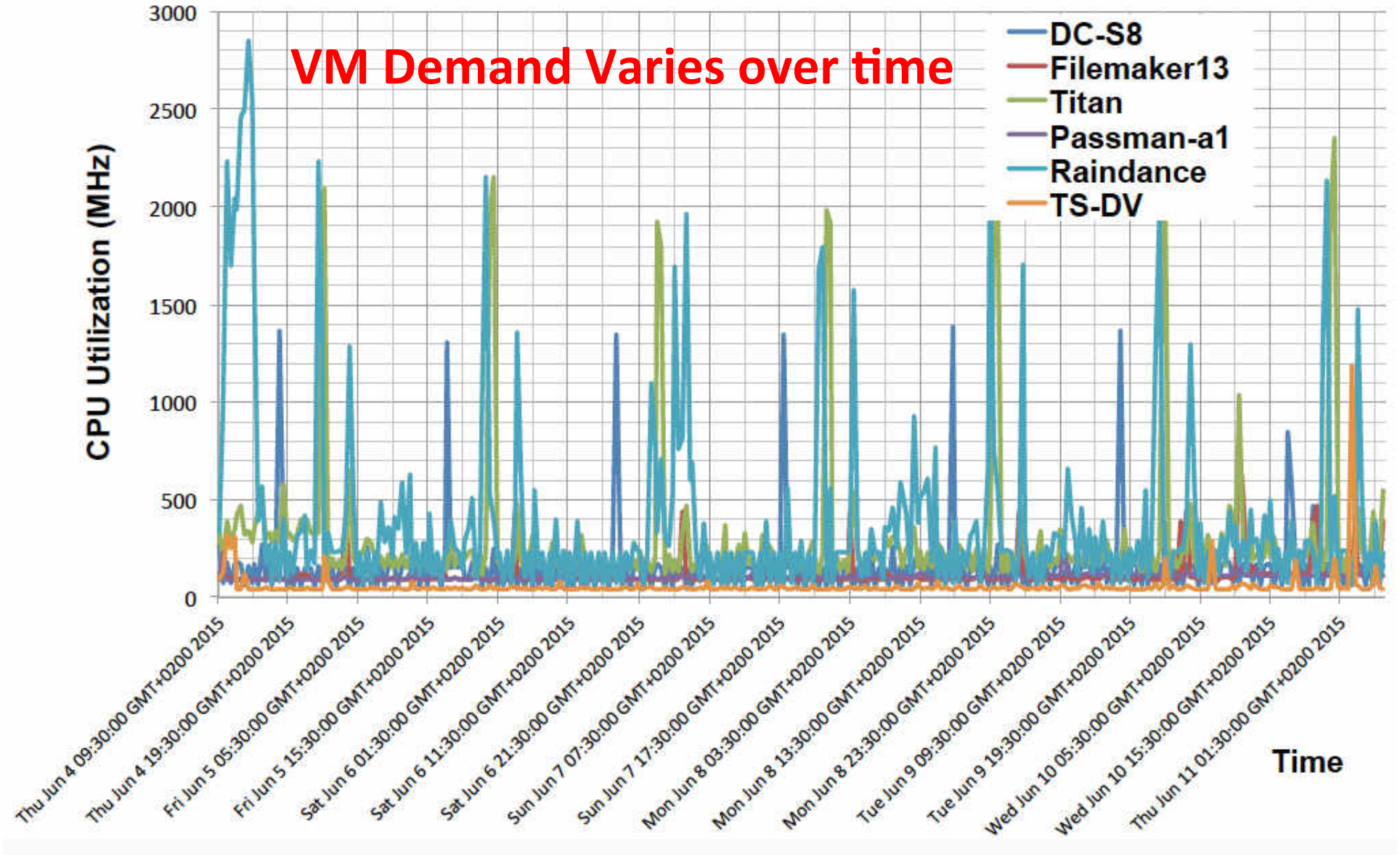
- For example, save 20% energy for this datacenter results in:
  - Total CO2 footprint avoided per year
    - 846t California
    - 690t Sweden
    - 1387t China
    - 1407t Australia
  - Monetary savings per year
    - 167.000 USD for California
    - 1.335.000 SEK for Sweden
    - 872.000 Yuan for China
    - 141.000 $ for Australia

VM CONSOLIDATION: MOTIVATION

VM Workload

- Varies over time due to unpredictable workload
- May require
  - VM resizing, VM creation, VM termination
- Result in the physical servers to be
  - Underutilized
  - Overutilized
- Consequences for Cloud Operators
  - SLA Violations versus Minimum Energy Consumption
- Case Study
  - Evaluated Workload of 6 VMs in KAU Compute Service Department

VM CONSOLIDATION: KAU WORKLOAD TRACES



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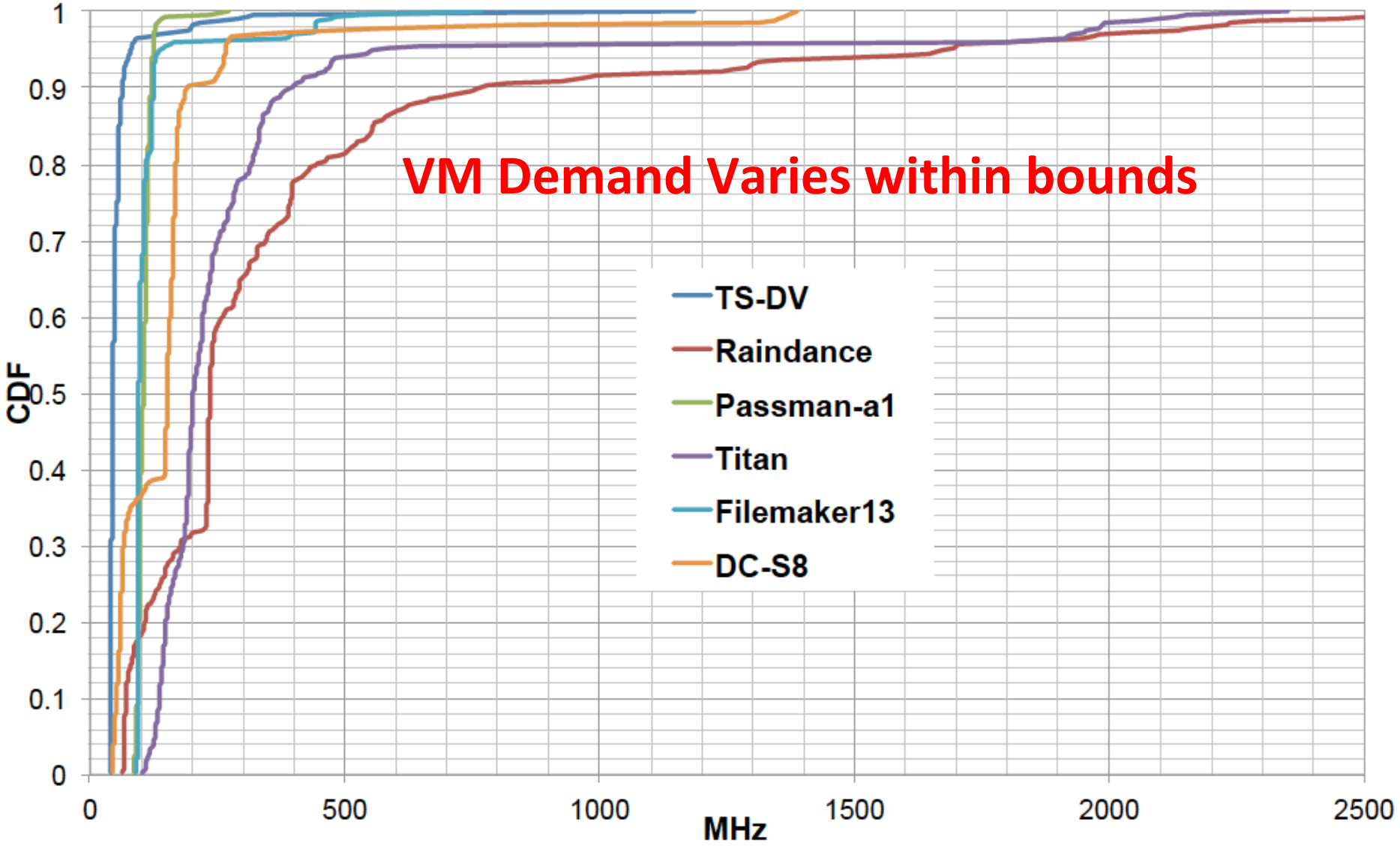
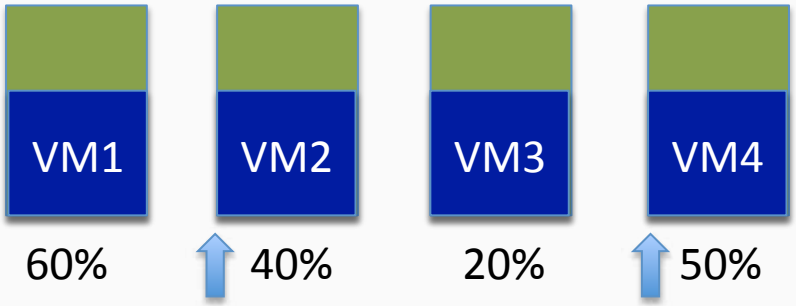
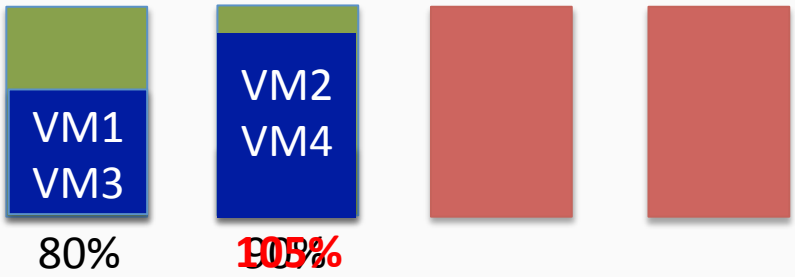


VM CONSOLIDATION - REVISITIED

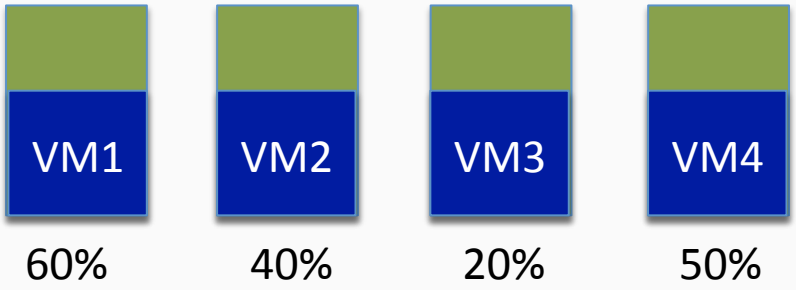


VM demands vary over time…
SLA may be violated!!!



GOAL: Provide a solution that is **robust** against input variability

VM CONSOLIDATION - REVISITED



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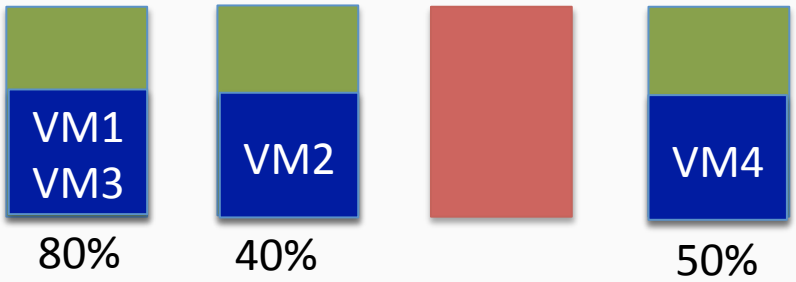


GOAL: Provide a solution that is **robust** against input variability

Deterministic Optimization: Too conservative

Apply robust optimization theory

Higher energy consumption and more unused resources
Less probability of SLA violation

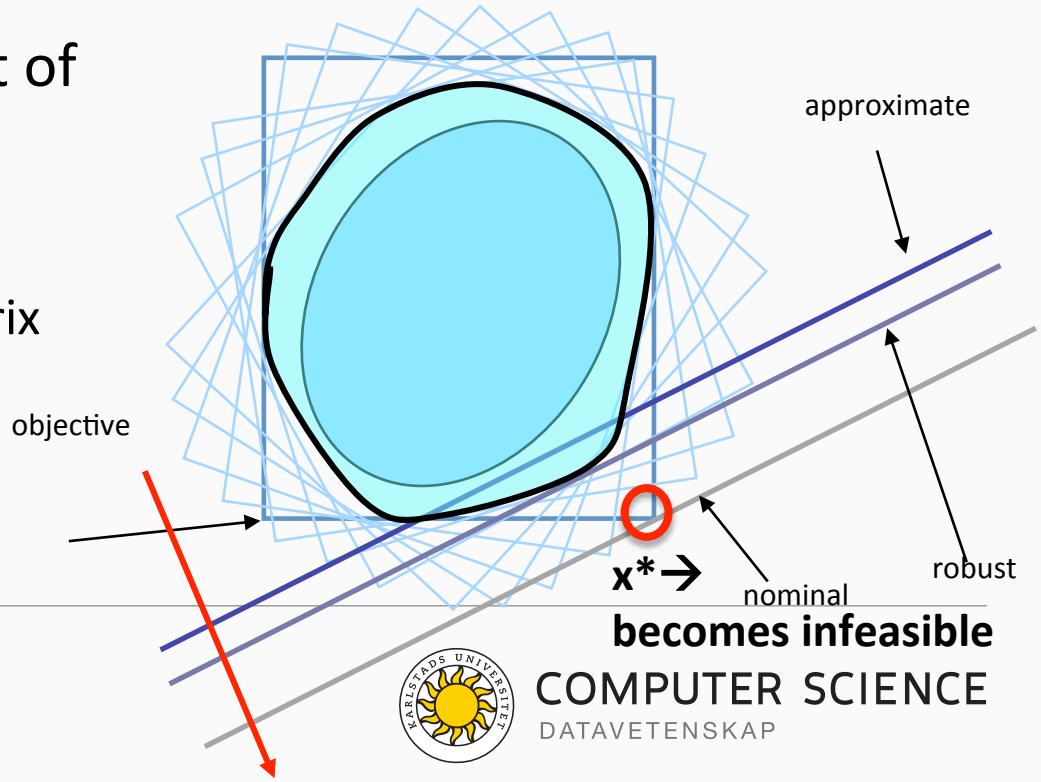
CLASSICAL OPTIMIZATION FRAMEWORKS

- Almost all models for Cloud (any?) Optimisation (e.g. VM Consolidation) assume perfect knowledge!
  - **MIN $c^T(x)$ s.t. Ax<=b**
  - **Once x* calculated, it is used**
- BUT: Many factors not known precisely, e.g.
  - VM Resource Demands
  - Energy Model of Servers
  - We can only assume incomplete knowledge in A, b, c
- Consequence (Ben Tal+Nemirovski, 2000): Small errors in parameters can make x* highly unfeasible

ROBUST OPTIMIZATION PARADIGM

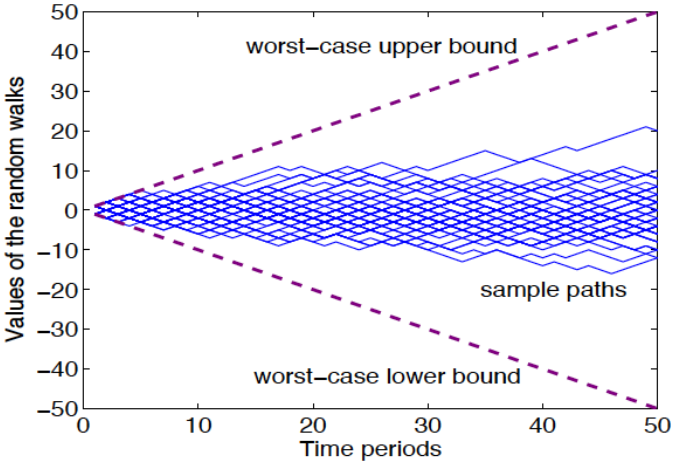
- Assume uncertainty model for data is known (e.g. bounds)
- Define a solution is robust feasible as one that is guaranteed to remain feasible for all admissible data values (out of uncertainty set U)
- Optimize objective over set of robustly feasible solutions
- Robust counterpart
  - a_i' i-th row of uncertain matrix

$$\begin{aligned} &\textit{minimize} \;\; c'x \\ &s.t. \;\; \min_{a_i \in U} \; a_i'x \leq b_i, \quad \forall i, \end{aligned}$$



ROBUST VM CONSOLIDATION MODEL

- ROBUST Mixed Integer Linear Problem
  - Solution x* is robust feasible if it satisfies all uncertain constraints $[a_i' x \leq b, \forall a_i' \in U]$
  - Robust counterpart
    - Typically has infinite number of constraints
    - Depends on uncertainty set U
    - Solution typically has worse objective value
    - Tries to mitigate adverse effects of uncertainty
  - Special case: cardinality constraint uncertainty set (Bertsimas, Sim)
    - Polyhedral uncertainty set, budget of uncertainty in terms of cardinality constraints
    - Each coefficient in matrix is within $[a'_{ij} - \hat{a}'_{ij}, a'_{ij} + \hat{a}'_{ij}]$, max Γ_i coefficients deviate
    - Robust counterpart becomes after duality



$$
\begin{aligned}
&\textit{minimize } c'x \\
&s.t.\ \textstyle\sum_j a_{ij}x_j + z_i\Gamma_i + \sum_j p_{ij} \leq b_i \quad \forall i, \\
&z_i + p_{ij} \geq \hat{a}_{ij}y_j \qquad \forall i,j, \\
&-y_j \leq x_j \leq y_j \qquad \forall j, \\
&l \leq x \leq u, \\
&p \geq 0, \\
&y \geq 0
\end{aligned}
$$

UNCERTAINTY ON SERVER POWER MODEL

- Power of server can be modeled as linear function of resource utilization (e.g. CPU load, etc)
  - But errors up to 10-14% due to processor optimizations, etc
  - Power consumption is random variable from uncertainty set symmetrically distributed between with zero mean
  - Decision variable
  - Constraints depend on VM utilization, see next slide

$$uncP_{\Delta P_j, j}$$

$$[-\Delta P_j, +\Delta P_j] \cdot P_{max,j}$$

y_j is 1 if j is active after the consolidation, 0 otherwise

$$P_j = P_{idle,j} \cdot y_j + (P_{max,j} - P_{idle,j}) \cdot u_{ij} + uncP_{\Delta P_j, j} \cdot y_j, \quad i = CPU \tag{2}$$

$$P_{idle,j} \cdot y_j \leq P_j \leq P_{max,j} \cdot y_j \quad \forall j \tag{3}$$

P_j power consumption at server j after consolidation

UNCERTAINTY ON VM RESOURCE DEMANDS

- Power consumption depends on resource demands of VMs, which are uncertain
  - Resource demand is random variable symmetrically distributed with zero mean plus fixed demand

$$uncR_{\Delta R_k,k}$$

$$[-\Delta R_k, +\Delta R_k] \cdot r_{ik} \ (i=CPU)$$

x_{jk}^N is 1 if VM k is allocated to server j after consolidation, and 0 otherwise

  - Utilization

$$u_{ij} = \frac{\sum_{k=1}^{m} (r_{ik} + uncR_{\Delta R_k,k}) \cdot x_{jk}^N}{s_{ij}} \quad (4)$$

  - Budget constraint

Resource demands of Old assignment

VMs migrating towards server

$$\sum_{k=1}^{m} \left[(r_{ik} \cdot x_{jk}^O) + (r_{ik} + uncR_{\Delta R_k,k} + rovh_{ik}) \cdot z_{jk}^{<-} - (r_{ik} + uncR_{\Delta R_k,k} - rovh_{ik}) \cdot z_{jk}^{->} \right] \leq \eta_j \cdot (s_{ij} \cdot y_j) \quad (6)$$

VMs migrating away

Overprovisioning Factor

UNCERTAINTY MODEL – PRICE OF ROBUSTNESS

- Uncertainty set for cardinality constraint
  - Defines deviations from nominal values, i.e. mean values plus deviation bounds
  - Protection from deviation by introducing hard constraints that cut-off feasible solutions that may become unfeasible ones for some deviations

$$\sum_{j=1}^{n}\left|\frac{uncP_{\Delta P_j,j}}{\Delta P_j}\right| \leq \Gamma, \qquad \sum_{k=1}^{m}\left|\frac{uncR_{\Delta R_k,k}}{\Delta R_k}\right| \leq \Gamma \qquad (5)$$

- Price of robustness
  - Cloud Operator can tradeoff by modifying Γ
  - Higher risk aversion → consider more unlikely deviations → higher protection → higher energy consumption
  - Opportunistic solution → less protection → less energy consumption

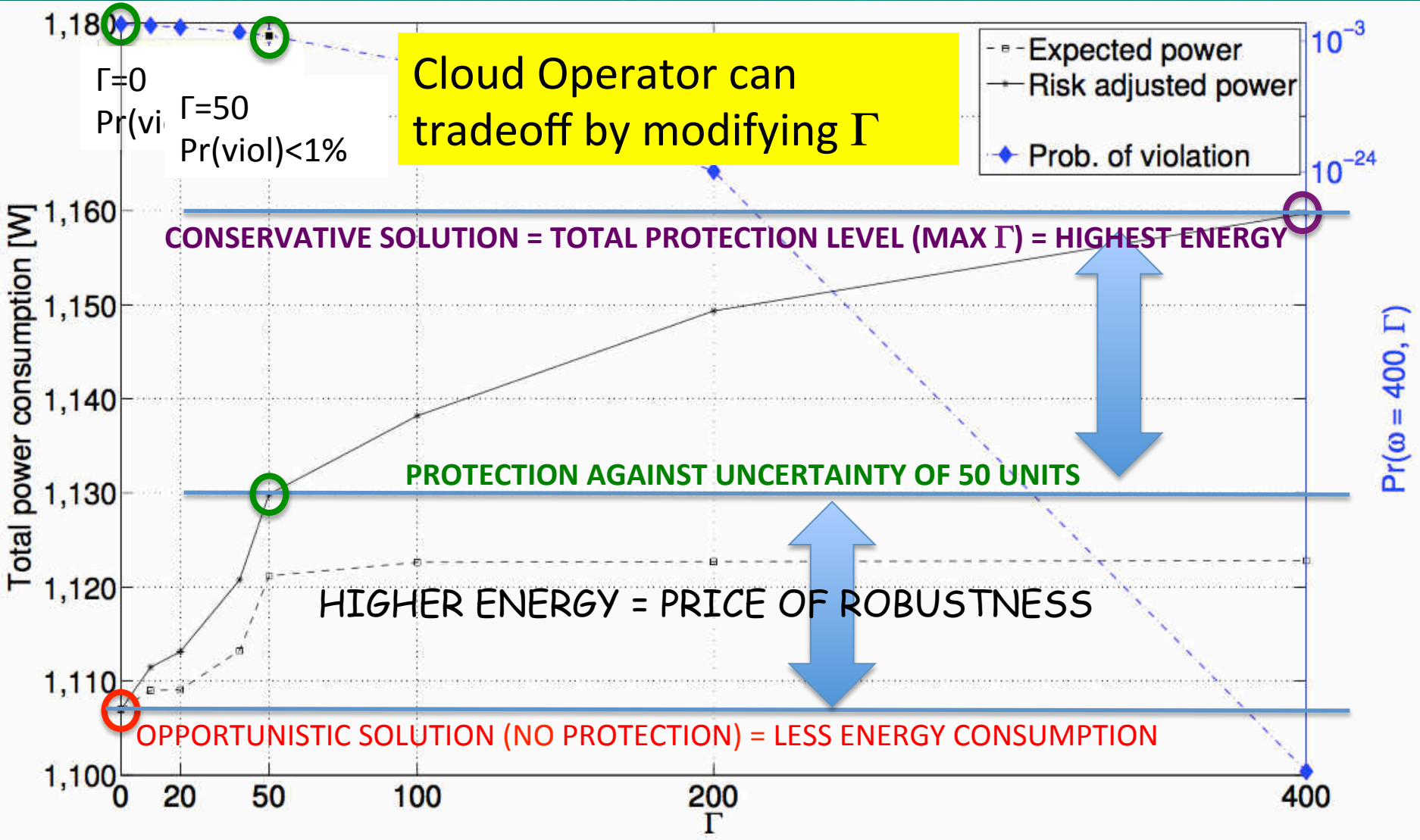
HOW MUCH RISK TO TAKE? TUNING OF Γ

EVALUATION

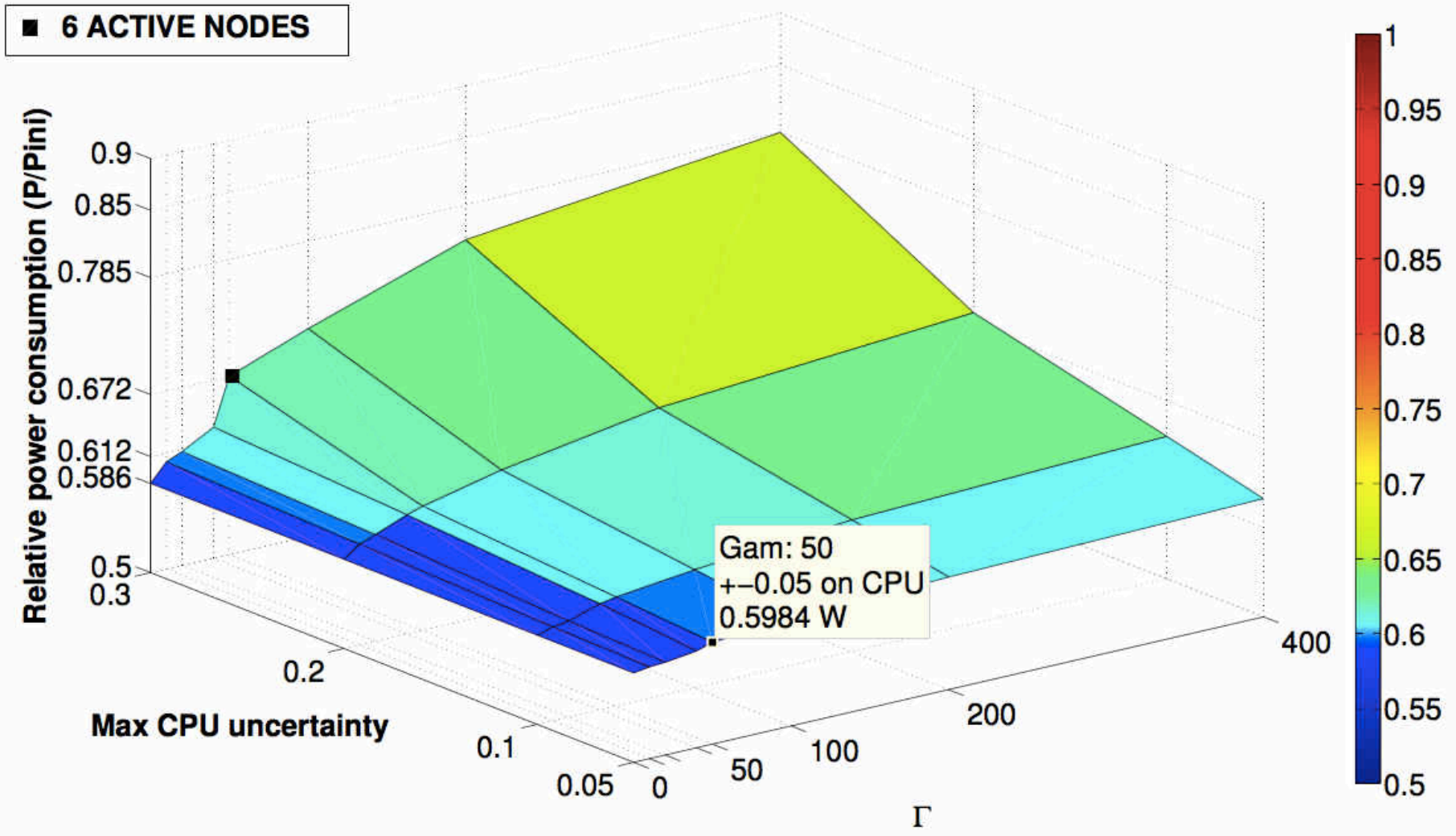
- Implementation in Matlab with IBM CPLEX
- Not suitable for online optimization
- Benchmark for heuristics
- Small example to demonstrate model capabilities
  - 0.1 CPU = 1 core
  - 0.1 RAM = 512 MB

Parameter	Value - CPU
n	10
m	400
$P_{max,j}$ [W]	rand(160; 290)
$P_{idle,j}$	rand(0.2; 0.4) $\cdot P_{max,j}$
CPU cores ($r_{1,k}$)	rand(1; 8)
RAM [GB]	rand(1; 5)
Avail. CPU cores ($s_{1,j}$)	rand(64; 512)
Avail. RAM [GB]	rand(3; 524)
α	0.9
ΔR_k	[0.05, 0.1, 0.2, 0.3]
Γ	[0,10,20,40,50,100,200,400]
ω	m

CPU DEMANDS UNCERTAIN (Δ=5%)

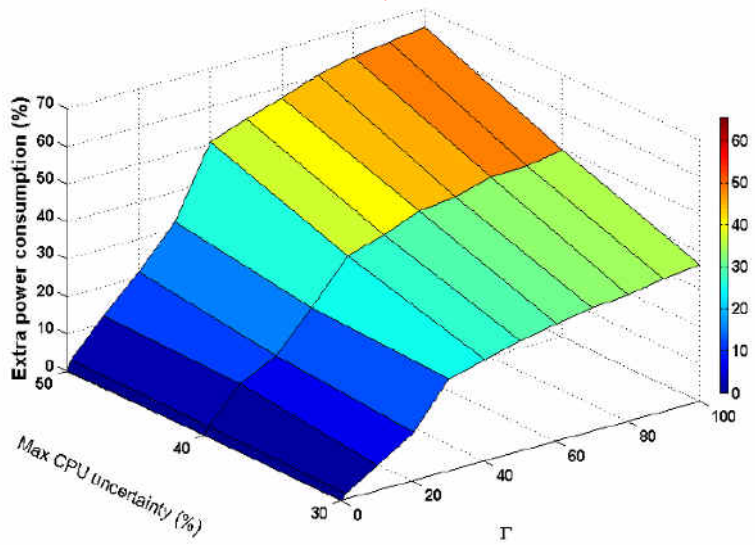


CPU DEMANDS UNCERTAIN

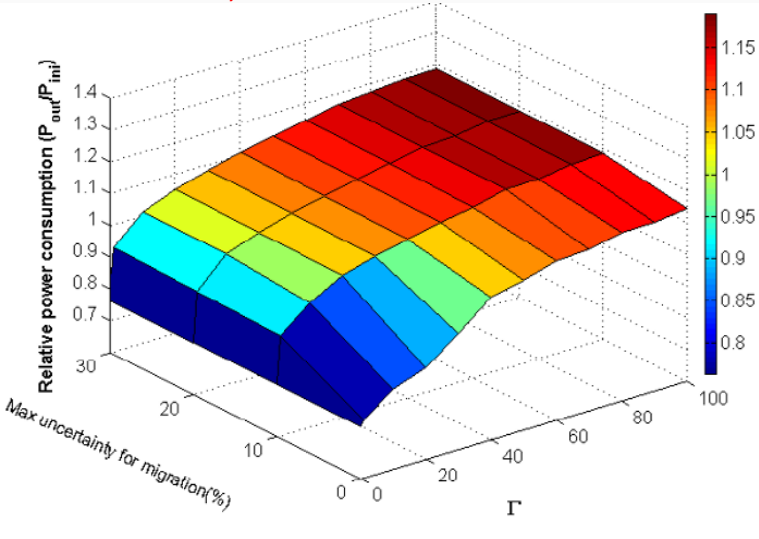


CPU DEMANDS UNCERTAIN – LARGE INSTANCE (100/14)

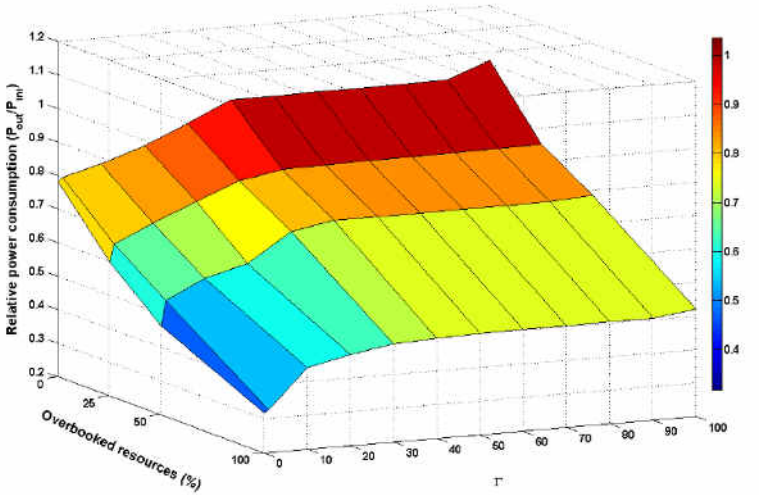
ADDITIONAL POWER, NO OVERBOOKING



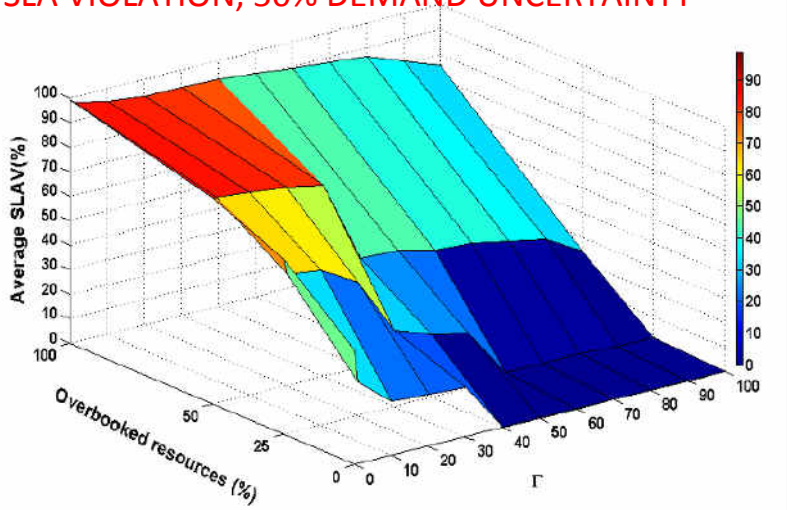
RELATIVE POWER, 40% UNCERTAINTY ON DEMAND



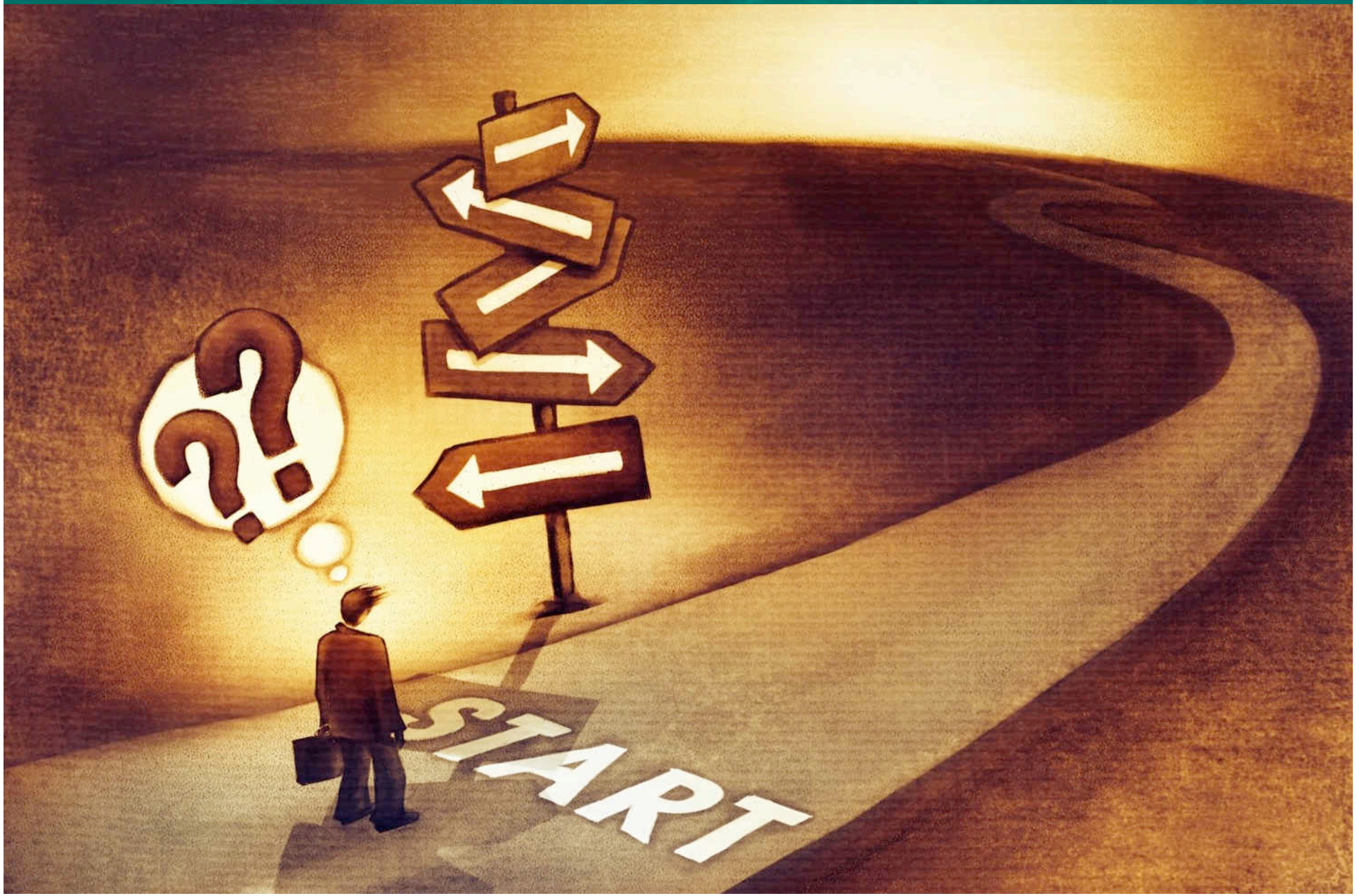
EXPECTED POWER, 50% DEMAND UNCERTAINTY



SLA VIOLATION, 50% DEMAND UNCERTAINTY



CONCLUSIONS AND FUTURE WORK

- **Conclusions**
  - Applied Robust Optimization Framework to cope with unknown and imprecise input data to VM Consolidation problem
  - Uncertainty on VM resource demands and Power model of servers
  - Γ uncertainty and constraint violation probability gives Cloud operators a tool to tradeoff robustness versus energy efficiency
  - Many more results with enhanced model with e.g. resource overbooking
- **Future work**
  - Comparison with robust heuristics
  - Integration of network model and NFV concept (service chain)
  - Apply Robust Optimization to 5G Network Optimization

THANK YOU FOR YOUR ATTENTION!