

ICEIS 2026

28th International Conference on Enterprise Information Systems
Benidorm, Spain | 22 - 24 May, 2026

ENASE 2026

21st International Conference on Evaluation of Novel Approaches to Software Engineering
BENIDORM, SPAIN | 22 - 24 MAY, 2026

ICEIS and ENASE 2026 Keynote Address

Decision Guidance Systems and their Applications

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Acknowledgements: my PhD students

Current

- Xu (Ethan) Han, *Decision Guidance Framework for Markets of Virtual Things*
- Anita Tadakamalla, *Guiding Decisions for Pareto-optimal Pandemic Interventions*
- Tahani Almanie, *OptiGuide: Interactive Decision Guidance System for Model-based Package Recommenders*
- Archange Destine, *Models and Algorithms for Unmanned Ground Vehicles in 3D Environments*
- Shriniketh Daylu, *Decision Guidance Assistant for Swarms of Unmanned Aerial Vehicles*
- Rana Alshehri, *Agentic AI Framework for Model-Based Decision Guidance*

Graduated

- Dr. Yong Xue, *Optimal Multidomain Provisioning of Virtual Networks*, 2025
- Prof. Bedor Alyahya, *Service Network Optimization to Guide Decisions on Infrastructure Investment*, 2023
- Dr. Mohan Krishnamoorthy, *Manufacturing Processes: Languages and Algorithms for Descriptive, Predictive and Prescriptive Analytics*, 2024
- Dr. Omar Nachawati, *Greybox Optimization Algorithms for Decision Guidance Management Systems*, 2021
- Dr. Roberto Levy, *A Decision Guidance Framework for Energy Public Policy and Investment*, 2022
- Dr. Fernando Boccanera, *Decision Guidance for Optimal Software Release Scheduling*, 2022
- Prof. Hanan Mengash, *Group Decision Guidance for Recommenders with Composite Alternatives*, 2016.
- Prof. Hesham Altaleb, *Market-based Decision Guidance for Electric Power Consortia*, 2015.
- Dr. John McDowal, *A Framework for Optimal Service Composition and Execution Based on Business Process Management Notation*, 2014
- Dr. Nathan Egge, *Decision Guidance Query Language (DGQL): Algorithms based on Preprocessing and Continuous Approximations*, 2014.
- Dr. Susan Farley, *Top-k Algorithms for SimQL: A Decision Guidance Query Language Based on Stochastic Simulation*, 2013.
- Prof. Ben Ngan, *A Framework and Algorithms for Multivariate Time Series Analytics: Learning, Monitoring, and Recommendation*, 2013.
- Dr. Gordon Shao, *Decision Guidance for Sustainable Manufacturing*, 2013.
- Prof. Judy Luo, *Regression Learning in Decision Guidance Systems: Models, Languages and Algorithms*, 2012.
- Dr. Khalid Alodhaibi, *Decision-Guided Recommenders with Composite Alternatives*, 2011.
- Dr. Lei Zhang, *Securing the Information Disclosure Process*, 2010.
- Prof. Malak Al-Nury, *Service Composition Framework to Unify Simulation and Optimization in Supply Chains*, 2010.
- Prof. Csilla Farkas, *Secure Databases: Constraints, Inference Channels and Monitoring Disclosures*, 1999.
- Dr. Jia Chen, *Multityped Constraint Algebras and Mathematical Programming in Constraint Databases*, 1999.
- Dr. Victor Segal, *Algorithms, Optimization and Implementation of Constraint Object-Oriented Database System*, 1999.
- Prof. Samuel Varas *On Optimal Constraint Decomposition, Monitoring and Management in Distributed Environments*, 1998.



Decision Guidance Systems: Why & What



Decision Guidance (DG) systems are a class of decision support systems geared to

- **elicit knowledge** from domain experts and stakeholders and
- **provide actionable recommendations** to human decision-makers with the goal of arriving at the **best possible course of action**.



Decision Guidance Systems (DGS) need to

- use and mine large amounts of data
- elicit knowledge about model structure from domain experts
- learn deterministic or stochastic models
- elicit metrics, KPI and decision objectives from decision makers
- perform analytic tasks
 - descriptive (e.g., monitoring)
 - diagnostic
 - predictive
 - prescriptive (deterministic or stochastic optimization)
 - pareto trade-off analysis
- explain actionable pareto-opt alternatives to decision-makers
- solicit decision-makers feedback for iterative improvement
- support group decisions

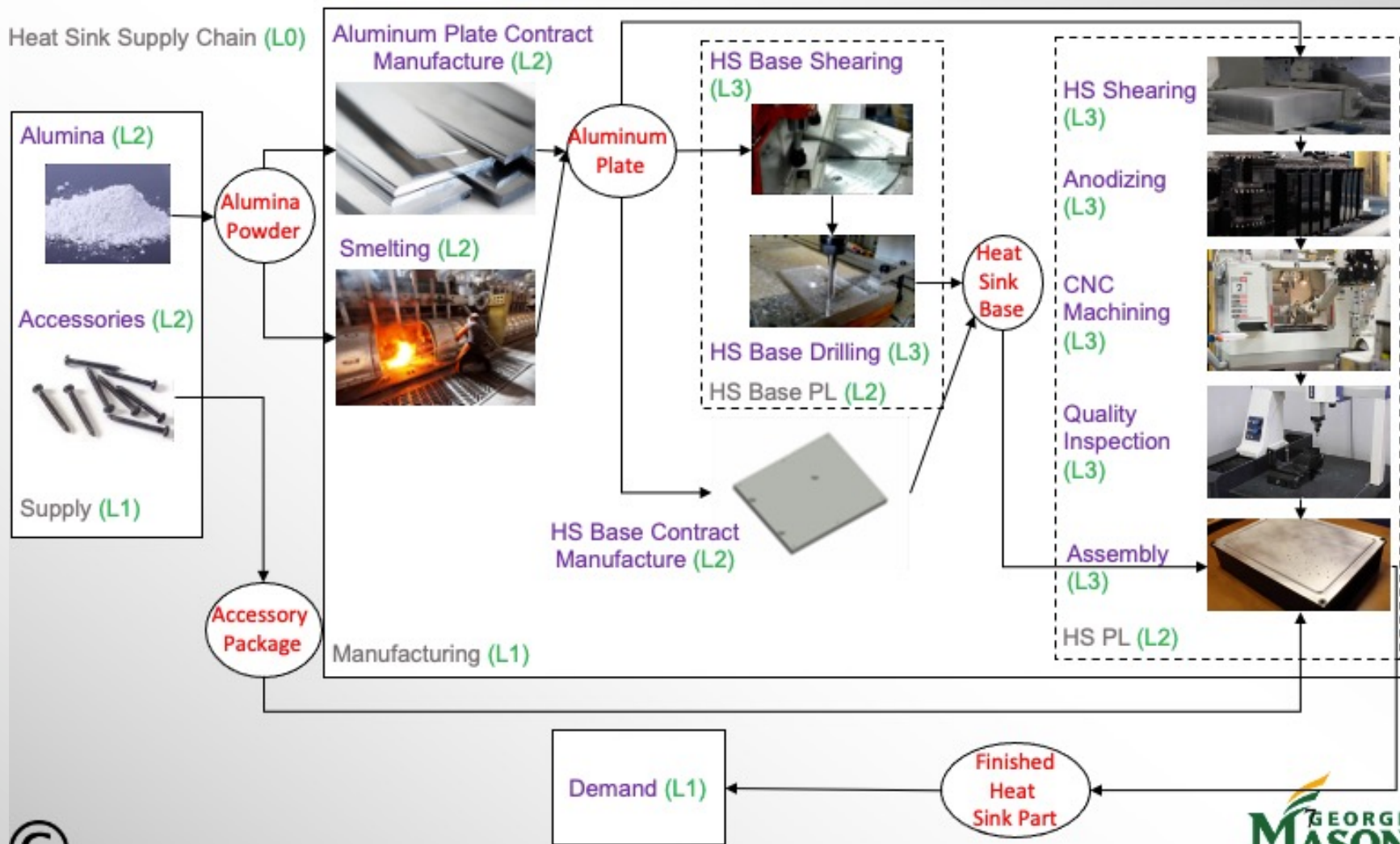


Outline

- DG applications by example
- DG Tools:
 - DG Analytics Language (DGAL) & Management System (DGMS)
 - Interactive DG for Virtual Things (DG-ViTh & OptiGuide)
- DG Algorithms: brief overview
- DG Applications
 - Green Assessment and DG Tool (GADGET): toward carbon neutrality
 - DG System for Comprehensive Pandemic Mitigation with Pareto-Optimal health, cost and productivity outcomes (GS-Mitigate)
- Grand Challenge: AI Agentic Framework for Model-Based Decision Guidance



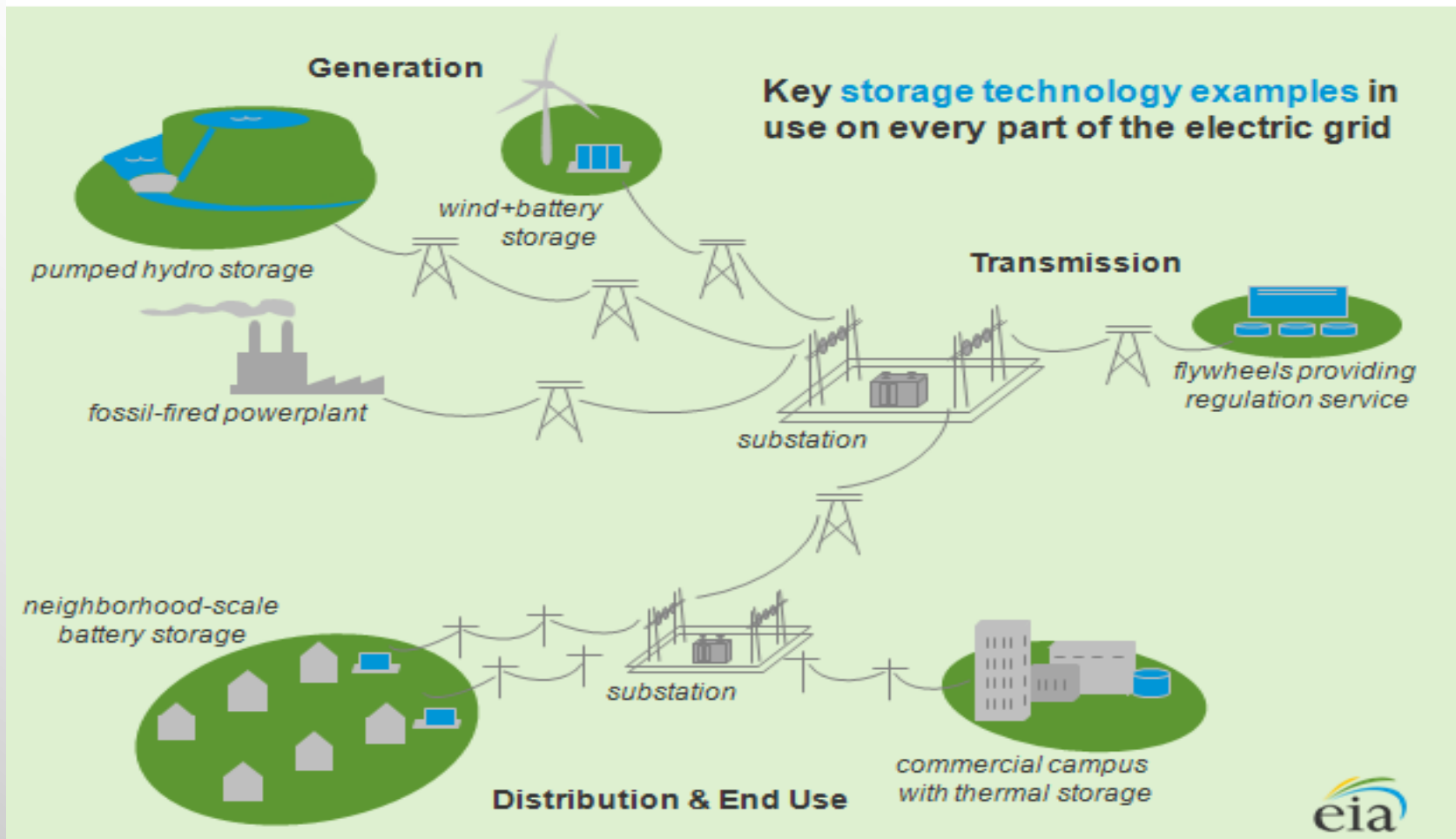
FACTORY OPTIMA for Pareto-Optimal manufacturing and supply chain service networks
 GMU project for NIST



Example: Renewable Power and Storage

GMU project for Dominion Virginia Power

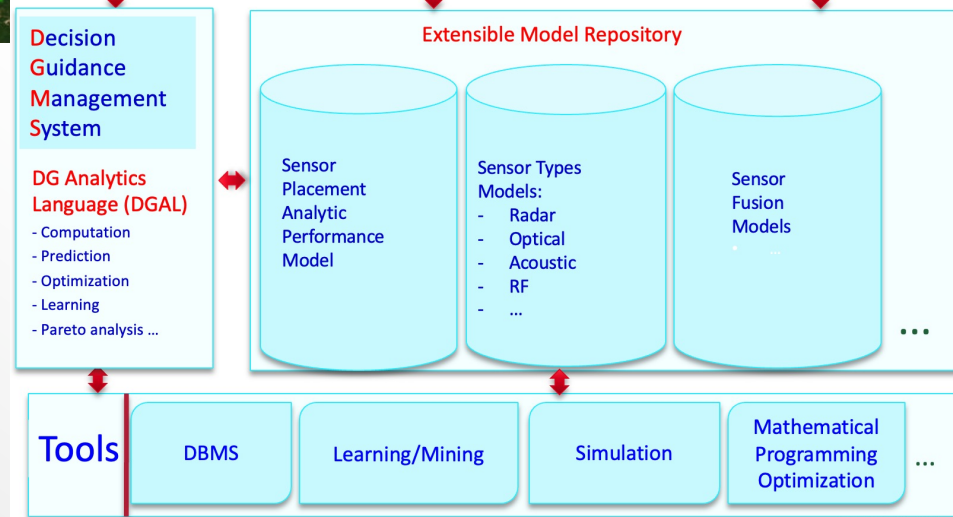
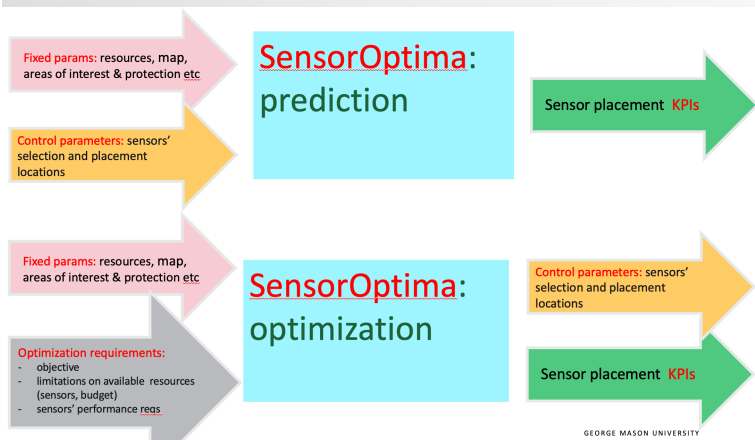
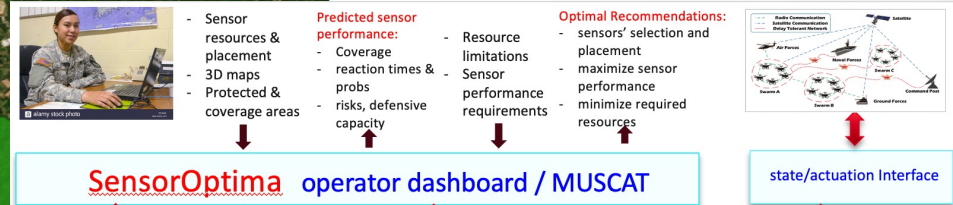
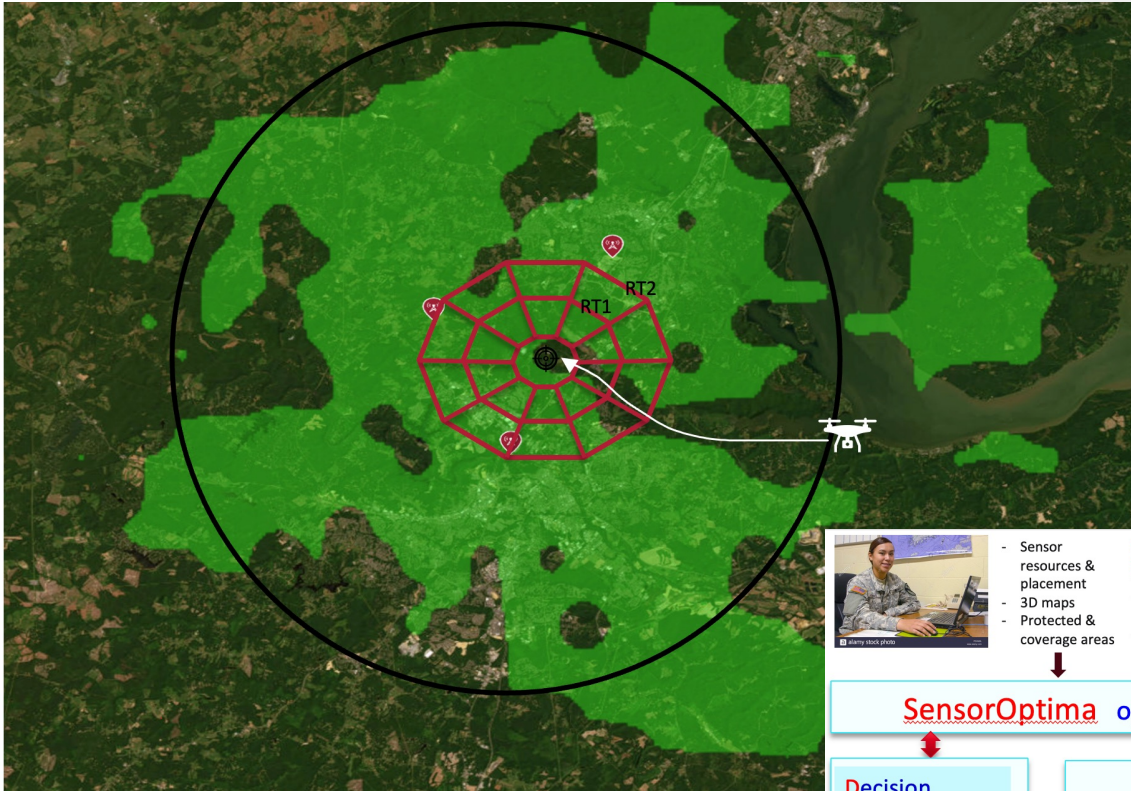
Hypothetical deployment of storage assets across an electric power system



SensorOptima: Decision Guidance System for Optimal Selection and Placement of UAV sensors – GMU project for US AFCENT

Stafford Airport
Coverage of 3 radars
Target at 100 ft

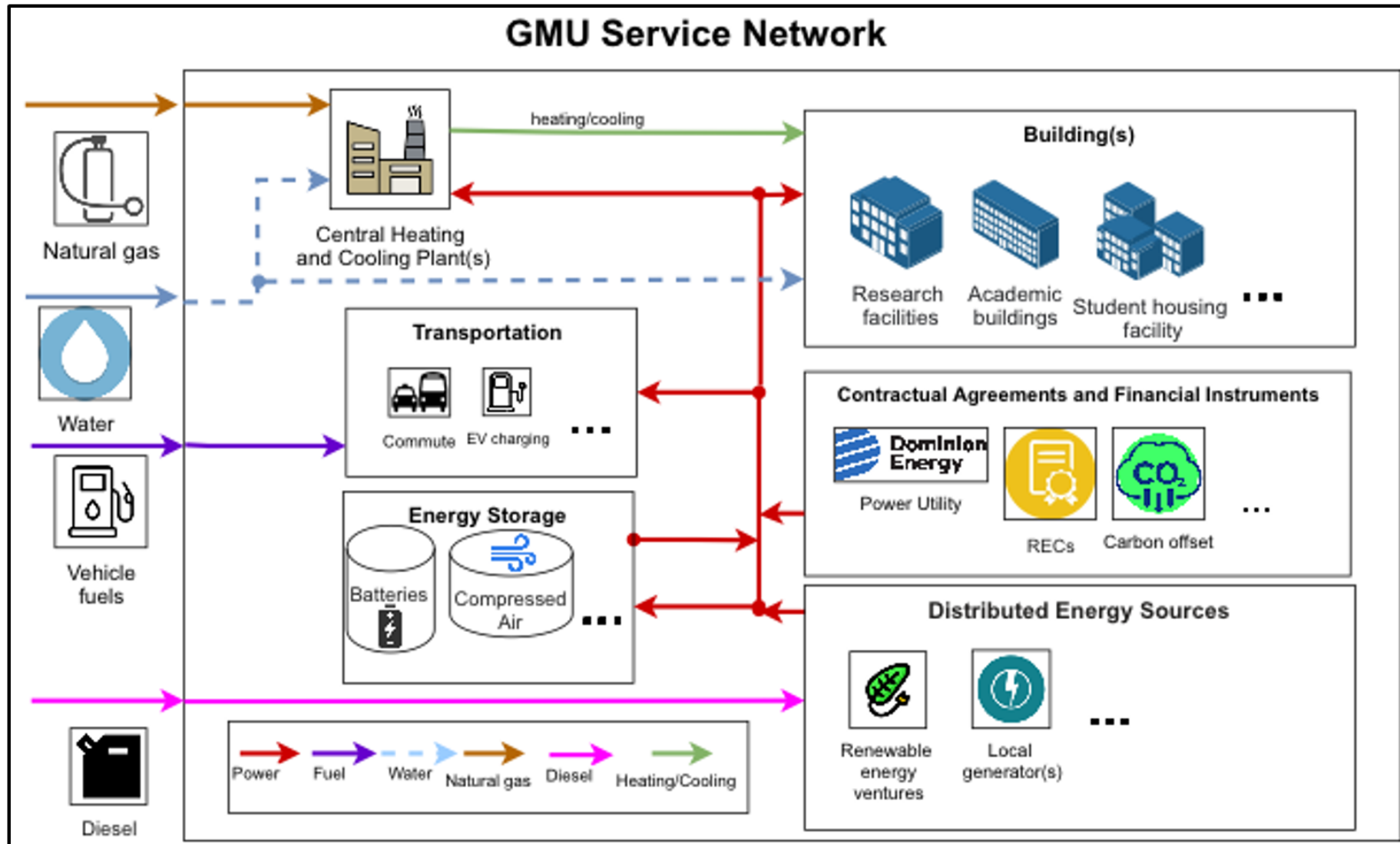
| Parameter | Radar 3 |
|---------------|------------------|
| pd | 0.8 |
| pfa | 10-6 |
| maxrange (m) | 45000 |
| Rangers (m) | 100 |
| numpulses | 20 |
| Fc (Hz) | 3e9 |
| Ant gain (dB) | 32 |
| | Target |
| RCS | 1 m ² |
| Alt | 30.5 m (100 ft) |



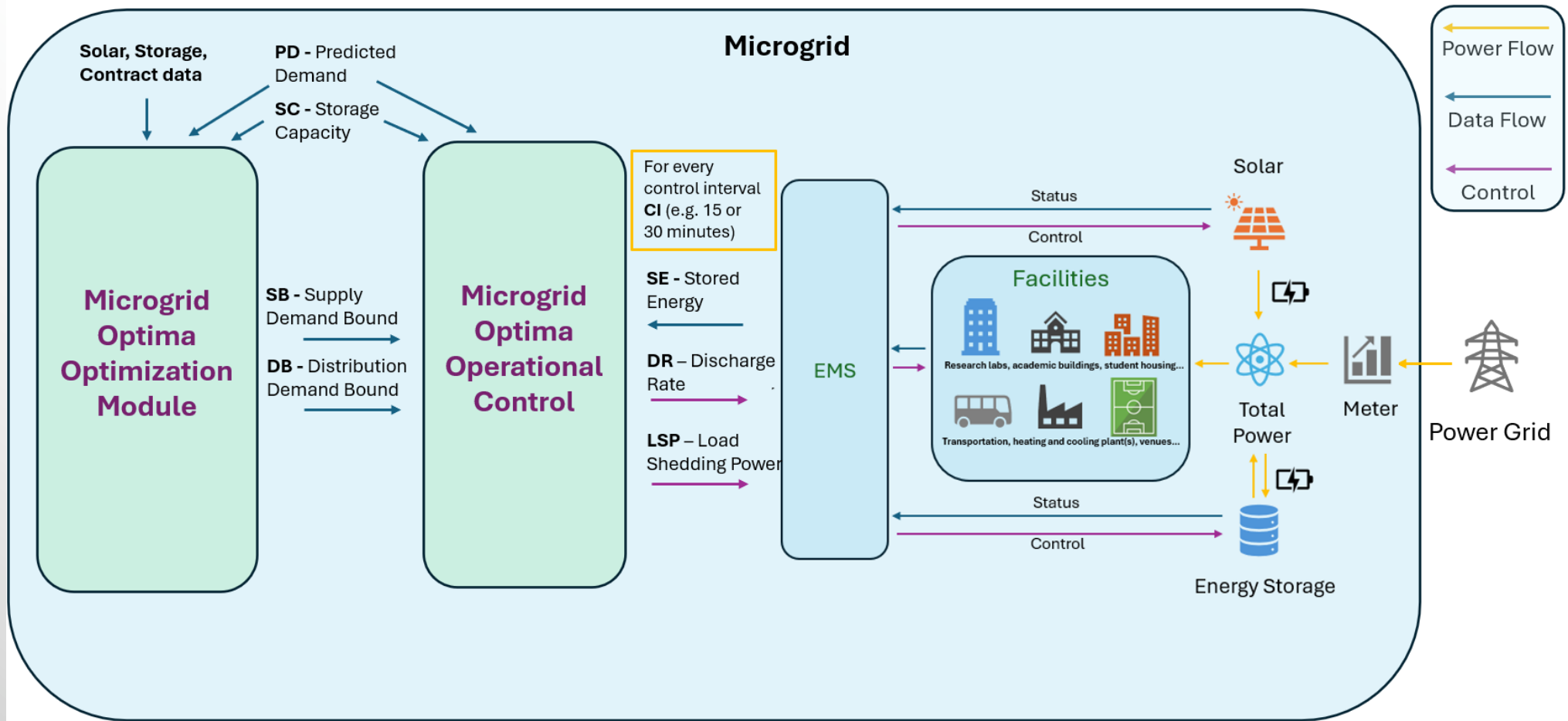
Example:

GADGET: Green Assessment and Decision GuidanceE Tool

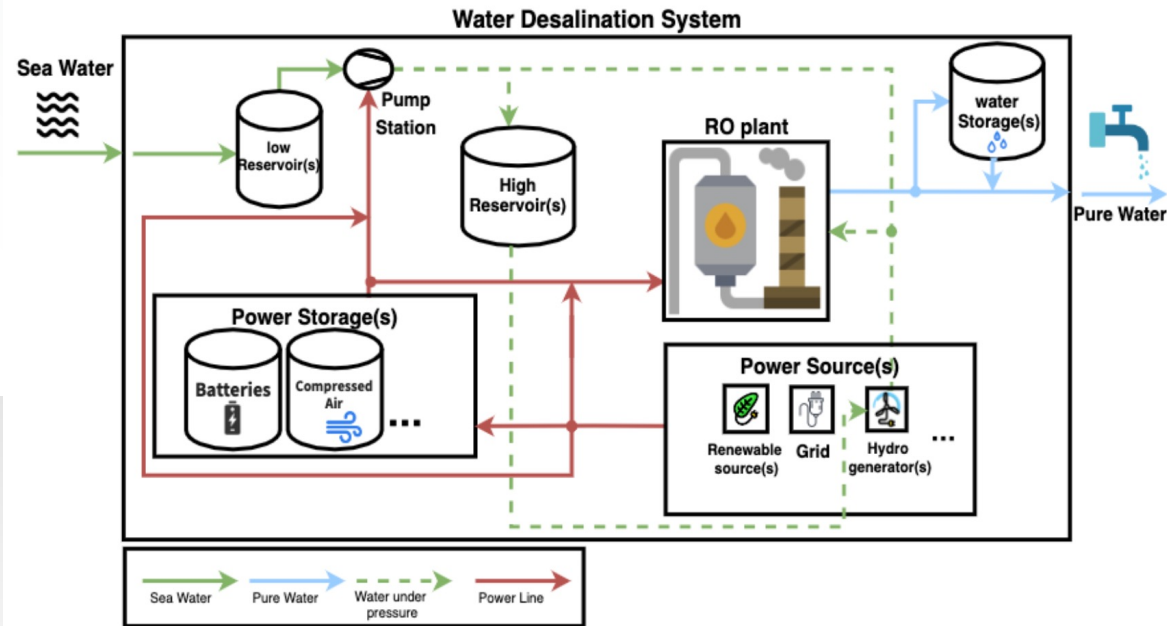
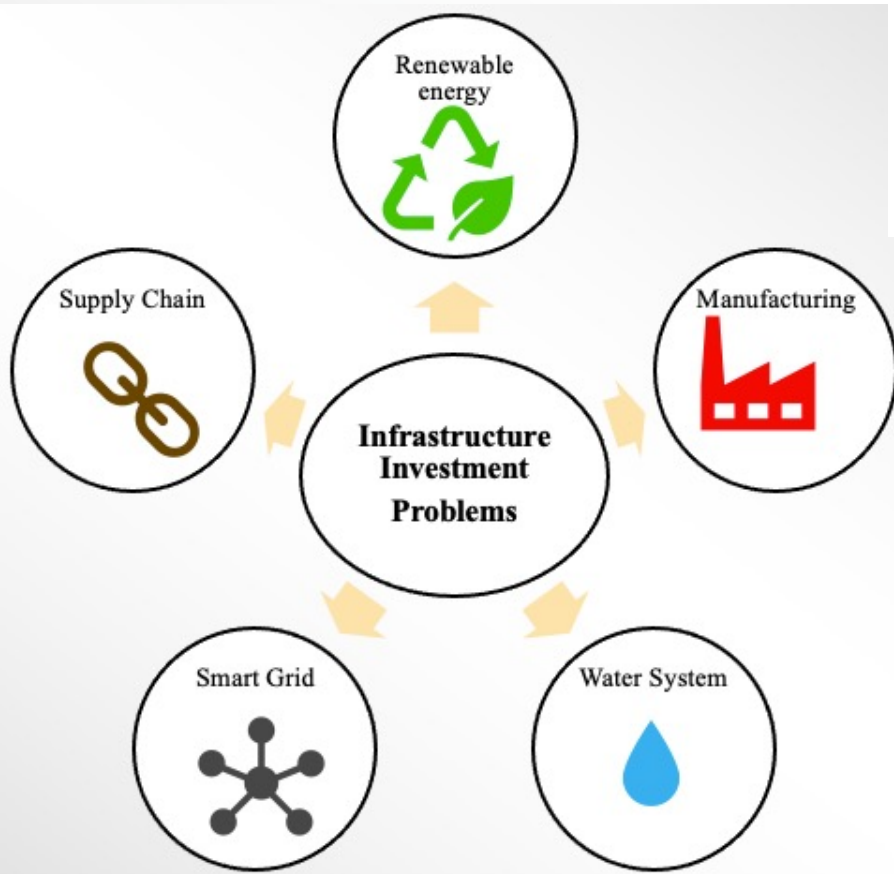
for Pareto-Optimal Investment to Achieve Carbon Neutrality- applied to GMU Fairfax campus



Microgrid Optima sponsored by GMU facilities



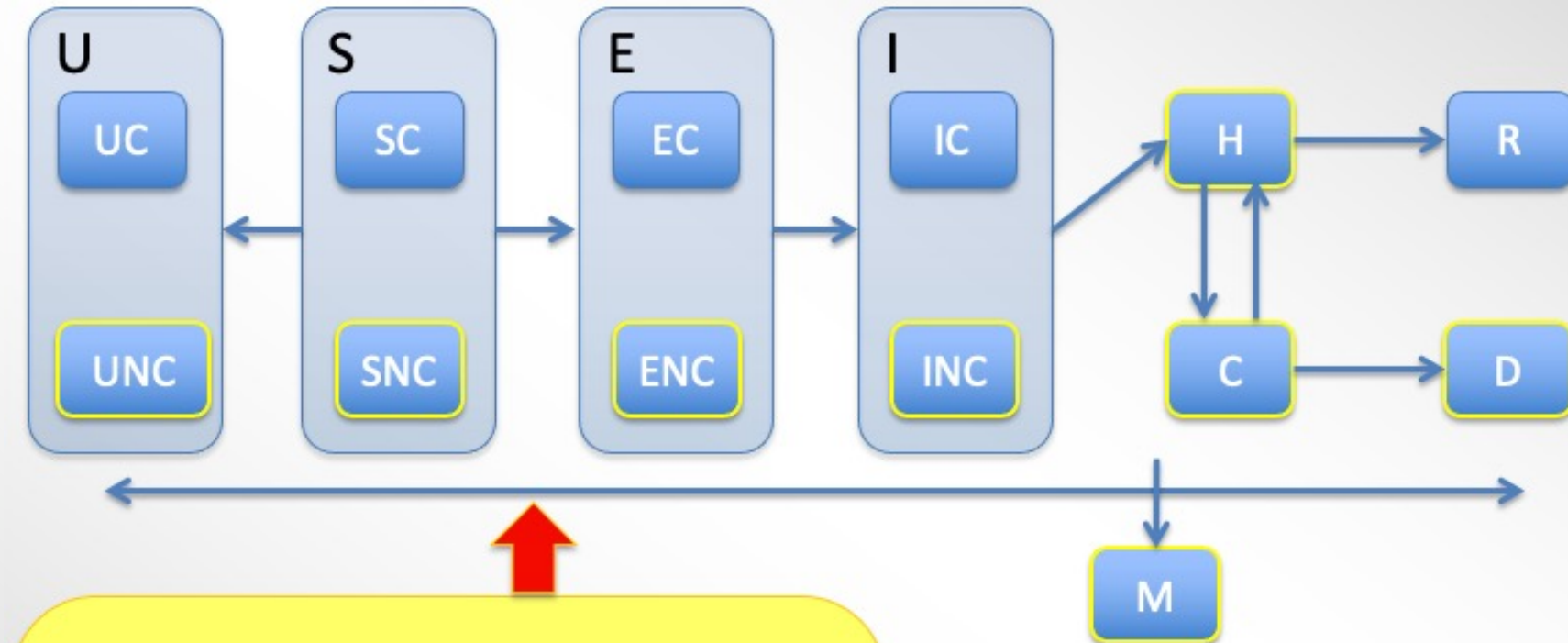
SNIM: Service Network Investment Model and DG system to decide on interrelated heterogeneous infrastructures: example of Desalination and Renewable Energy



Pandemic-Mitigation Decision Guidance System

to achieve Pareto-Optimal Health, Cost and Productivity Outcomes -

applied at GMU for Covid-19 mitigation



Parameterized Mitigation protocol:

- Social distancing and PPE
- Contact tracing
- Symptoms reporting
- Testing types and frequency

■ = Circulating population ■ = Not Circulating population

Legend:

- U = Unsusceptible (UC, UNC)
- S = Susceptible (SC, SNC)
- E = Exposed (EC, ENC)
- I = Infected (IC, INC)
- H = Hospitalized
- C = Critical care
- R = Recovered
- D = Dead due to COVID-19
- M = Dead not due to COVID-19



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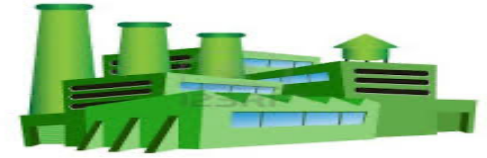


**Descriptive
Analytics
Tasks**

**Predictive
Analytics
Tasks**

**Diagnostic
Analytics
Tasks**

**Prescriptive/
Optimization
Analytics
Tasks**



Domain Specific Modeling & Analytics GUI

Interfaces / Mappers



TODAY every task is implemented:

- one off
- from scratch
- non-reusable
- non-modular
- requires math, OR, IT & domain-specific expertise
- high cost
- long development cycle
- difficult to modify/extend

Tools

DBMS: SQL,
XQuery,
JSONiq

Learning/Mining:
PMML, PFA, ...

Simulation:
Modelica-based,
Simulink, ...

Optimization:
MP/CP using
OPL, AMPL, ...

...



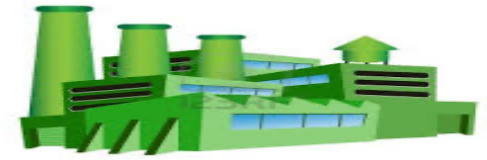


**Descriptive
Analytics
Tasks**

**Predictive
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Tasks**

**Diagnostic
Analytics
Tasks**

**Prescriptive/
Optimization
Analytics
Tasks**



Domain Specific Modeling & Analytics GUI

Interfaces / Mappers

**Decision
Guidance
Management
System**

**DG Analytics
Language:**

- Computation
- Prediction
- Optimization
- Learning
- Pareto analysis ...

Reusable, extensible, modular KB of analytic models (AM)

domain-
specific
analytics
dashboard
views

domain-
specific
atomic
models &
instances

domain-
specific
composite
models &
instances

...

Tools

**DBMS: SQL,
XQuery,
JSONiq**

**Learning/Mining:
PMML, PFA, ...**

**Simulation:
Modelica-based,
Simulink, ...**

**Optimization:
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...



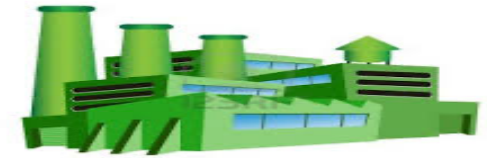


**Descriptive
Analytics
Tasks**

**Predictive
Analytics
Tasks**

**Diagnostic
Analytics
Tasks**

**Prescriptive/
Optimization
Analytics
Tasks**



Domain Specific Modeling & Analytics GUI

Interfaces / Mappers

**Decision
Guidance
Management
System**

**DG Analytics
Language:**

- Computation
- Prediction
- Optimization
- Learning
- Pareto analysis ...

Reusable, extensible, modular KB of analytic models (AM)

analytical-views

- ▶ dashboards
- ▶ diagnostics
- ▶ monitors
- ▶ param-calibration
- ▶ process-metrics
- ▶ scheduling
- ▶ unit-optimization
- ▶ what-if-analysis

atomic-models

- ▶ additive
- ▶ casting
- ▶ forming
- ▶ joining
- ▶ machining
- ▶ molding

process-models

- ▼ factory
- ▶ manuf-cell
- ▶ manuf-unit
- ▶ prod-line
- ▶ templates

...

Tools

DBMS: SQL,
XQuery,
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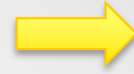
...



P: fixed params
V: control params



AM



M: metrics
C: constraints

P: fixed params
V: control params



AM



M: metrics
C: constraints

```
demand:  
  chair: 16  
  table: 4  
purchaseInfo:  
  ppu:  
    supplier1:  
      chair: 50  
      table: 110  
    supplier2:  
      chair: 60  
      table: 100  
  co2pu:  
    supplier1:  
      chair: 0.2  
      table: 1.3  
    supplier2:  
      chair: 0.4  
      table: 0.9  
  manuTimePu:  
    supplier1:  
      chair: 0.5  
      table: 0.75  
    supplier2:  
      chair: 0.8  
      table: 1.5  
  available:  
    supplier1:  
      chair: 15  
      table: 3  
    supplier2:  
      chair: 20  
      table: 4
```

```
qty:  
  supplier1:  
    chair: 10  
    table: 2  
  supplier2:  
    chair: 6  
    table: 3
```

```
cost: 1380  
co2: 9.7  
manuTime: 15.8  
constraints: true
```



P: fixed params
V: control params



M: metrics
C: constraints

```
def mcProcurementAM(input):
    demand = input["demand"]
    purchaseInfo = input["purchaseInfo"]
    ppu = purchaseInfo["ppu"]
    co2pu = purchaseInfo["co2pu"]
    manufTimePu = purchaseInfo["manufTimePu"]
    available = purchaseInfo["available"]
    qty = purchaseInfo["qty"]

    cost = sum([ppu[s][i] * qty[s][i] for s in qty for i in qty[s]])
    co2 = sum([co2pu[s][i] * qty[s][i] for s in qty for i in qty[s]])
    manufTime = sum([manufTimePu[s][i] * qty[s][i] for s in qty for i in qty[s]])
    qtySeq = [qty[s][i] for s in qty for i in qty[s]]
    constrSeq = [qty[s][i] >= 0 for s in qty for i in qty[s]]
    nonNegQtysConstraint = dgal.all(constrSeq)
    availabilityConstraint = dgal.all([qty[s][i] <= available[s][i] for s in qty for i in qty[s]])
    supply = {}
    for i in demand: supply.update({i: sum(qty[s][i] for s in qty)})
    demandSatisfiedConstraint = dgal.all([demand[i] <= supply[i] for i in demand])
    constraints = dgal.all([nonNegQtysConstraint, availabilityConstraint, demandSatisfiedConstraint])

    return {"cost": cost, "co2": co2, "manufTime": manufTime, "constraints": constraints }
```

P: fixed params
V: control params



M: metrics
C: constraints

```
demand:  
  chair: 16  
  table: 4  
purchaseInfo:  
  ppu:  
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P: fixed params
V: control params



AM



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    supplier2:  
      chair: 0.4  
      table: 0.9  
  manuTimePu:  
    supplier1:  
      chair: 0.5  
      table: 0.75  
    supplier2:  
      chair: 0.8  
      table: 1.5  
available:  
  supplier1:  
    chair: 15  
    table: 3  
  supplier2:  
    chair: 20  
    table: 4
```

```
qty:  
  supplier1:  
    chair: ???  
    table: ???  
  supplier2:  
    chair: ???  
    table: ???
```

```
cost: '???'  
co2: '???'  
manuTime: '???'  
constraints: true
```



P: fixed params
V: control params



AM



M: metrics
C: constraints

AM

P: fixed params
V: ???



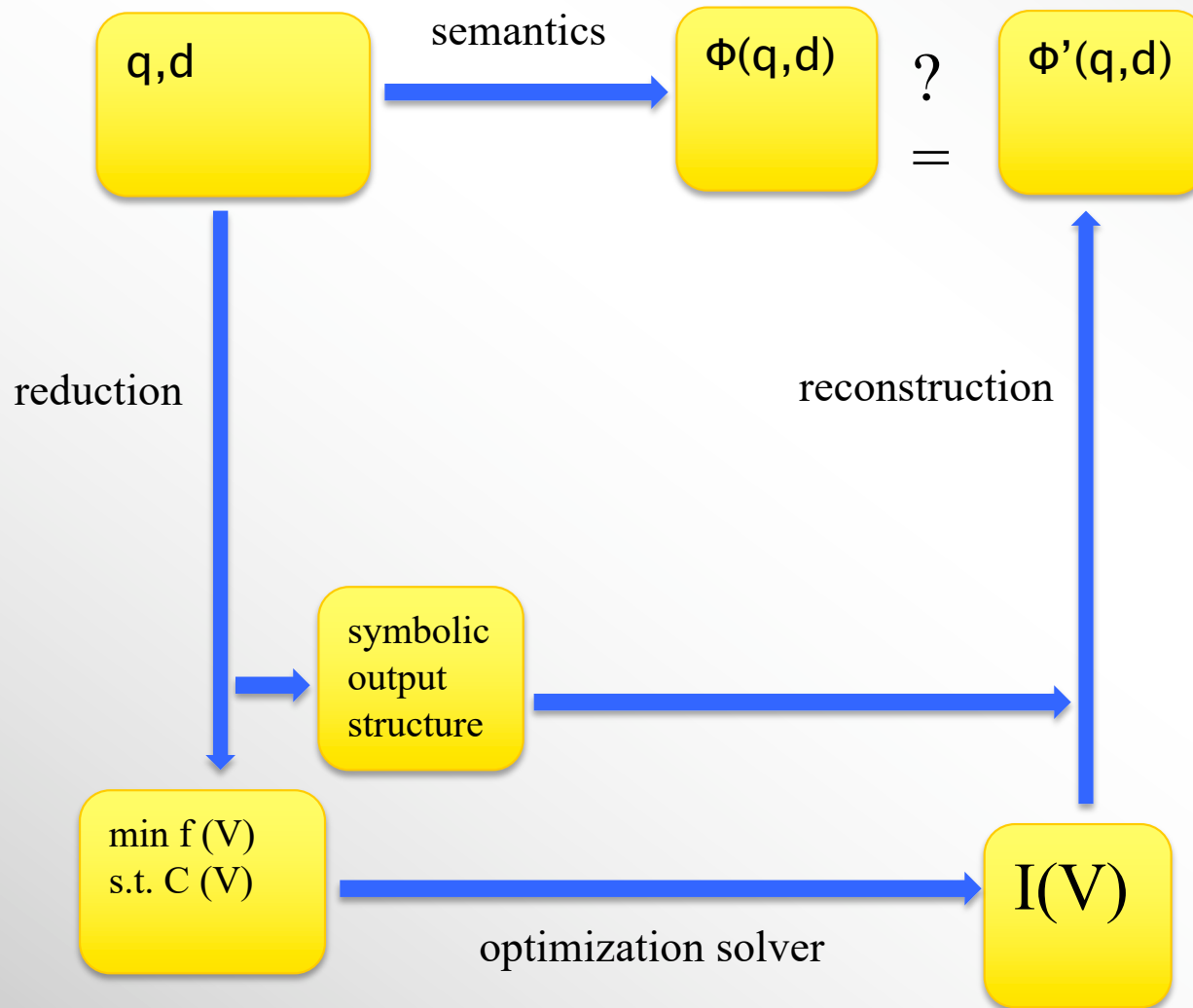
Minimize/
Maximize



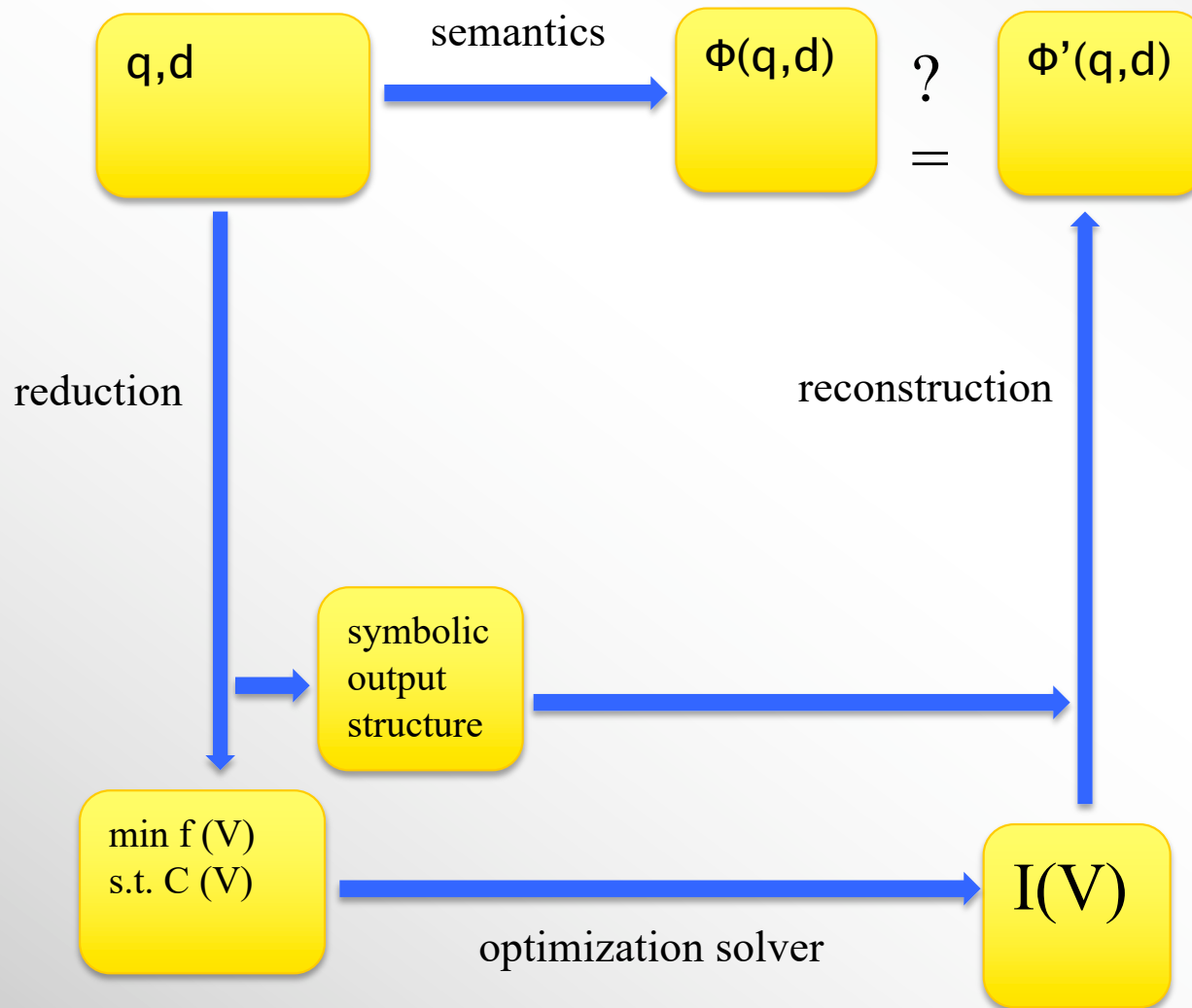
P: params
V: optimal control

O: objective

Soundness and Completeness of Reduction



Soundness and Completeness of Reduction



Theorem:

The reduction procedure is

1. **sound:**

$$\Phi'(q, d) \subseteq \Phi(q, d)$$

2. **complete:**

$$\Phi'(q, d) \supseteq \Phi(q, d)$$

P: fixed params
V: control params



M: metrics
C: constraints

AM

P: fixed params
V: ???



Minimize/
Maximize



P: params
V: optimal control

O: objective

AM

P: ???
V: ???



Learn
Parameters



P: best fit params
V: ???

LS: training
set of input-
output pairs

P: fixed params
V: control params



Stochastic
AM



M: metrics
C: constraints

```
declare function local:stochProcurementPM($procurementInput){
  let $demand := $procurementInput.demand,,
      $suppliers := keys($procurementInput.purchaseInfo.ppu),
      $ppu := $procurementInput.purchaseInfo.ppu,
      $available := $procurementInput.purchaseInfo.available,
      $qty := $procurementInput.purchaseInfo.qty
  let $cost := sum ( for $s in $suppliers, $i in keys($qty($s))
                    let $stochPpu := $ppu($s)($i) + G(0.0,0.01*$ppu($s)($i))
                    return $stochPpu * $qty($s)($i)
                  )
  let $availabilityConstraint := (
    every $s in $suppliers, $i in keys($qty($s))
    satisfies ( $qty($s)($i) <= $available($s)($i) )
  )
  let $supply := { |
    for $i in keys($demand)
    return {$i: sum ( for $s in $suppliers return $qty($s)($i) ) }
  }
  let $demandSatisfiedConstraint :=
    every $i in keys($demand)
    satisfies $supply($i) >= $demand($i) + G(0.0, 0.02 * $demand($i))
  let $feasibilityConstraint :=
    $availabilityConstraint and $demandSatisfiedConstraint
  return { cost: $cost, constraints: $feasibilityConstraint }
};
```



P: params
V: control vars



Stochastic
AM



M: metrics
C: constraints

AM

P: params
V: control vars



(stochastic)
prediction



E(M): mean & std. dev. of metrics
P(C): prob. of constraint satisfaction

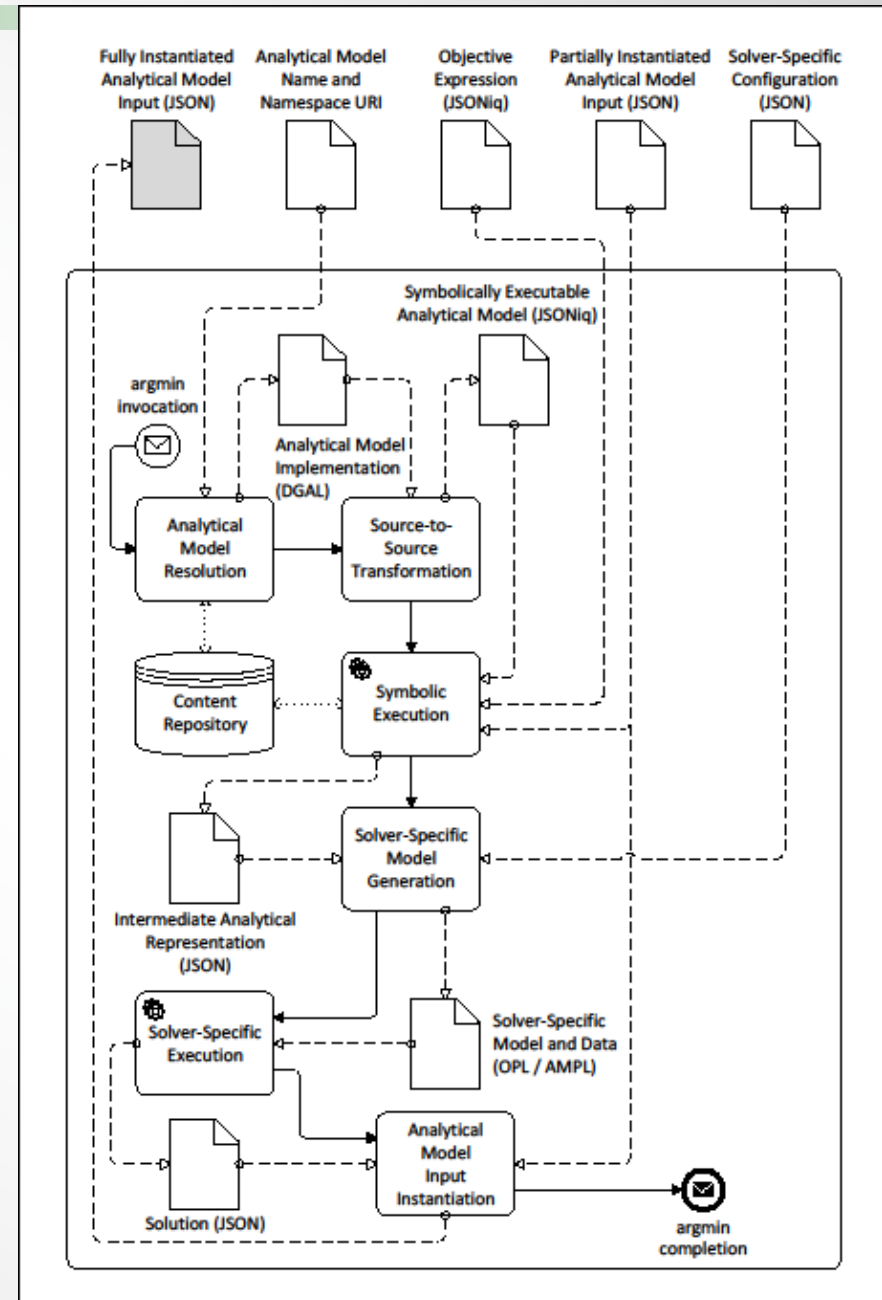
```
{ "cost": {"mean": 2120, "sigma": 8.76},  
  "constraints": { "prob": 0.92},  
}
```

Compiling Optimization Queries

Six steps:

1. Reusable Analytic Model Resolution
2. Source-to-Source Transformation
3. Symbolic Execution
4. Target Model Generation
5. Target Solver Execution
6. Input Instantiation

Steps 1-3 & 6 (tasks) can be used to implement other DGAL operators:
e.g. learn & predict



DGAL / DGMS summary:

- Is based on KB of analytic (performance) models (AMs) that:
 - Express constraints and metrics of interest as a function of fixed & control parameters (of a process)
 - Are independent of analytical tasks & tools/algorithms
- Allows reuse of AMs as operands to diverse analytics operators (forming analytics algebra on AMs) :
 - Simulation
 - Prediction
 - Deterministic or stochastic optimization
 - Learning parameters of AM for regression or classification
 -
- Performs these operators/tasks by automatic reduction to specialized low-level models and algorithms, w/out the need to manually craft low-level models.
- Uses query / data manipulation language (JSONiq) over JSON data format to
 - Express AMs
 - Express analytics algebra operators / tasks



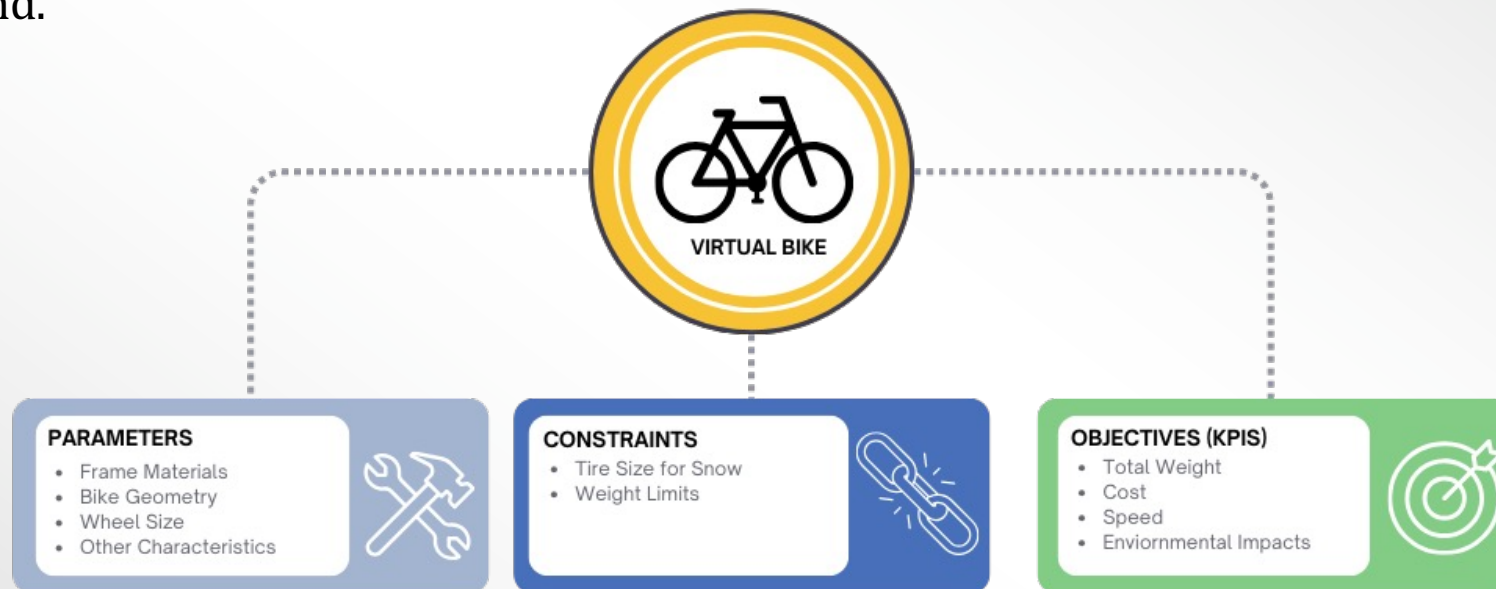
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Virtual Things at a Glance

- **Virtual Things (VTs):** parameterized specifications of products or services associated with analytic models that describe the consumer characteristics, which can be instantiated on demand.



- How to extract a user utility as a function of KPIs ?
- How to choose a specific instantiation of a Virtual Thing that optimizes the utility?

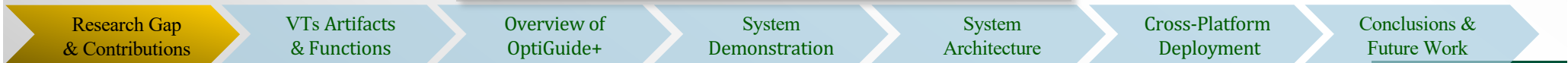
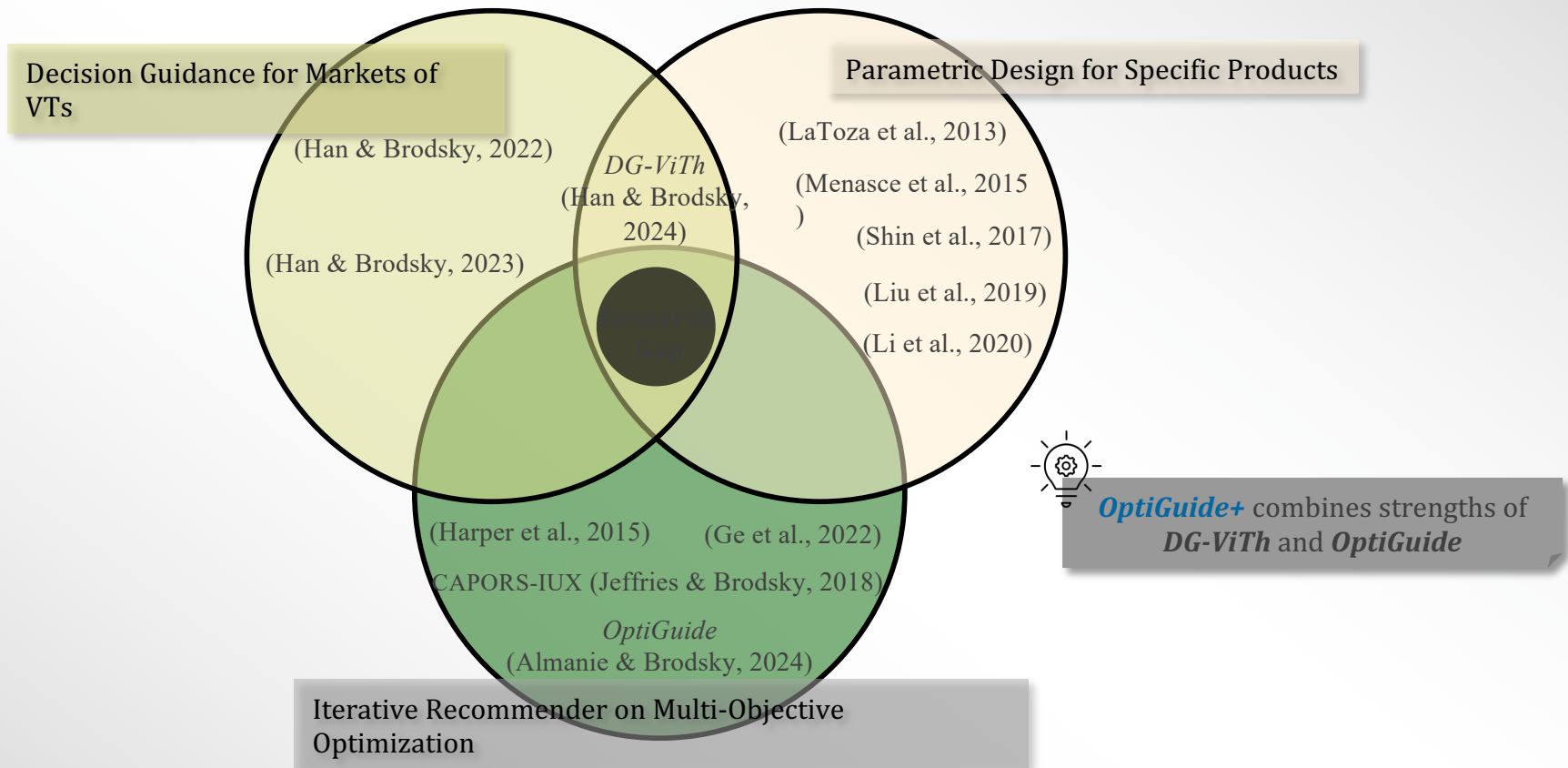
Motivating Example

- A bike enthusiast wants a customized performance bike to ride on snow
- She fills in the template of bicycle requirement spec.
- Then, searches any existing bicycle VT similar to her idea in the market of virtual things, consistent with her requirements
- The bike enthusiast requests suggestions for Pareto-optimal instances, e.g., minimal cost subject to constraints on bike weight, ability to ride on snow, and efficiency.
- The system instantiates an optimal instance of the bike should all constraints be satisfied
- The bike enthusiast orders the bike for herself or launches the bike in the market of virtual things for potential buyers
- The manufacturers proceed to make and ship the bike as a real product

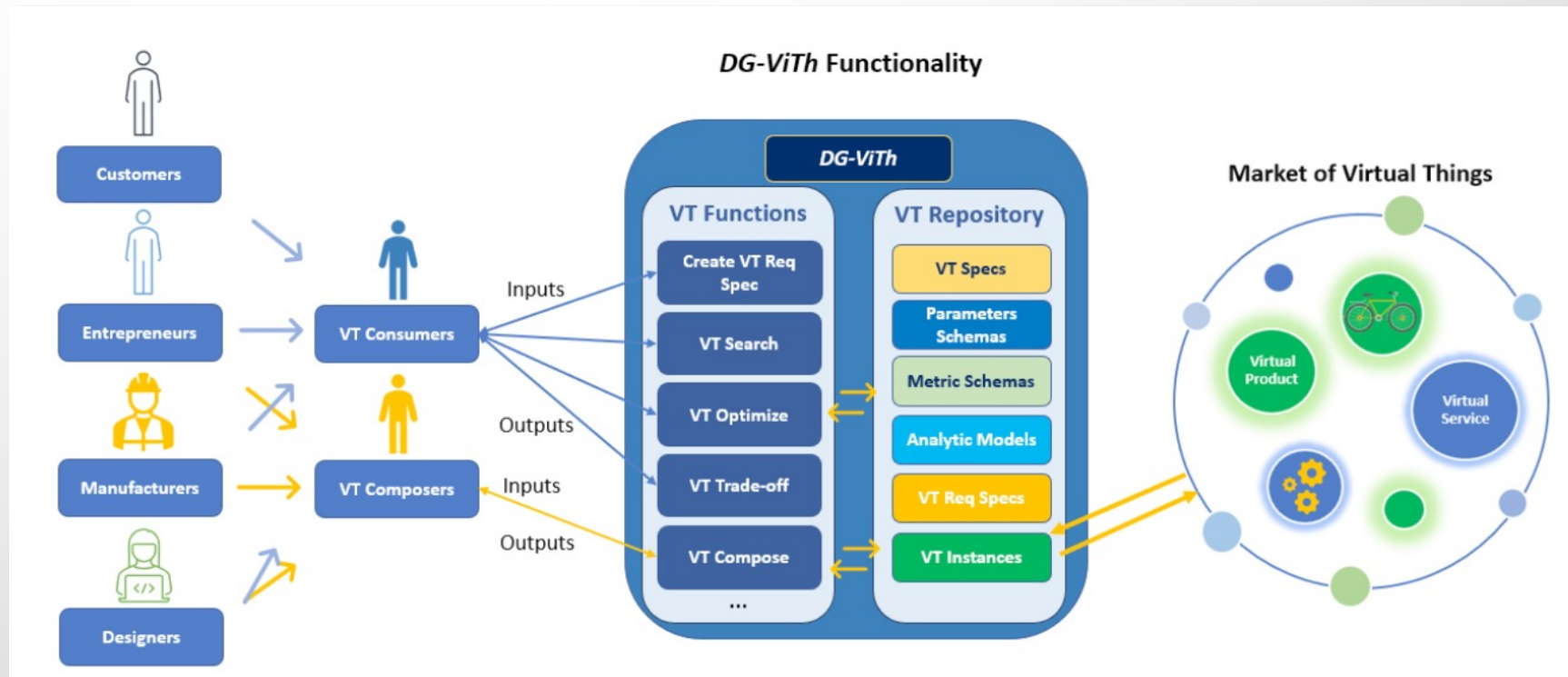


Problem and Research Gap

- Problem:** Dual challenge of utility extraction and optimal instantiation of Virtual Things.



Virtual Things Artifacts and Functions



Research Gap & Contributions

VTs Artifacts & Functions

Overview of OptiGuide+

System Demonstration

System Architecture

Cross-Platform Deployment

Conclusions & Future Work

Key Artifacts of Virtual Things

VT design Spec (*vtSpec*)

- Core VT artifact, defined by the AM Python function (Analytic Model)
- $AM: MI \rightarrow MO$, where:
 - $MI = \text{domain of parameters' inputs}$
 - $MO = \text{domain of model outputs of computed metrics}$

VT Requirements Specification (*vtReqSpec*)

- Used to specify requirements for finding optimal instances of *vtSpecs*.
- $objs: MO \rightarrow O$ and $constraints: MO \rightarrow \{T,F\}$, where:
 - $MO = \text{domain of model outputs of computed metrics}$

utility

- $O = \text{domain of all possible objectives value (KPIs)}$
- A function that maps the objectives with their weights to a real number.
- $U: O \rightarrow \mathbb{R}$, where:
 - $O = \text{domain of all possible objectives value}$
 - \mathbb{R} is the set of real numbers

Key Function of Virtual Things: VT Optimize

▪ $vtOptimalInstance(vtSpec, vtReqSpec, Utility)$

- Given: $AM : MI \rightarrow MO$ } vtSpec
 $constraints : MO \rightarrow \{T, F\}$ } vtReqSpec
 $objs : MO \rightarrow O$ }
 $U : O \rightarrow \mathbb{R}$ } utility

$$\begin{aligned} \text{ARGMAX} &= \underset{mi \in MI}{\text{argmax}} \quad U(objs(AM(mi))) \\ \text{s.t.} \quad & constraints(AM(mi)) \wedge \\ & vtMetricBounds(AM(mi)) \wedge \\ & reqMetricBounds(AM(mi)) \wedge \\ & objsBounds(objs(AM(mi))) \end{aligned}$$

• Output

1. If ARGMAX = \emptyset , return INFEASIBLE
2. Else, if $(\forall mi \in MI)(\exists mi' \in MI)$
 $s.t. U(objs(AM(mi'))) > U(objs(AM(mi)))$,
return UNBOUNDED
3. Else return $i \in \text{ARGMAX}$

Key Function of Virtual Things: VT Trade-off

- $paretoOptimalDB(vtSpec, vtReqSpec)$

A VT instance i is Pareto-optimal w.r.t. $vtReqSpec$ if there does not exist a valid instance $i' \in vtValidInstances$ such that :

- All objective values $o_1(i'), \dots, o_n(i')$ are at least as good as $o_1(i), \dots, o_n(i)$, and
- At least one objective value $o_k(i')$ for $1 \leq k \leq n$ is strictly better than $o_k(i)$

Overview of *OptiGuide+*

OptiGuide+ is an interactive recommender system built on the foundational ***OptiGuide*** framework.

- Domain-independent.
- Employs multi-objective optimization.
- Guides users in extracting utility and finding Pareto-optimal recommendations.

OptiGuide+ expands by:

- ✓ Integrating VT framework from *DG-ViTh*, enabling real-time interactive utility extraction.
- ✓ Enhancing accessibility and scalability by being web deployable.
- ✓ Enhancing user interface for visualizing trade-offs and exploring Pareto-optimal solutions.

Research Gap
& Contributions

VTs Artifacts
& Functions

Overview of
OptiGuide+

System
Demonstration

System
Architecture

Cross-Platform
Deployment

Conclusions &
Future Work

System Demonstration

Example: Virtual Supply Aggregator for Procurement

- A **procurement package** includes furniture items such as tables, chairs, and cabinets, each with specific demand.
- Our **VTs repository** offers options from multiple supply aggregators.
- A **recommendation** is an optimal VT instance, comprising a selected supply aggregator and a set of item quantities to be purchased from associated suppliers.
- Orders must satisfy demand and availability **constraints** while optimizing multiple **objectives**, including **cost**, **CO₂ emissions**, and **manufacturing time**.
- To initialize the system, users provide: **AM**, **vtSpec**, **vtReqSpec**, and configuration artifacts.
- OptiGuide+ learns the **user's utility** through interaction and Pareto-optimal trade-offs.
- **Goal:** Generate recommendations with the **highest** predicted utility.



Demo

Research Gap
& Contributions

VTs Artifacts
& Functions

Overview of
OptiGuide+

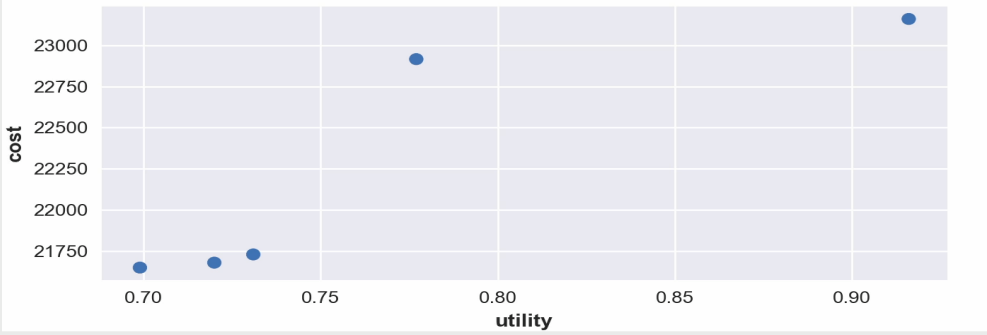
System
Demonstration

System
Architecture

Cross-Platform
Deployment

Conclusions &
Future Work

Current Trade-off

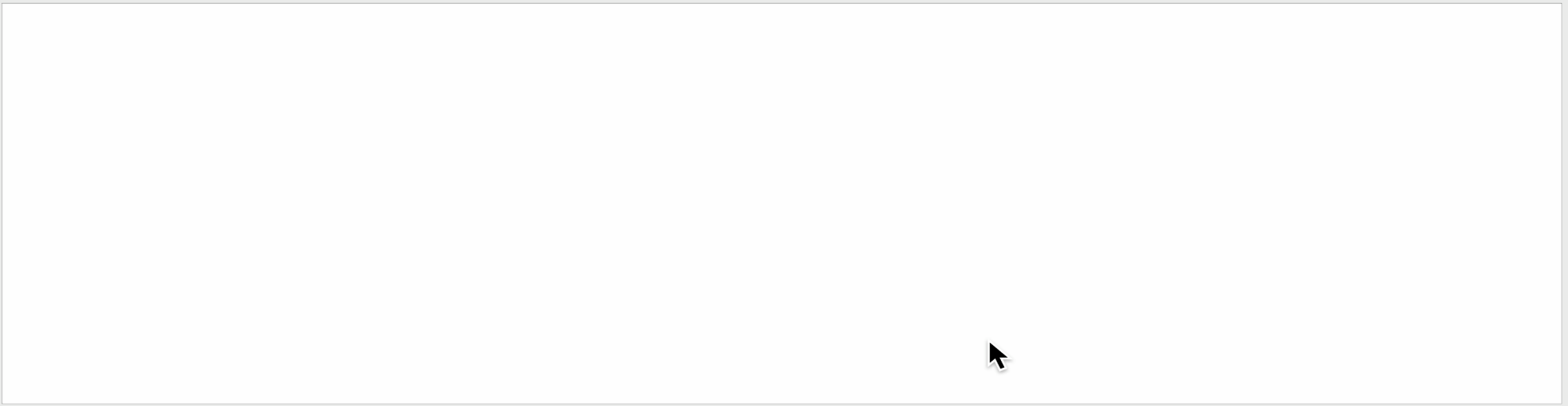


Sort Table By: utility

| | Rec 1 |
|-----------|-------------------------|
| utility | 0.916 |
| cost | 23160.0 |
| co2 | 264.4 |
| manufTime | 242.15 |
| Solution | Details |
| Remove? | <input type="radio"/> |
| Best? | <input type="radio"/> |

Weights of Current Utility: cost: 0.333 , co2: 0.333 , manufTime: 0.333

Best So Far



Research Gap & Contributions

VTs Artifacts & Functions

Overview of OptiGuide+

System Demonstration

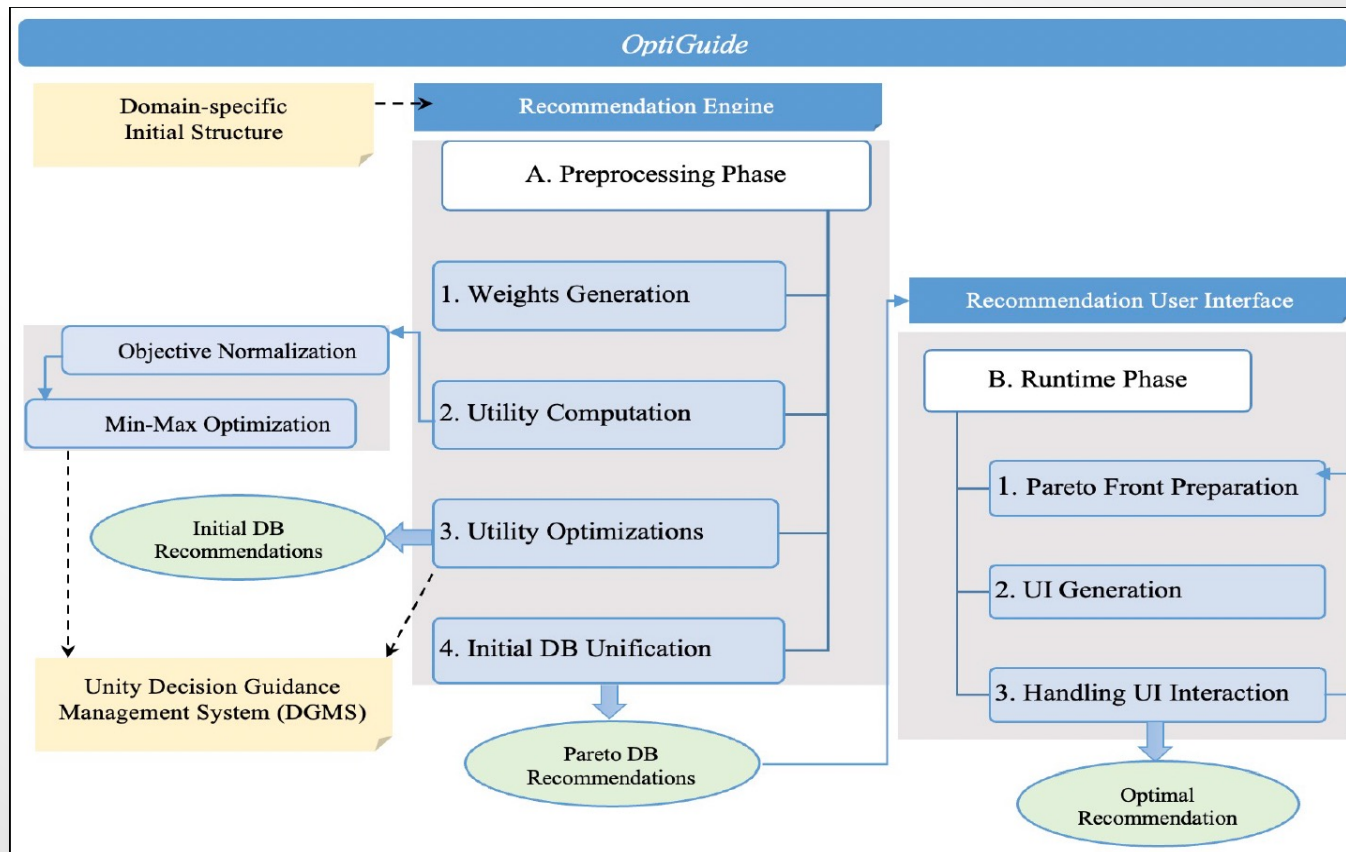
System Architecture

Cross-Platform Deployment

Conclusions & Future Work



System Architecture and Implementation



Research Gap & Contributions

VTs Artifacts & Functions

Overview of OptiGuide+

System Demonstration

System Architecture

Cross-Platform Deployment

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Outline

- DG applications by example
- DG Tools:
 - DG Analytics Language (DGAL) & Management System (DGMS)
 - Interactive DG for Virtual Things (DG-ViTh & OptiGuide)
- DG Algorithms: brief overview
- DG Applications
 - Green Assessment and DG Tool (GADGET): toward carbon neutrality
 - DG System for Comprehensive Pandemic Mitigation with Pareto-Optimal health, cost and productivity outcomes (GS-Mitigate)
- Grand Challenge: AI Agentic Framework for Model-Based Decision Guidance



DG Algorithms: brief overview

- DG reduction algorithms
- Process optimization by decomposition and pre-processing
- Stochastic optimization through deterministic surrogates
- Grey-box optimization
- Regression of n-dimensional piece-wise linear functions
- Classification over multivariate time series
- Top-K recommendations using simulation and regression
- Probabilistic algorithms to optimize recommendation diversity
- Group decision algorithms
- ...

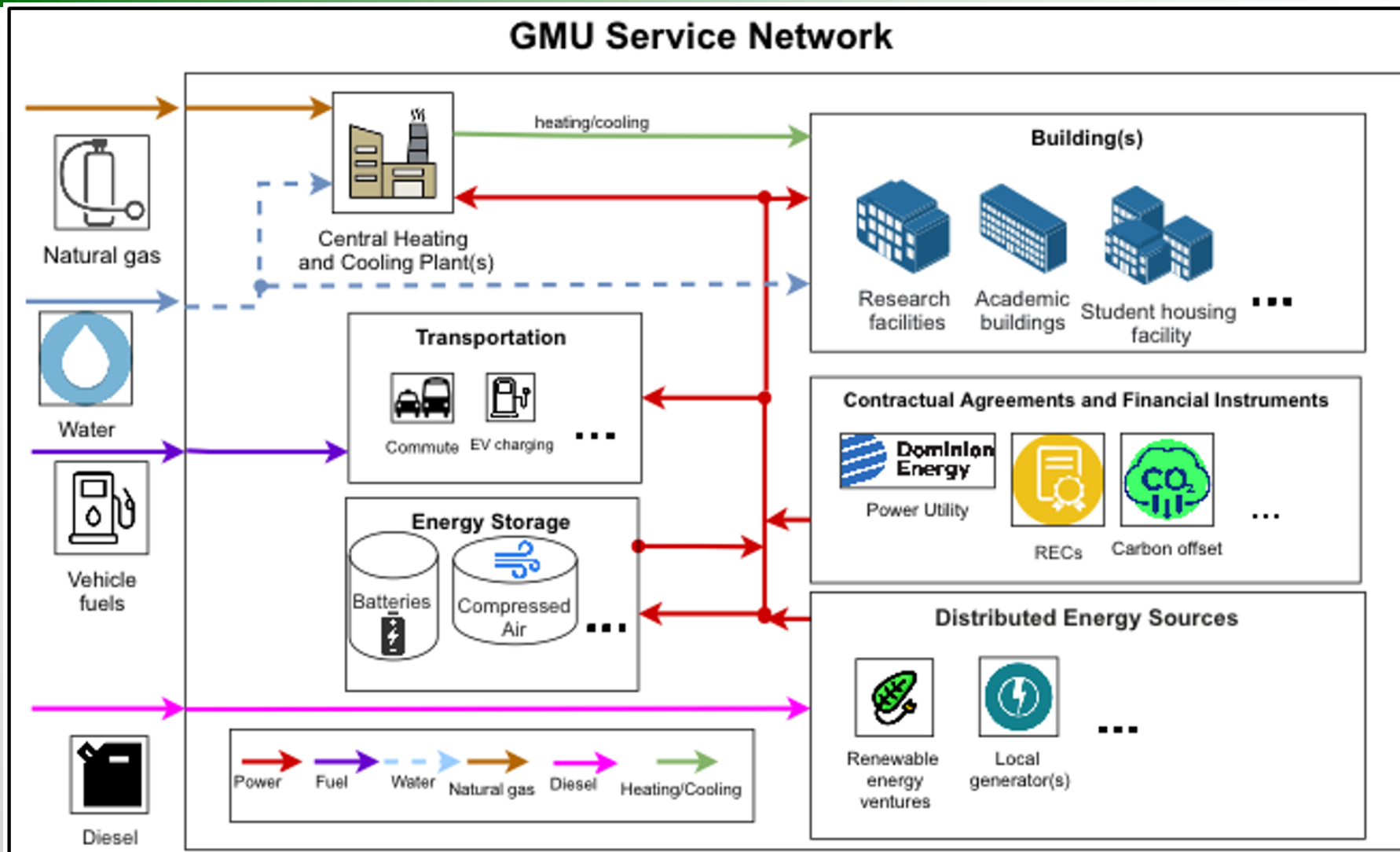


Outline

- DG applications by example
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Example:

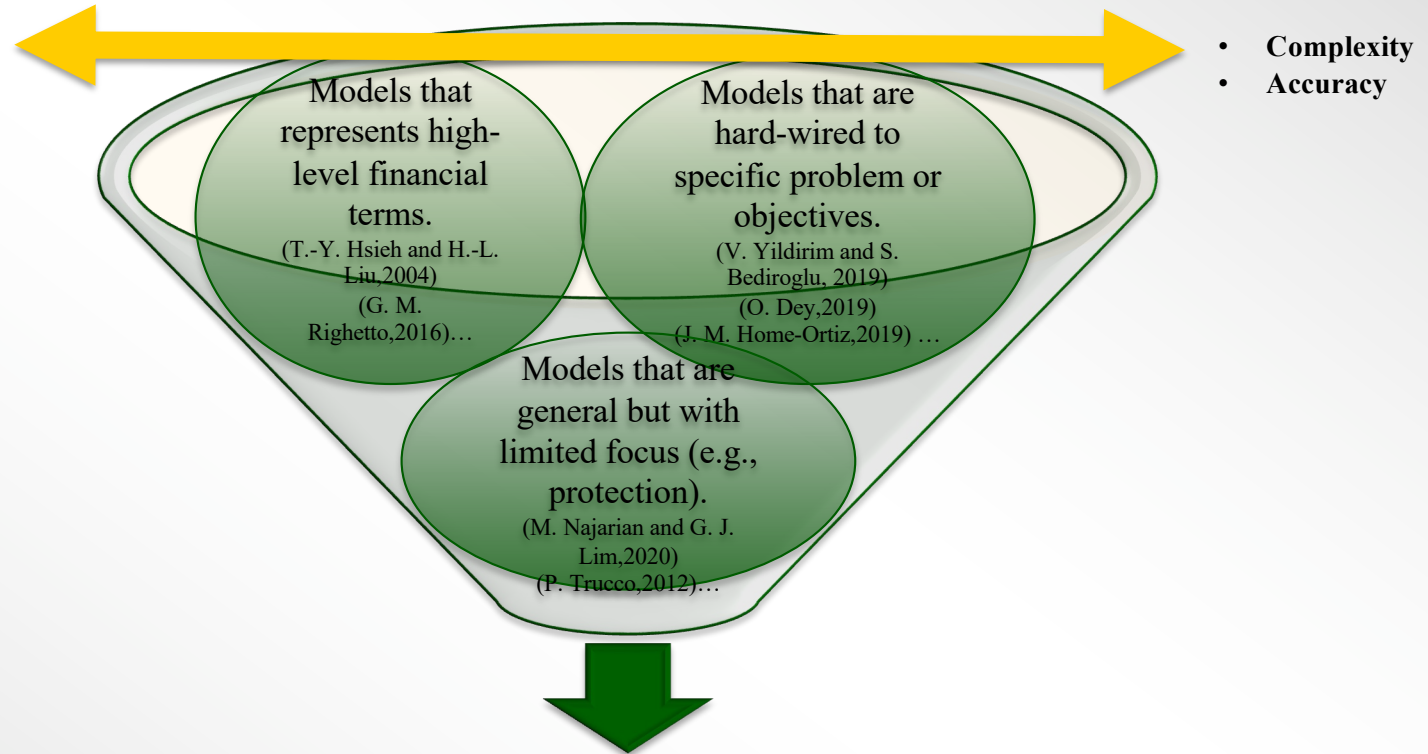
GADGET: Green Assessment and Decision Guidance Tool for Pareto-Optimal Investment to Achieve Carbon Neutrality



Research Gap and Challenges



- Reusability
- Extend
- Cost
- Development time

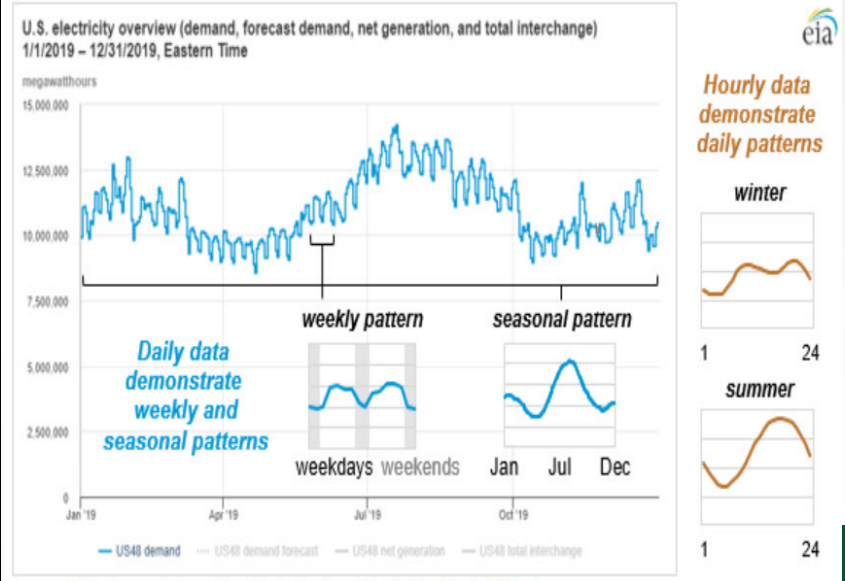
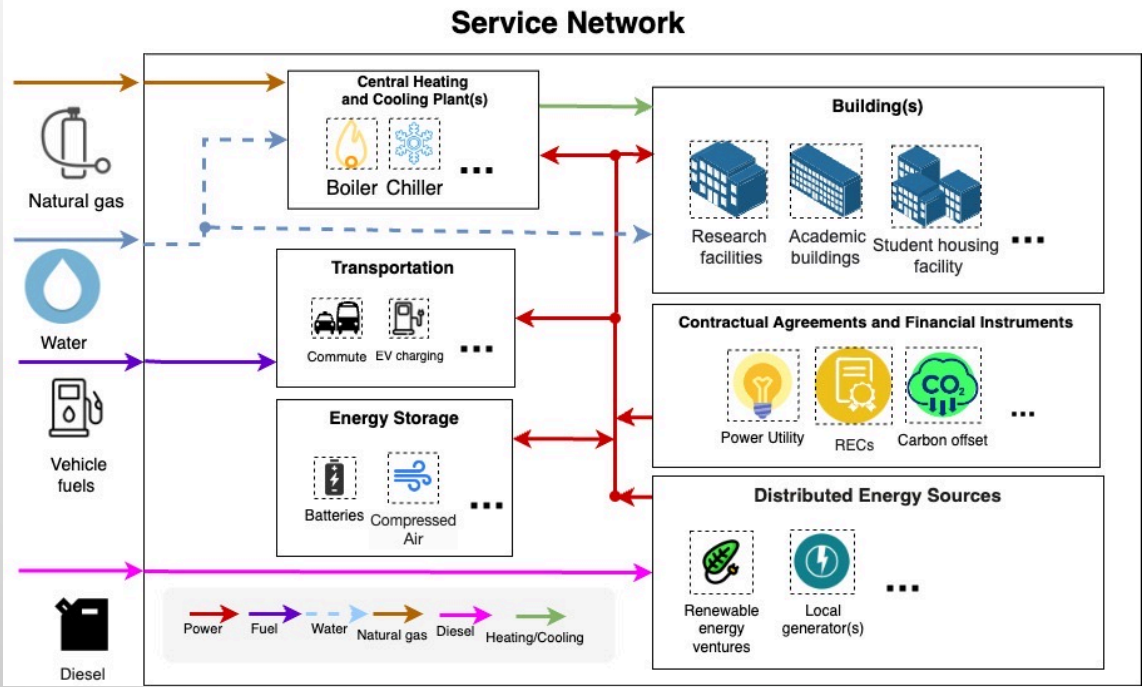


How to build a **general** model and a decision guidance system to recommend on investment in service networks that represents complex heterogeneous infrastructure based on optimizing **both investment and operational controls**?



Transient Service Network Investment Model (T-SNIM)

How to build a general model and a decision guidance system to recommend on investment in service networks that represents complex heterogeneous infrastructure based on optimizing **both investment and operational controls?**

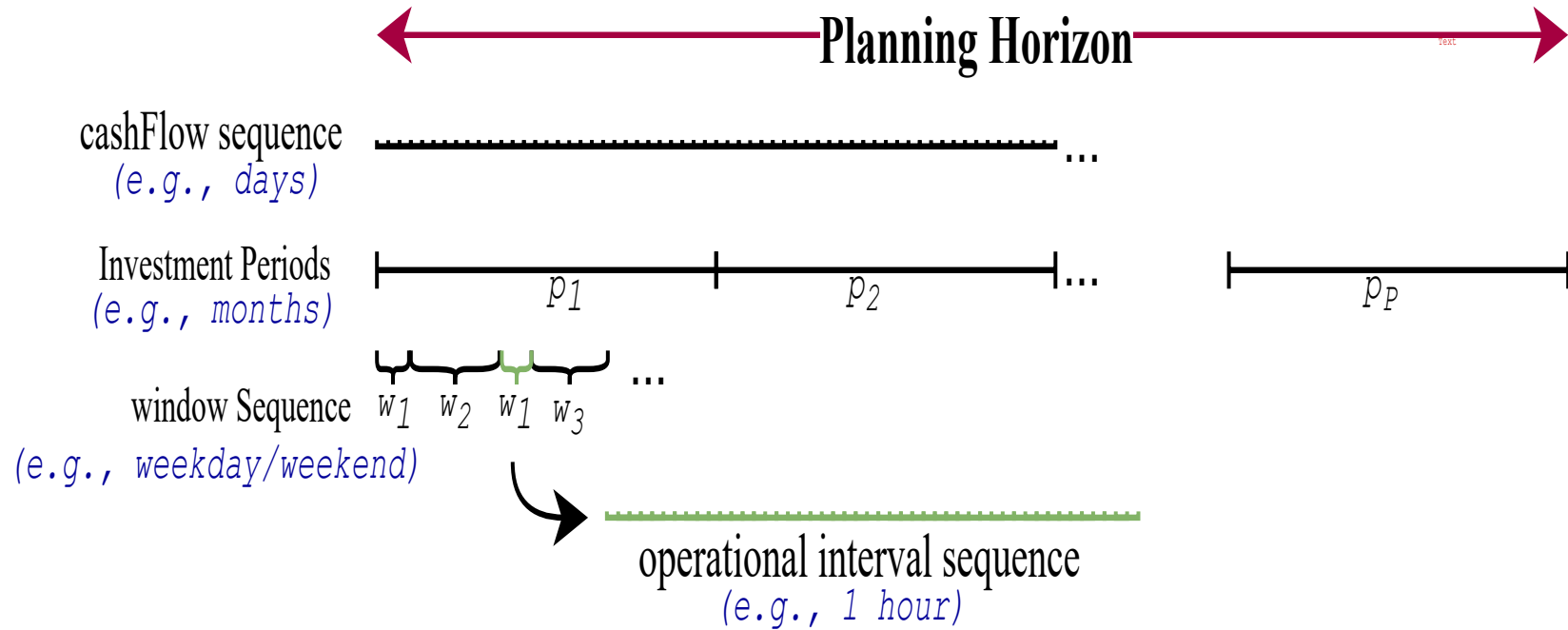


Source: U.S. Energy Information Administration, *Hourly Electric Grid Monitor*



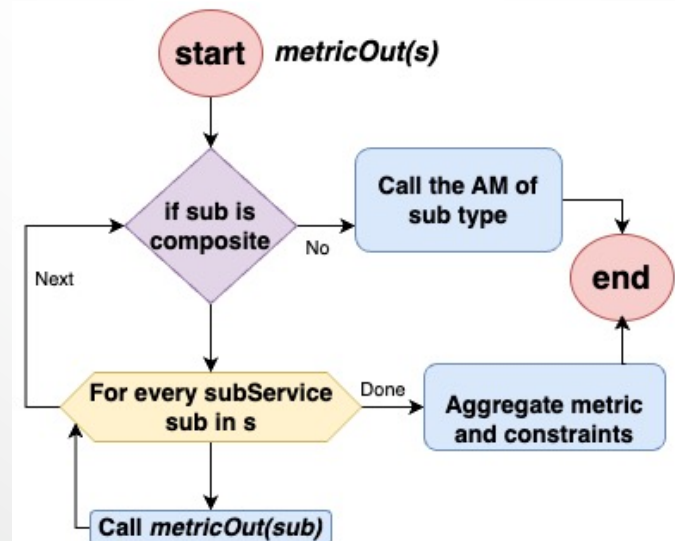
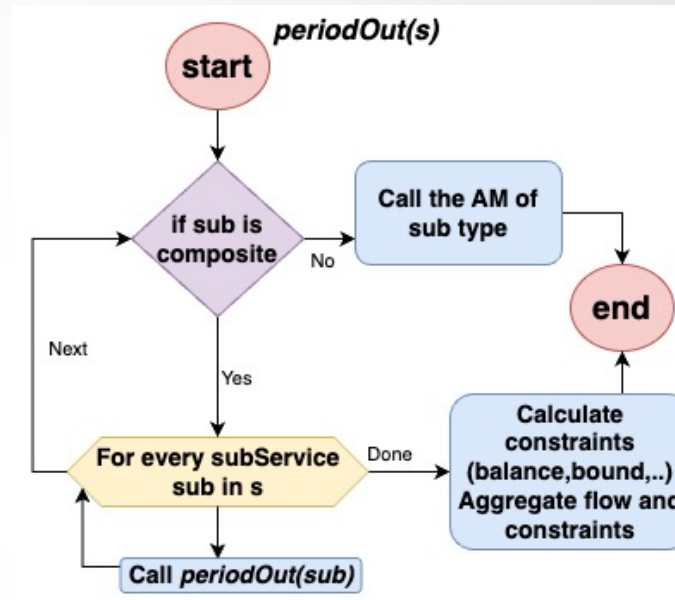
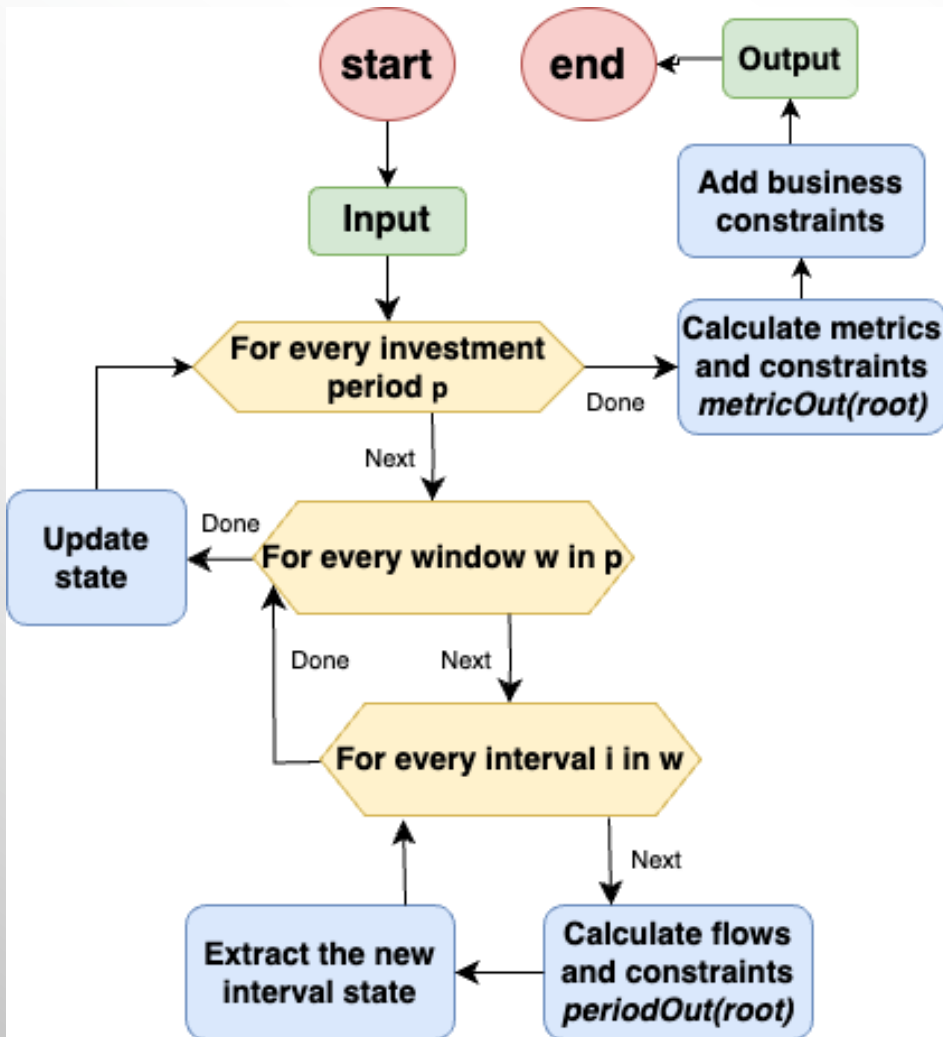


Time horizon





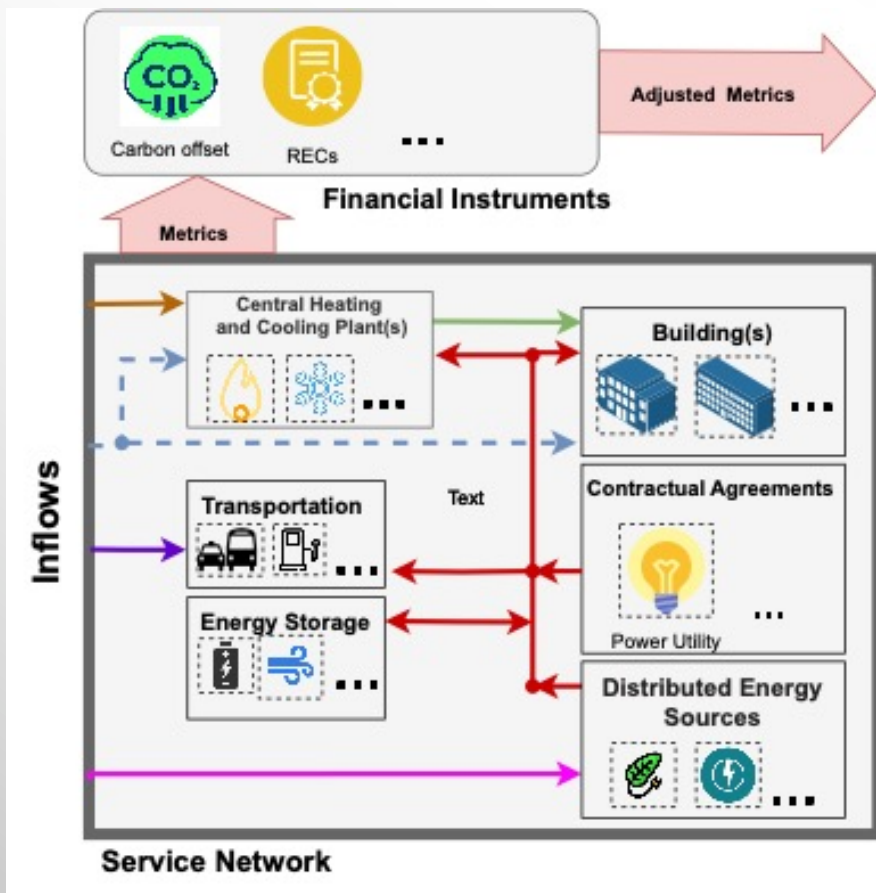
Service Network analytical Model



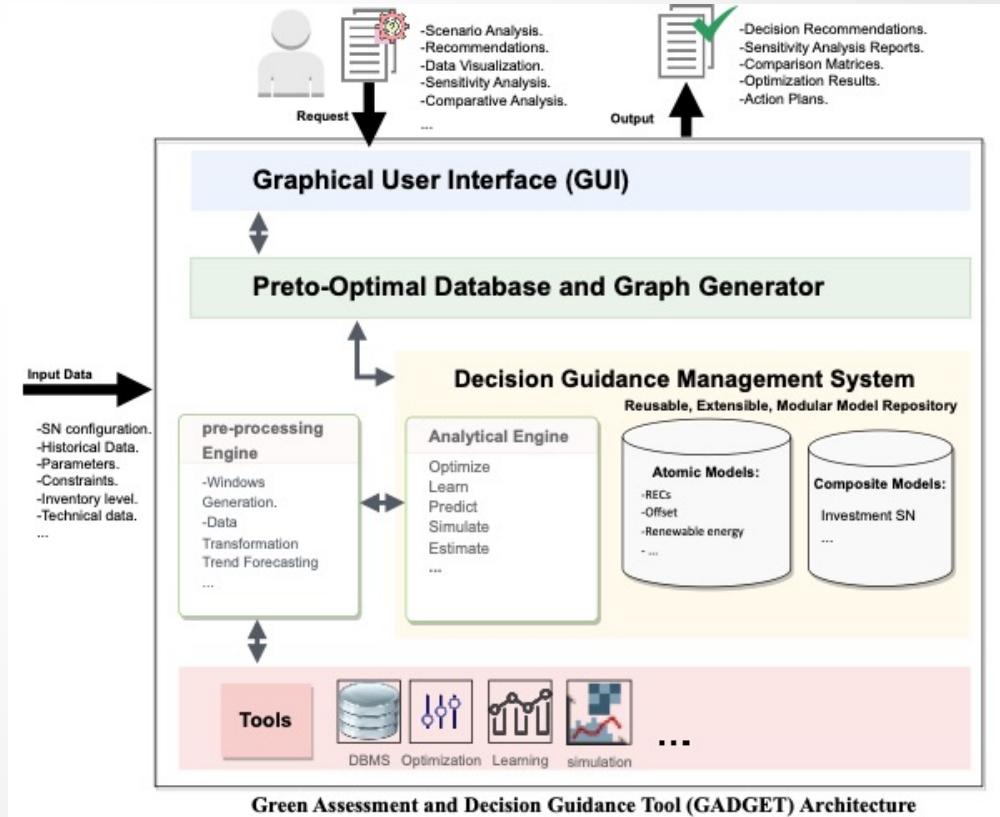
Development of GADGET



T-SNIM

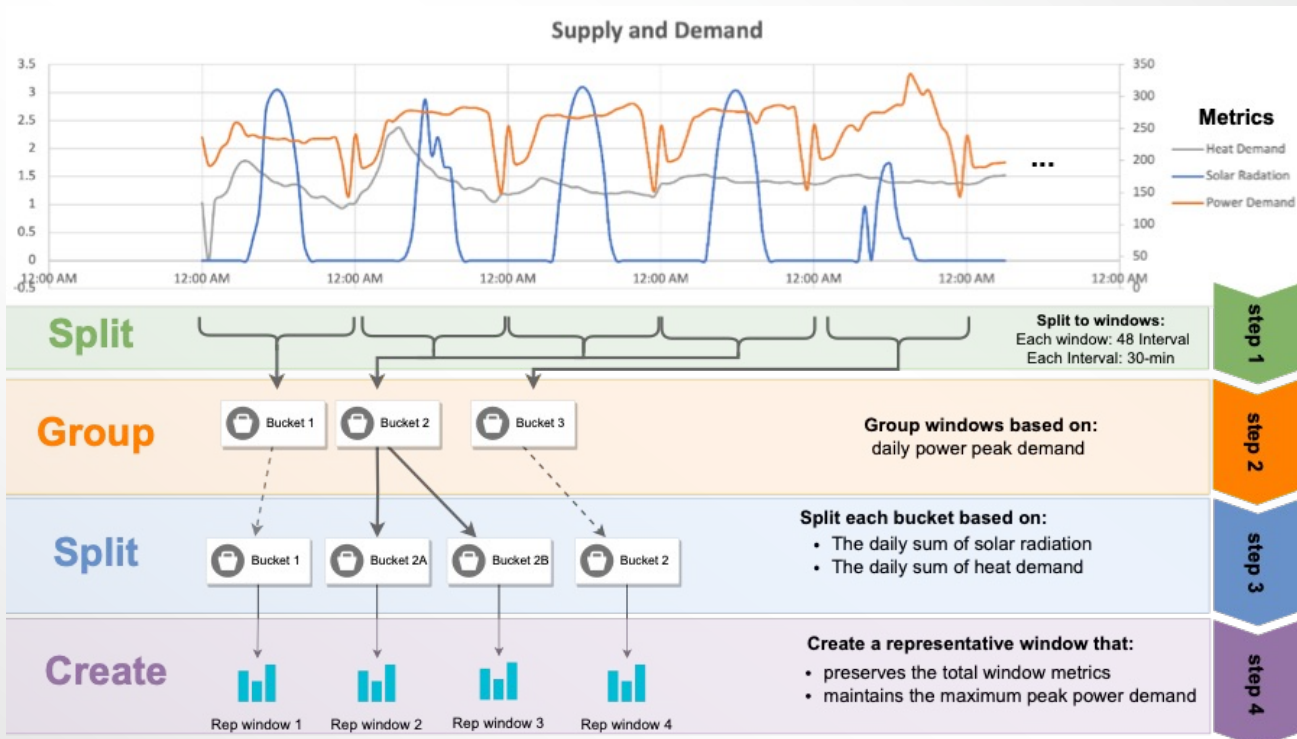


GADGET Architecture





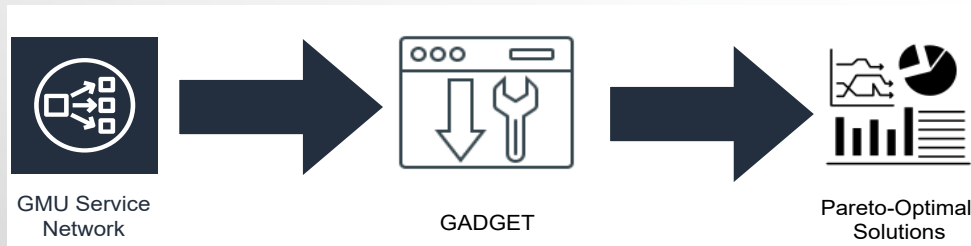
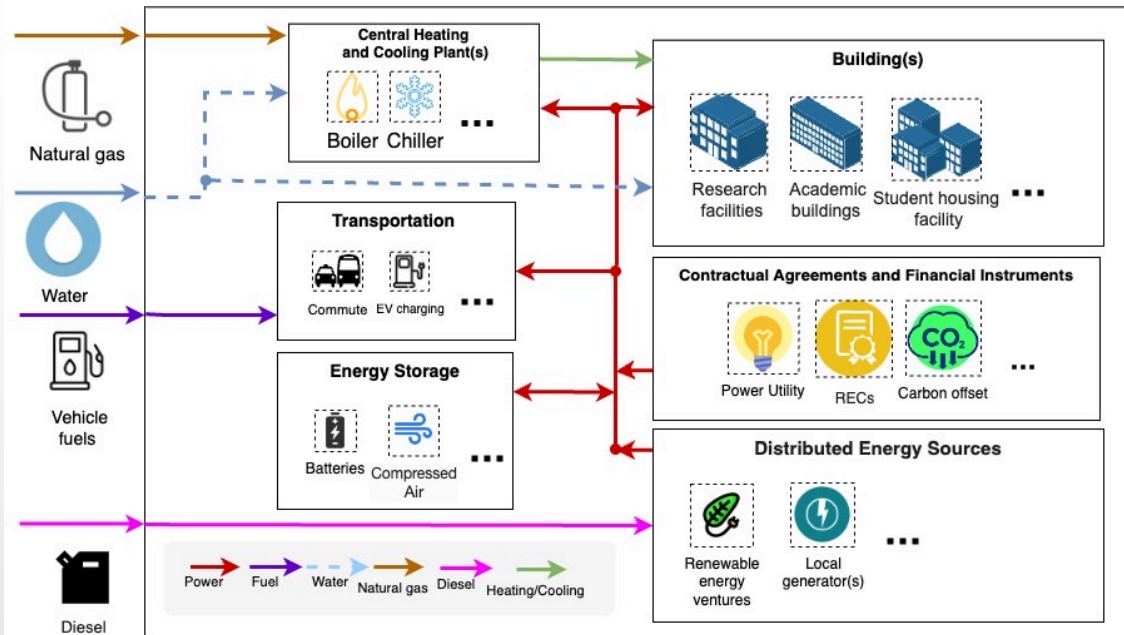
Pre-processing: Generation of Representative Operational Windows





The George Mason University Case Study

Service Network



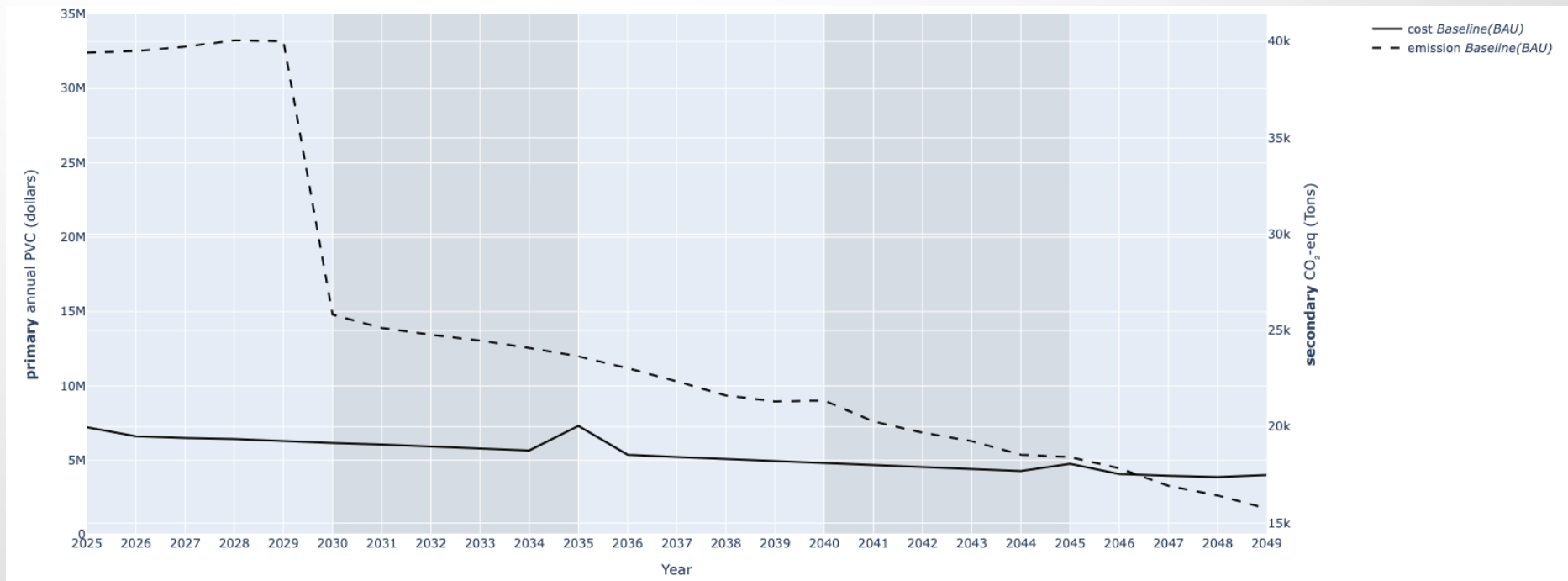
Stakeholders need to decide on how to invest in heterogeneous inter-related infrastructures to achieve carbon neutrality, incl.:

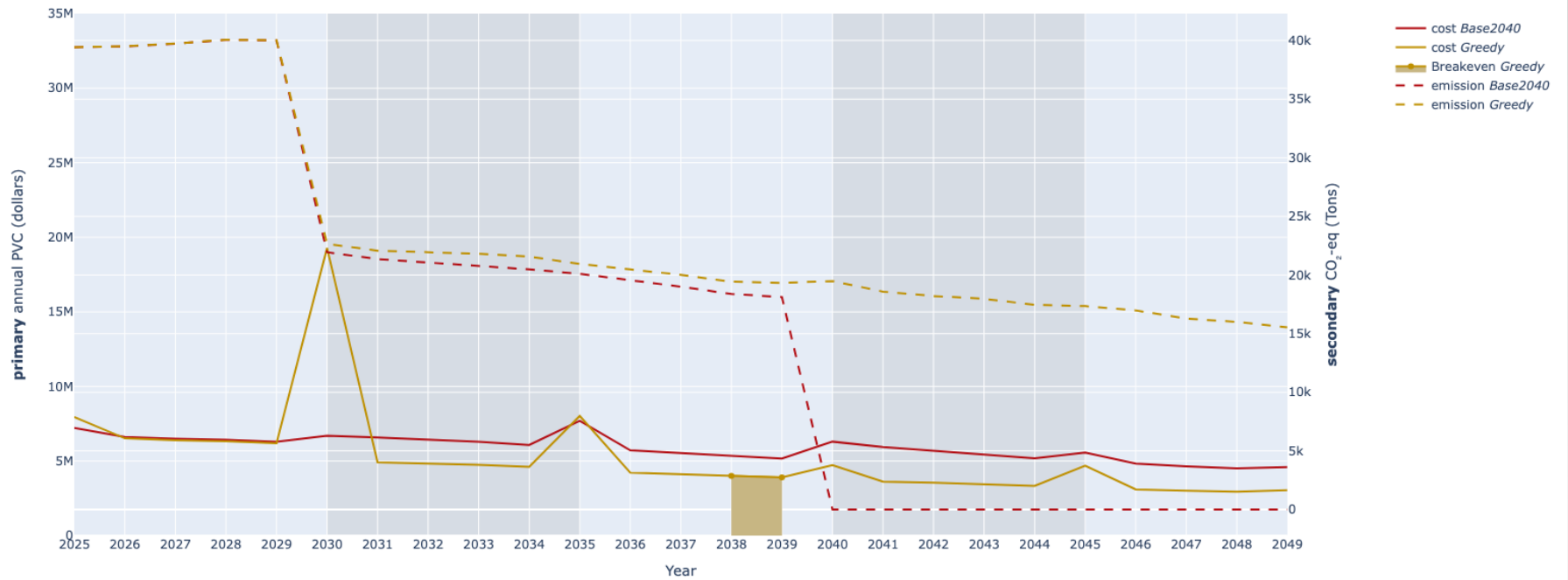
- Building efficiency measures, such as retrofitting, insulation, lighting sensors, and certifications for new buildings.
- Heating/cooling efficiency, e.g., in chillers and boilers;
- renewable sources of energy.
- Energy storage.
- Management of schedulable loads such as in heating/cooling and EV charging.
- RECs and carbon offset credits.
- Investment in renewable energy ventures.
- Peak demand control and management vis-à-vis power utility contracts, e.g., with Dominion Virginia Power.
- Incentives for using green transportation.





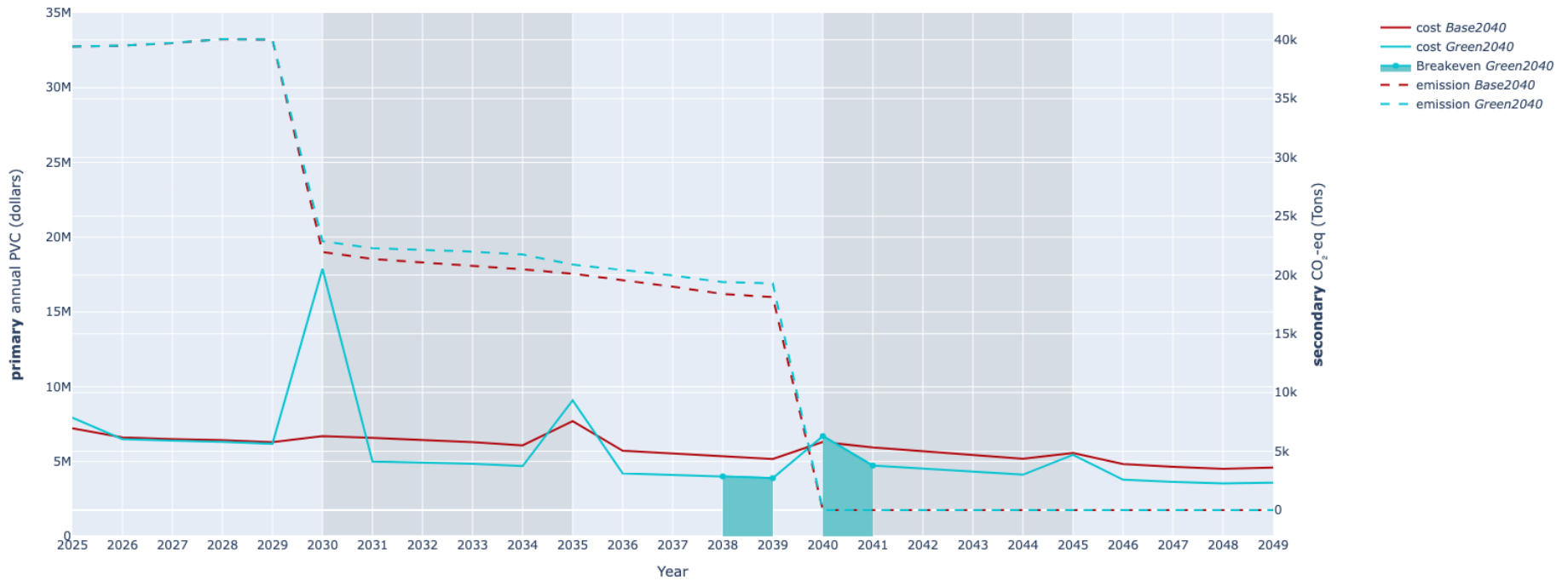
Business as usual (BAU) : No carbon reduction efforts





| | | | | | | | | |
|---------------|---|--|---|--|--|---------|--------|-------|
| Baseline 2040 | Gas Boiler(18.75): 1 | REC: 11,337 Offset: 7,270 | Gas Boiler (25): 1 Gas Boiler(18.75): 1 Offset: 16,760 | Offset: 99,132 | Gas Boiler(18.75): 1 Offset: 85,393 | 146.7 M | 0% | N/A |
| Greedy | Gas Boiler(18.75): 1 Energy Storage: 1 | Solar Panels: 4,720 Energy Storage: 1 | Gas Boiler (25): 1 Gas Boiler(18.75): 1 Solar Panels: 883 | Solar Panels: 434 Energy Storage: 1 | Gas Boiler(18.75): 1 Solar Panels: 632 Energy Storage: 1 | 127.8M | 14.36% | 8.23% |





| | | | | | | | | |
|---------------|---|------------------------------|--|--|---|---------|--------|-------|
| Baseline 2040 | Gas Boiler(18.75): 1 | REC: 11,337 Offset: 7,270 | Gas Boiler (25): 1 Gas Boiler(18.75): 1 Offset: 16,760 | Offset: 99,132 | Gas Boiler(18.75): 1 Offset: 85,393 | 146.7 M | 0% | N/A |
| Green 2040 | Gas Boiler(18.75): 1 Energy Storage: 1 | Solar Panels: 4,394 | Gas Boiler (25): 1 Gas Boiler(18.75): 1 Solar Panels: 1,197 Energy Storage: 1 | Solar Panels: 702 Energy Storage: 2 Offset: 90,910 | Gas Boiler(18.75): 1 Solar Panels: 851 Offset: 81,998 | 136.2M | 11.67% | 2.94% |



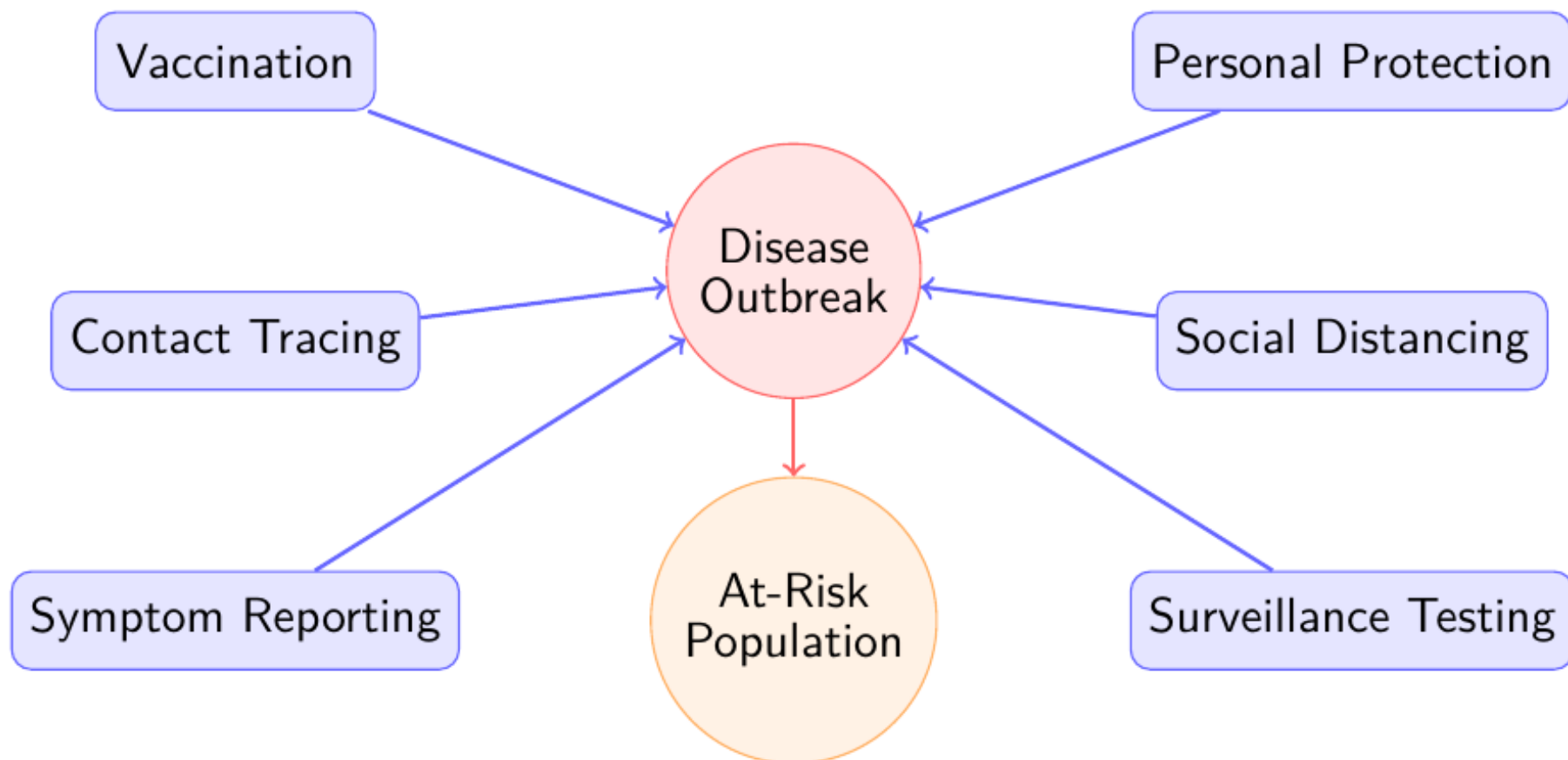
| | Period 1 | Period 2 | Period 3 | Period 4 | Period 5 | PVC | Break Point | IRR (Baseline2040) | IRR (BAU) |
|------------------------------------|---|---|---|--|---|--|---------------------------|--------------------|-----------|
| BAU | Gas Boiler(18.75): 1 | | Gas Boiler (25): 1 Gas Boiler(18.75): 1 | | Gas Boiler(18.75): 1 | Total: 133.31 M Investment: 2.67 M Sunk: 0 Residual: 0.67 M Saving: 0 | N/A | N/A | 0% |
| Base 2040 (RECs and Offset) | Gas Boiler(18.75): 1 | REC: 11,337 Offset: 7,270 | Gas Boiler (25): 1 Gas Boiler(18.75): 1 Offset: 16,760 | Offset: 99,132 | Gas Boiler(18.75): 1 Offset: 85,393 | Total: 146.66 M Investment: 2.67 M Sunk: 13.32 M Residual: 0.67 M Saving: 0 | N/A | 0% | NA |
| Greedy | Gas Boiler(18.75): 1 Energy Storage: 1 | Solar Panels: 4,720 Energy Storage: 1 | Gas Boiler (25): 1 Gas Boiler(18.75): 1 Solar Panels: 883 | Solar Panels: 434 Energy Storage: 1 | Gas Boiler(18.75): 1 Solar Panels: 632 Energy Storage: 1 | Total: 127.81 M Investment: 18.31 M Sunk: 0 Residual: 3.71 M Saving: 21.14 M | 2038-10-17 | 14.36% | 8.23% |
| Green 2040 | Gas Boiler(18.75): 1 Energy Storage: 1 | Solar Panels: 4,394 | Gas Boiler (25): 1 Gas Boiler(18.75): 1 Solar Panels: 1,197 Energy Storage: 1 | Solar Panels: 702 Energy Storage: 2 Offset: 90,910 | Gas Boiler(18.75): 1 Solar Panels: 851 Offset: 81,998 | Total: 136.21 M Investment: 18.35 M Sunk: 8.66 M Residual: 4.09 M Saving: 21.34 M | 2038-12-17, 2040-04-16 | 11.67% | 2.94% |
| Green 2040 enhanced | Gas Boiler(18.75): 1 Energy Storage: 1 | Solar Panels: 6,004 REC: 275 Energy Storage: 2 Offset: 923 | Gas Boiler (25): 1 Solar Panels: 961 Electric Boiler(1800): 3 Offset: 834 Transformer: 1 | Solar Panels: 1,728 Offset: 82,731 Energy Storage: 1 Electric Boiler(1800): 1 | Gas Boiler(18.75): 1 Solar Panels: 359 Offset: 74,086 | Total: 137.15 M Investment: 24.11 M Sunk: 8.08 M Residual: 4.8 M Saving: 25.69 M | 2042-01-16 | 9.44% | 3.13% |
| Green 2035 | Gas Boiler(18.75): 1 Energy Storage: 1 | Solar Panels: 6,004 Energy Storage: 2 REC: 301 Offset: 938 | Gas Boiler(18.75): 1 Solar Panels: 2,303 Electric Boiler(1800): 4 Offset: 90,858 Transformer: 1 | Solar Panels: 386 Energy Storage: 1 Offset: 83,164 | Gas Boiler(18.75): 1 Solar Panels: 485 Offset: 73,227 Electric Boiler(1800): 1 | Total: 145.63 M Investment: 25 M Sunk: 16.32 M Residual: 4.76 M Saving: 26.33 M | 2046-06-16 | 5.55% | -0.47% |
| Green 2030 | Energy Storage: 1 Electric Boiler(1800): 2 Transformer: 1 | Solar Panels: 8,577 Energy Storage: 2 Electric Boiler(1800): 3 REC: 20,731 Offset: 74,434 | Gas Boiler (25): 1 Solar Panels: 130 Offset: 88,692 | Solar Panels: 152 Offset: 82,119 Energy Storage: 1 | Gas Boiler(18.75): 1 Solar Panels: 562 Offset: 73,215 Energy Storage: 1 | Total: 160.17 M Investment: 28.65 M Sunk: 29.2 M Residual: 4.58 M Saving: 28.32 M | N/A | 1.47% | -3.03% |
| Green 2025 | Energy Storage: 1 REC: 26,269 Offset: 172,757 Electric Boiler(1800): 2 Transformer: 1 | Solar Panels: 8,601 Energy Storage: 2 REC: 20,721 Offset: 74,252 Electric Boiler(1800): 3 | Gas Boiler (25): 1 Gas Boiler(18.75): 1 Solar Panels: 98 Offset: 88,683 | Solar Panels: 147 Energy Storage: 1 Offset: 82,254 | Gas Boiler(24.89): 1 Solar Panels: 332 Offset: 73,268 | Total: 168.77 M Investment: 27.8 M Sunk: 37.67 M Residual: 4.4 M Saving: 27.33 M | N/A | 0.04% | -4.11% |



Outline

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When an outbreak strikes — what do you do?



*Which interventions? How much of each?
For whom? At what cost?*

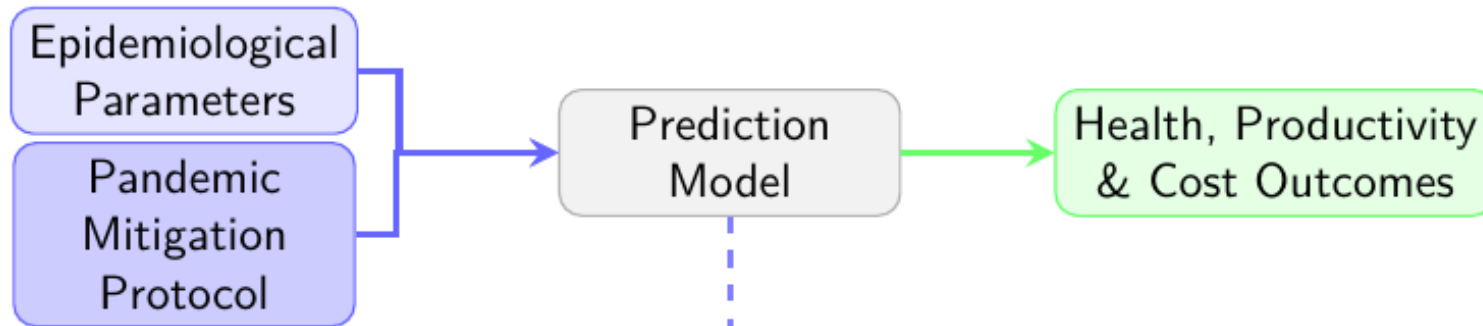
Table of Contents

- 1 Problem, Research Gap & Key Contributions
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- 5 Conclusions & Future Work

The Mitigation Prediction & Decision Problems

Prediction

What outcomes result?



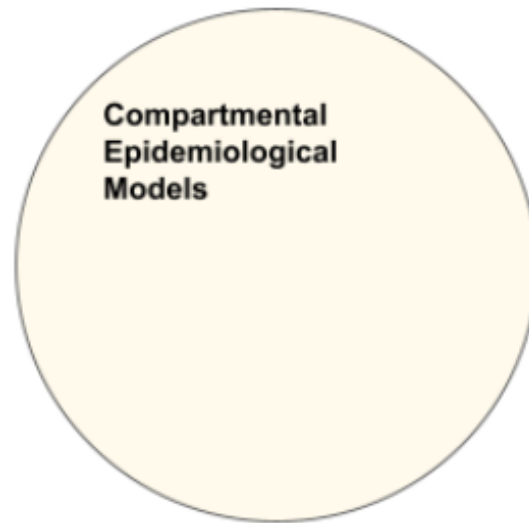
Decision

What protocol is best?



This work: GS-Mitigate solves prediction → enables optimization

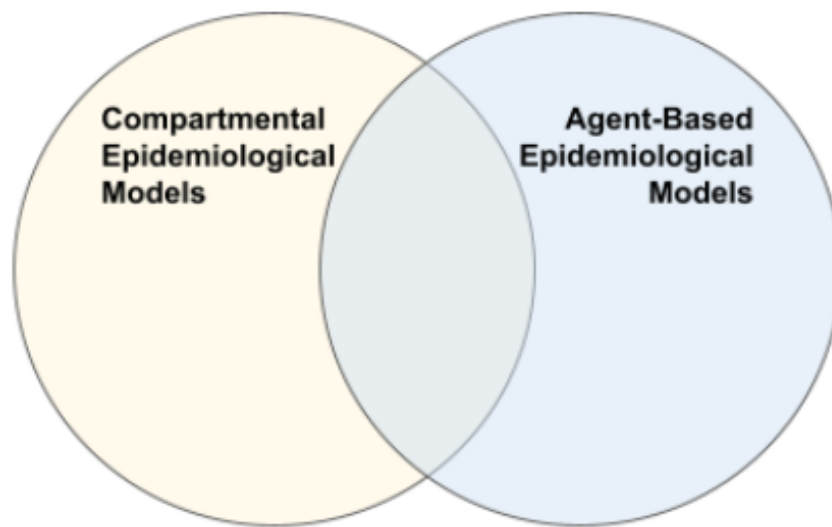
Research Gap



Prior Work:

- Kermack & McKendrick, 1927
- Anderson & May, 1992
- Bertozzi et al., 2025
- Ngcobo et al., 2025
- Podnar et al., 2022
- Childs et al., 2021

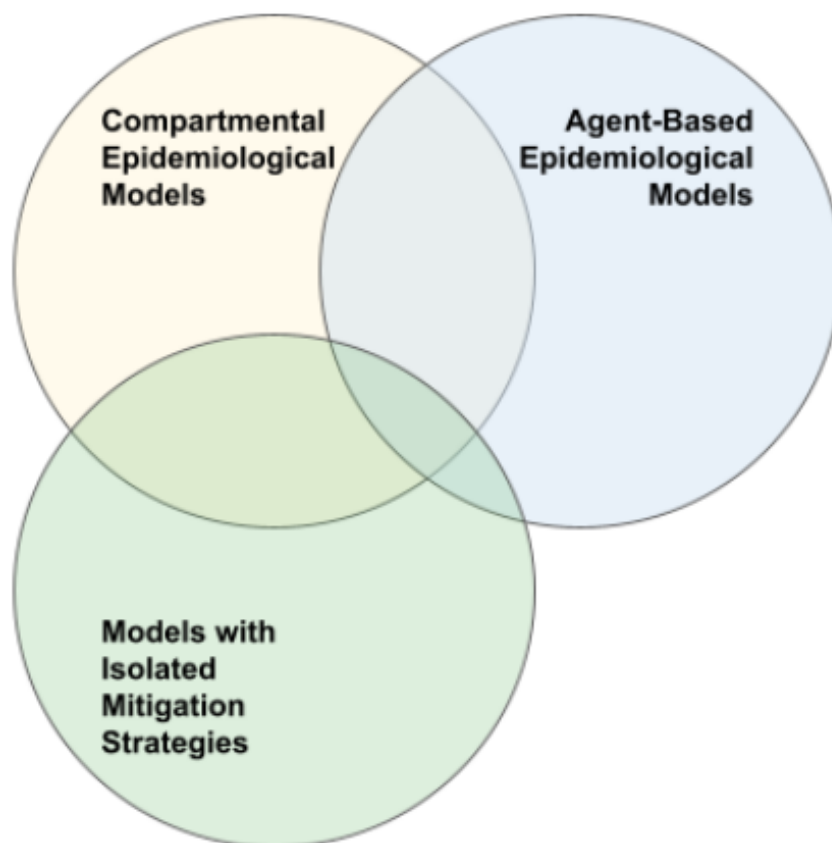
Research Gap



Prior Work:

- Kerr et al., 2021 (Covasim)
- Ferguson et al., 2005 (Imperial College influenza model)
- Ajelli et al., 2010 (spatial ABM for influenza)

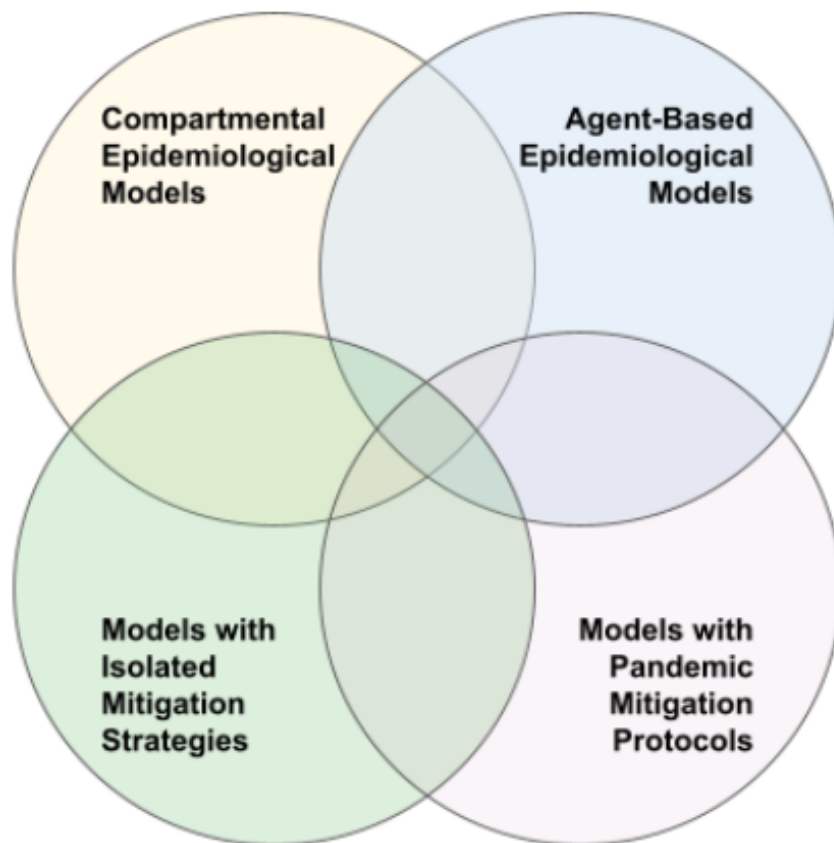
Research Gap



Prior Work:

- Single-intervention studies
- Ozmen et al., 2025 (Operations research integration)
- Verwer et al., 2024 (Reinforcement learning for policies)

Research Gap



Prior Work:

- Brodsky et al., 2021
- Tadakamalla et al., 2021

Research Gap

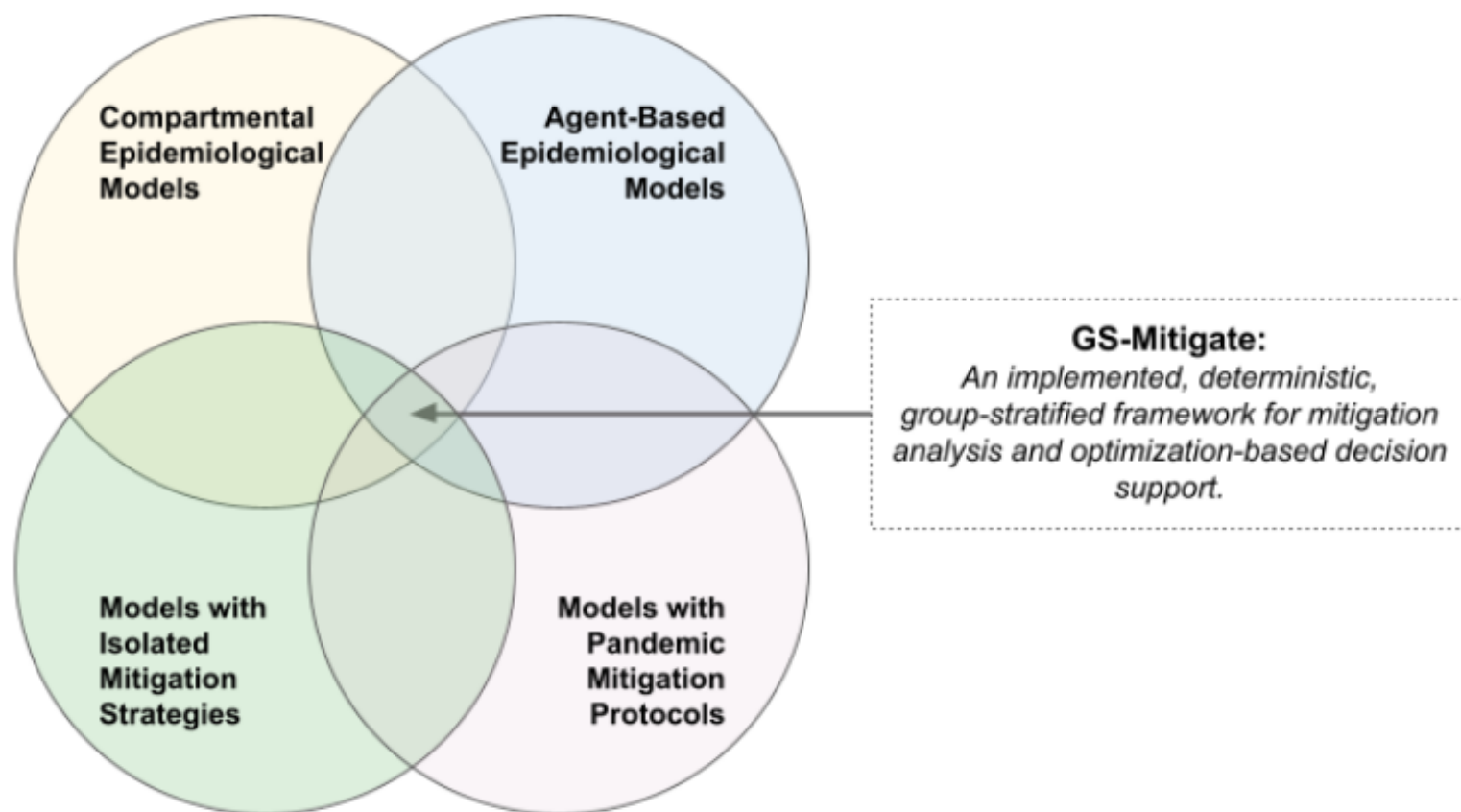


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Pandemic Mitigation Protocol (Parameterized)

Behavioral Interventions

- 1 High-risk sheltering
- 2 Social distancing
- 3 Personal protection

Digital Interventions

- 4 Enhanced contact tracing apps
- 5 Symptom reporting apps

Testing & Monitoring

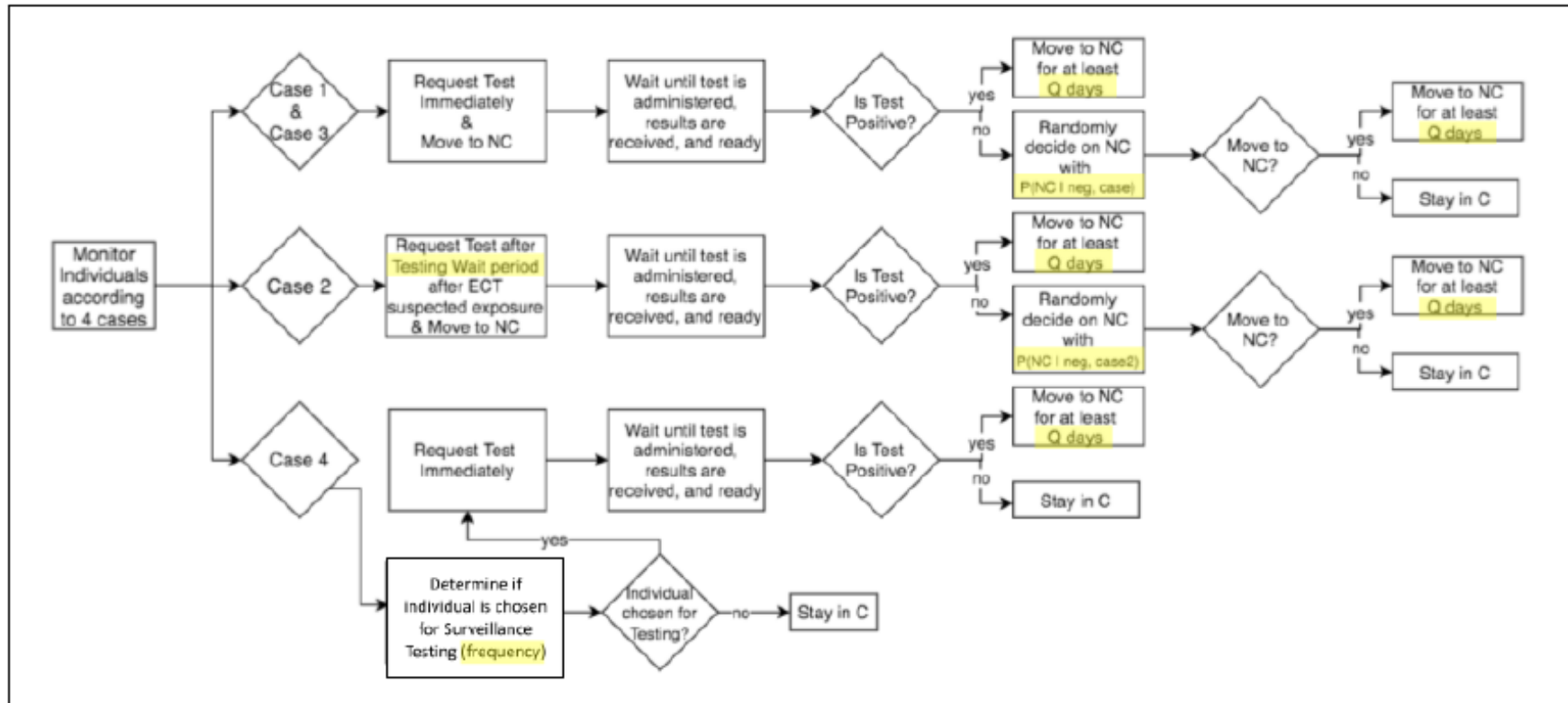
- 6 Surveillance testing
- 7 Case monitoring & response

Parametrization

Each modality defined by continuous parameters:
e.g., adoption ratios, reduction factors, surveillance testing frequency

Enables fine-grained policy exploration and optimization

Modality 7: Case Monitoring & Response



Highlighted = Parameters that define protocol behavior

Different parameter combinations → different mitigation strategies

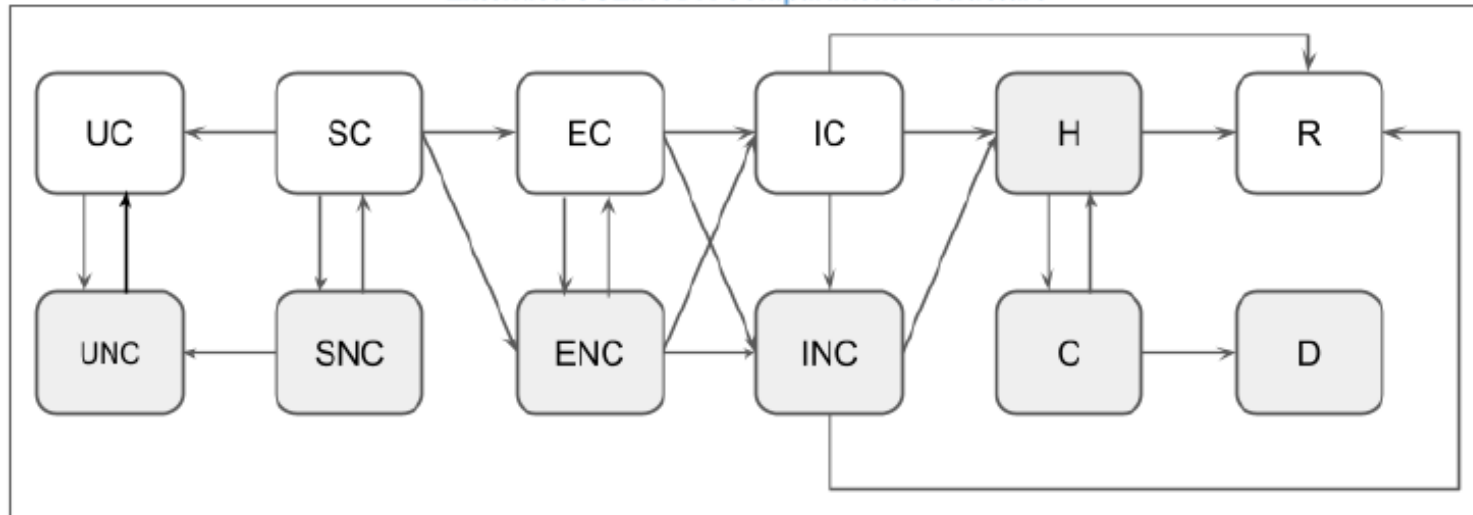
- Case 1:** Symptomatic individuals (SR)
- Case 2:** Contact-traced suspected exposure (ECT)
- Case 3:** Symptomatic & Contact-traced suspected exposure (ECT)
- Case 4:** Asymptomatic surveillance testing

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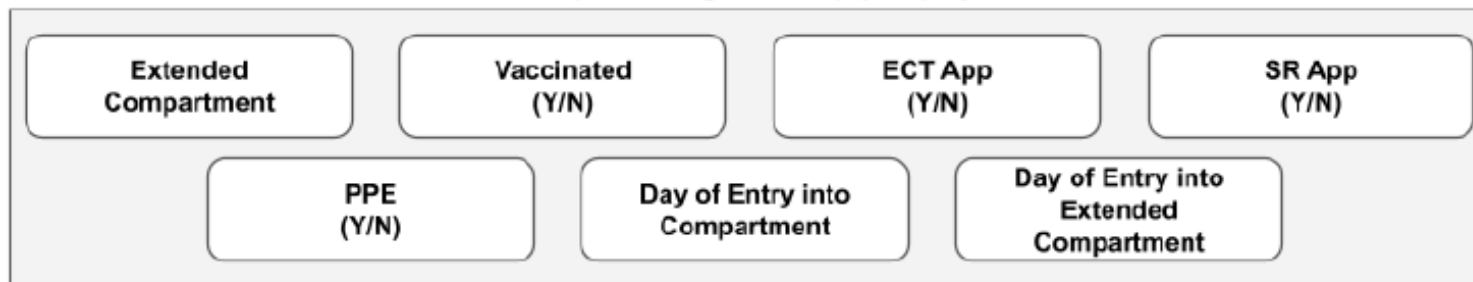
- 1 Problem, Research Gap & Key Contributions
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- 4 Illustrative Demo & Insights
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Extended SUEIHCDR + Epidemiological Groups Definition

Extended SUEIHCDR Compartmental Structure



Epidemiological Group (7 Tuple)

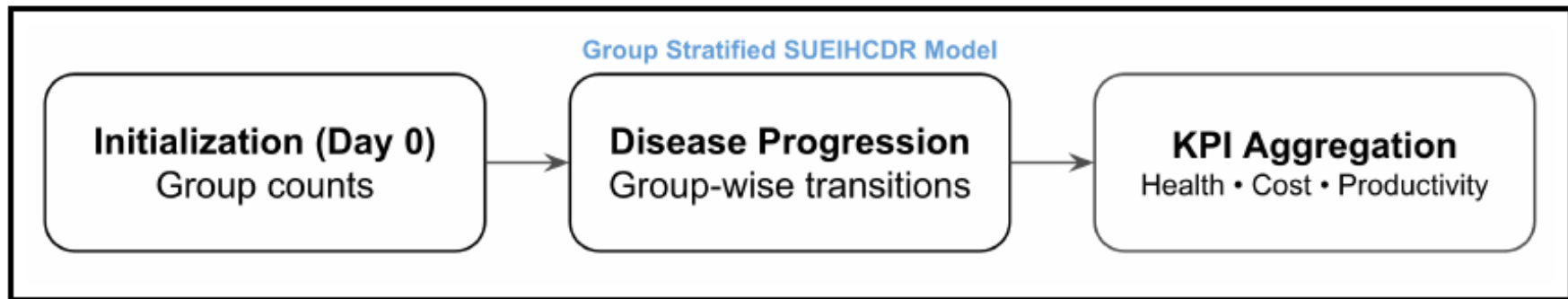


- Num. of compartments = 8 (SUEIHCDR compartmental model)
- Num. of groups in GS-Mitigate = 2.1M over 105-day time horizon

Note: Only circulating groups participate in transmission.



Computation Pipeline & KPIs



Disease Progression & GTR

Algorithm Disease Progression over time horizon

for $d = 1$ to K **do**

for each group $g \in G$ **do**

$$in(g, d) = \sum_{g' \in G} GTR(g', g, d - 1) * count(g', d - 1)$$

$$out(g, d) = \sum_{g' \in G} GTR(g, g', d - 1) * count(g', d - 1)$$

$$count(g, d) = count(g, d - 1) + in(g, d) - out(g, d)$$

end for

end for

Disease Progression & GTR

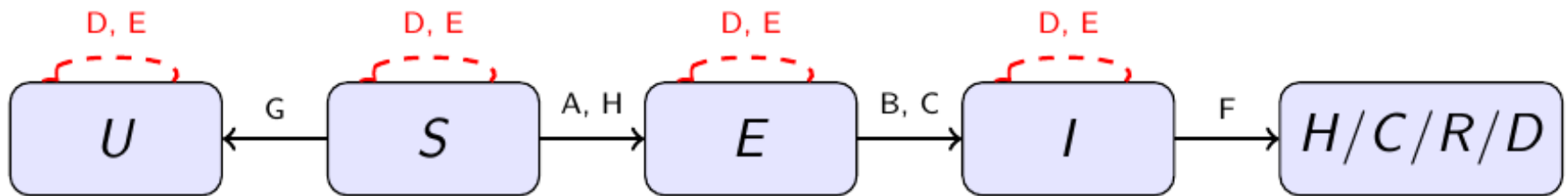
Algorithm Disease Progression over time horizon

```
for  $d = 1$  to  $K$  do  
  for each group  $g \in G$  do  
     $in(g, d) = \sum_{g' \in G} GTR(g', g, d - 1) * count(g', d - 1)$   
     $out(g, d) = \sum_{g' \in G} GTR(g, g', d - 1) * count(g', d - 1)$   
     $count(g, d) = count(g, d - 1) + in(g, d) - out(g, d)$   
  end for  
end for
```

GTR

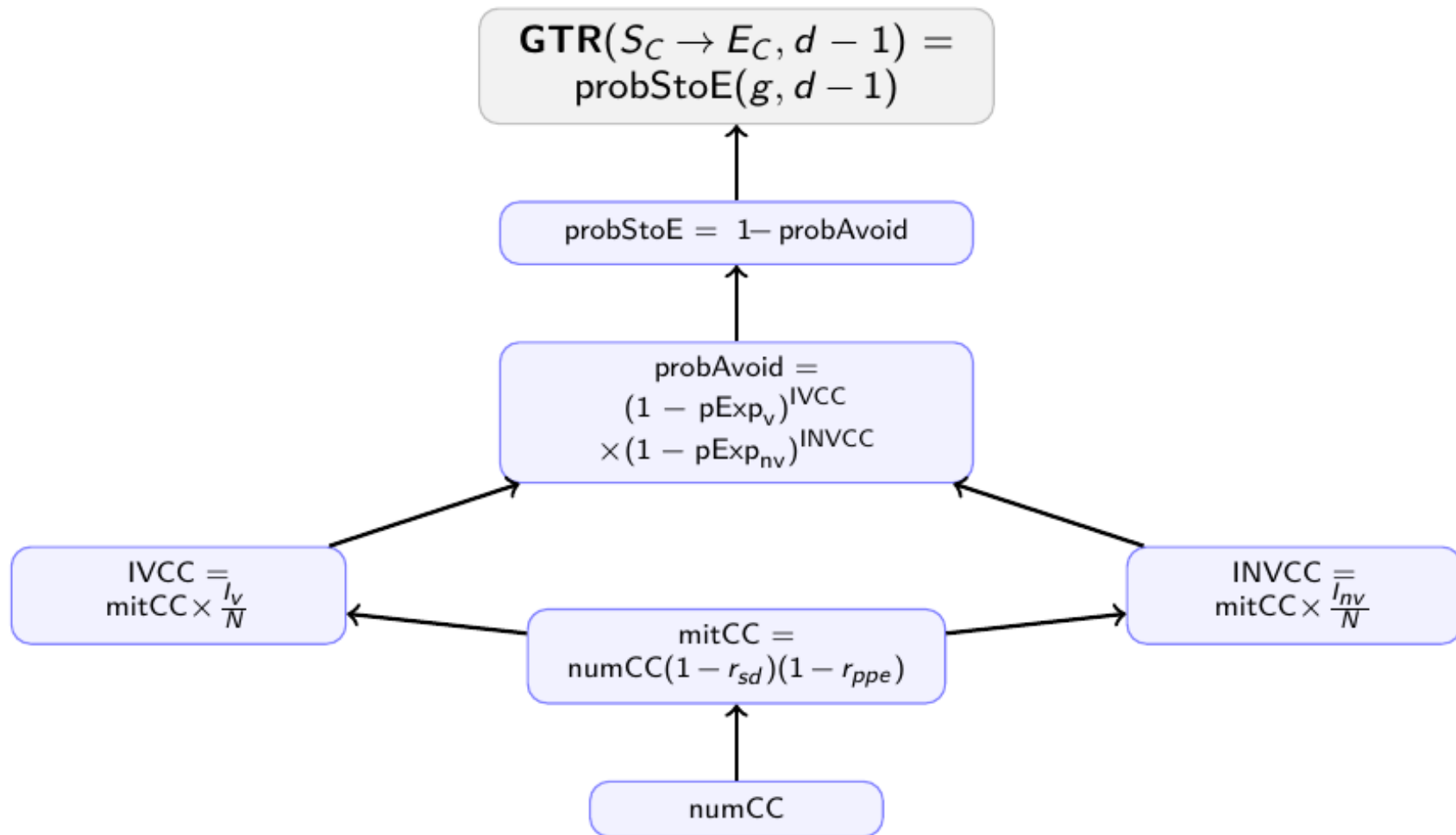
$GTR(g' \rightarrow g, d-1)$ = fraction of individuals moving from group g' to group g in one day

GTR($g' \rightarrow g, d - 1$)



| Case | Transition ($g' \rightarrow g$) | Description |
|------|-----------------------------------|-------------------------------------|
| A | $S_C \rightarrow E_C$ | Exposed, stays circ |
| H | $S_C \rightarrow E_{NC}$ | Exposed, enters non-circ |
| B | $E_{NC} \rightarrow I_{NC}$ | Infected, enters in non-circ |
| C | $E_{NC} \rightarrow I_C$ | Infected, released from non-circ |
| D | $X_{NC} \rightarrow X_C$ | Exit non-circ (remains in S/U/E/I) |
| E | $X_C \rightarrow X_{NC}$ | Enter non-circ (remains in S/U/E/I) |
| F | $I \rightarrow R/H, \text{ etc.}$ | Standard disease progression |
| G | $S \rightarrow U$ | Time-dependent unsusceptibility |

GTR Computation of Case A ($S_C \rightarrow E_C$)



Cases B-H similar. Further details in Section 4 of paper.

$pExp_v$, $pExp_{nv}$, $numCC$, r_{sd} , r_{ppe} provided as input parameters

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Selected Pareto-Optimal Scenarios (Illustrative)

| Strategy | Inputs | | | Health | | | Cost | Prod. |
|--------------------|--------|-----|-------|------------|-----------|------------|---------------|---------------|
| | App | Vac | Surv | Peak H. | Inf. | Deaths | Tests | Isol. PD |
| High vac + apps | 0.7 | 0.9 | 0.000 | 2.0 | 180 | 4.0 | 812 | 1,790 |
| Balanced approach | 0.7 | 0.7 | 0.000 | 5.1 | 342 | 8.2 | 3,188 | 4,987 |
| Vac + surveillance | 0.7 | 0.9 | 0.005 | 1.2 | 98 | 2.1 | 5,789 | 6,187 |
| App-intensive | 0.9 | 0.5 | 0.005 | 4.2 | 215 | 7.5 | 8,234 | 9,456 |
| Testing-reliant | 0.7 | 0.0 | 0.010 | 8.2 | 567 | 15.3 | 15,482 | 15,988 |

Key insight: Multiple Pareto-optimal strategies exist—decision depends on budget constraints, policy priorities, and tolerance for health vs. productivity losses

Outline

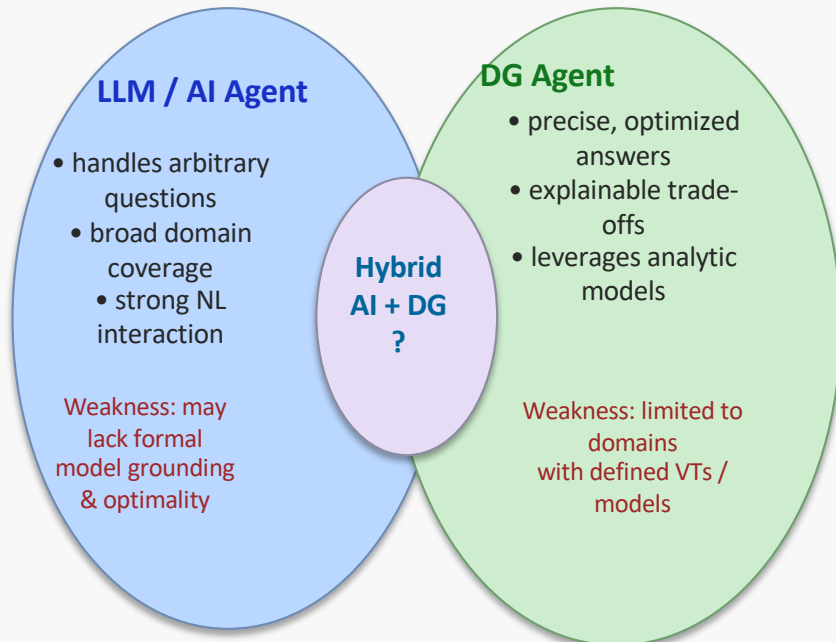
- DG applications by example
- DG Tools:
 - DG Analytics Language (DGAL) & Management System (DGMS)
 - Interactive DG for Virtual Things (DG-ViTh & OptiGuide)
- DG Algorithms: brief overview
- DG Applications
 - Green Assessment and DG Tool (GADGET): toward carbon neutrality
 - DG System for Comprehensive Pandemic Mitigation with Pareto-Optimal health, cost and productivity outcomes (GS-Mitigate)
- Grand Challenge: AI Agentic Framework for Model-Based Decision Guidance



Grand Challenge: AI Agentic Framework for Model-Based Decision Guidance

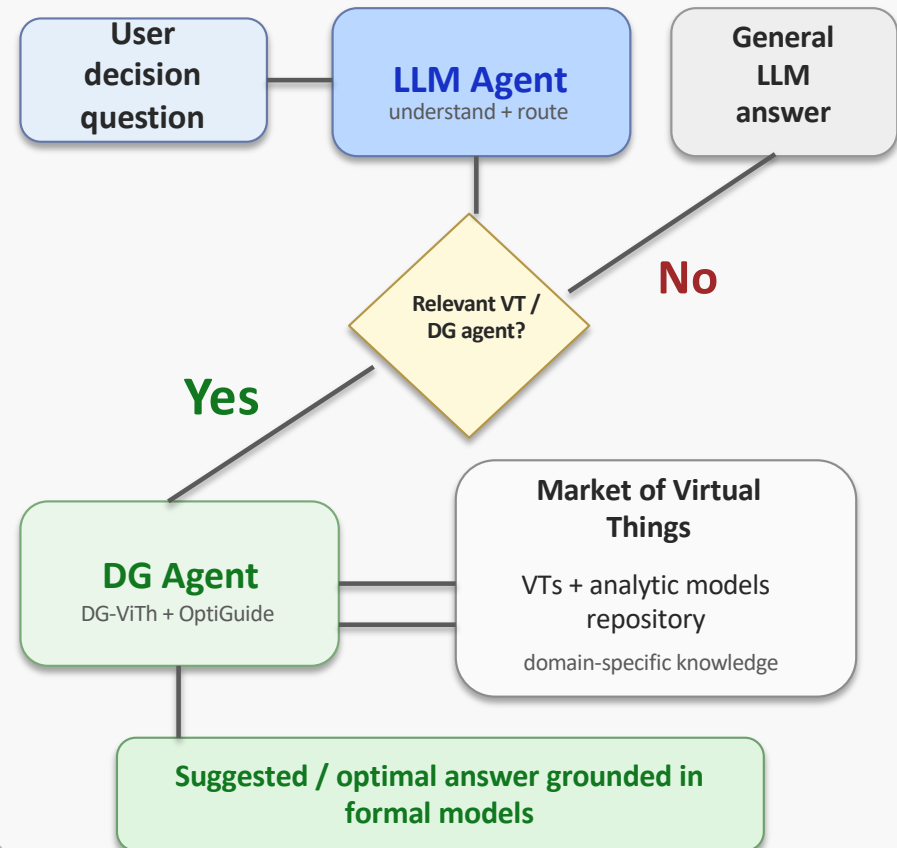
Merging the generality of LLM agents with the model-based optimality of DG-ViTh and OptiGuide+

1. Why a Hybrid AI + DG Agent?



Key idea: route to DG when a relevant virtual thing exists; otherwise fall back to LLM.

2. High-Level Integration Framework Idea



Conclusions

- Technical research challenges with impact on real-world problems
- Main goal: a robust interactive DGMS
- DBMS have revolutionized the development of modern Information Systems
- Can DGMS have similar impact on the development of Decision Guidance Systems?
- Is AI Agentic Framework for Model-Based Decision Guidance feasible?

Questions ???

