

Emerging Architectures for Global System Science

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Our society is organized around a number of (interdependent) global systems. Logistic and supply chains, health services, energy networks, financial markets, computer networks, and cities are just a few examples of such global, complex systems. These global systems are socio-technical and involve interactions between complex infrastructures, man-made processes, natural phenomena, multiple stakeholders, and human behavior. For the first time in the history of mankind, we have access to data sets of unprecedented scale and accuracy about these infrastructures, processes, natural phenomena, and human behaviors. In addition, progress in high-performing computing, data mining, machine learning, and decision support opens the possibility of looking at these problems more holistically, capturing many of these aspects simultaneously.

Global System Science (GSS) (Jaeger et al. 2013) is the evidence-based study of such complex systems. Its goal is to identify fundamental concepts that help structure problems, identify phenomena, and organize actions. GSS looks at systems holistically, studying their main components and how they interact. In particular, GSS jointly studies

- The underlying complex **infrastructure/organization**, including the physical laws and the process governing it.
- The **environment** influencing and being influenced by the system.
- The **human factor** driving and perturbing the dynamics of such systems.
- The **conflicting interests** of a number of self-interested actors involved in the process.
- The **different time/geographical scales** at which the system components operate.

The goals of GSS research are already present in the study of many isolated subsystems and they include:

- *Descriptive analytics*: Understanding the system behaviour, its components, and their relations.
- *Predictive analytics*: Predicting how the system will behave over time.
- *Operational Control*: Controlling and optimizing the dynamics of the system.

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- *Strategic and Tactical Planning*: Deciding how to influence and optimize the medium- and long-term behaviour of the system.

What is novel in GSS is the focus on holistic modeling. Indeed, these above tasks have been traditionally performed in isolation. This is the case in many logistics and supply-chain systems where the separation of strategic, tactical, and operational levels creates fundamental issues at the operational level. The real GSS challenge is to tightly integrate the operations of the infrastructure/organization, human behaviour and mechanisms to influence it, social and environmental considerations, and strategic and tactical planning.

The rest of this paper presents a general architecture to manage global systems, a number of case-studies to showcase GSS challenges and opportunities, and emerging architectures in GSS. It is important to point out that global systems have been investigated in the past. What is novel is the availability of data sets of unprecedented accuracy and the computational progress in optimization and machine learning, which opens tremendous opportunities for AI research.

The Emerging Architecture

Global systems must reason about complex infrastructures, natural phenomena, and behavioral models for individuals and communities; they aim at modeling both social and economic objectives; and they need to find mechanisms encouraging collaboration between selfish stakeholders. An emerging architecture capturing all these aspects is depicted in Figure 1. The strategic, tactical, and operational layers contain both predictive and decision models. Interactions among layers enable the tight integration advocated earlier. Despite its generality, the architecture is instrumental in crystalizing many critical aspects of global systems. For space reasons, this paper does not discuss the monitoring components despite its critical importance in adapting the system behavior to the dynamic environments it is operating under.

It is worth mentioning that fields such as logistics (Bilgen and Ozkarahan 2004) or supply chain management (Steven 2006) are often presented through strategic, tactical, and operational layers. *What is typically missing in these fields is a feedback loop between the levels and tight vertical and horizontal integrations between various components. These integrations are precisely the topic of this paper.*

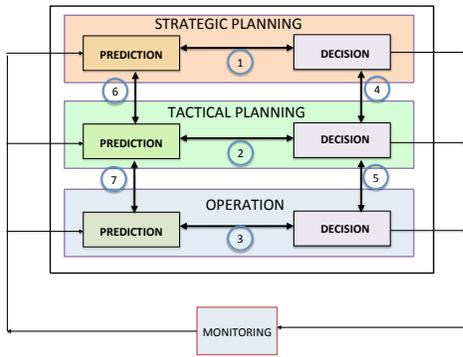


Figure 1: Emerging Architecture for Global Systems.

Motivating Case Studies

This section instantiates the emerging architecture to three case studies in incentive design for energy policies, power restoration, and evacuation planning and scheduling.

Incentive Design for Energy Policies

Policy making in the energy sector accounts for both energy production and efficiency. It covers long-term plans defining regional energy strategies (over an horizon of 3–7 years) as well as medium-term policy instruments to implement such policies (for an horizon of few months). The strategic energy plan is a complex optimization problem taking into account land use constraints, geographical budget constraints, the stability of the electric grid, the complex infrastructure underlying the energy market, as well as environmental and economic impacts and social acceptance.

However, the strategic plan only represents a *desiderata* of the administration because the energy market is a complex system with its own dynamics that is heavily influenced by people behaviour. The tactical plan consists in devising policy instruments (feed-in-tariffs, investment grants, tax exemptions) and a budget allocation to drive the energy market toward the desired objective. The critical problem in this space is the irrational behavior of most of the population: Indeed, both economic and social aspects (environmental sensitivity, feeling of belongingness to a group, trust in the government and future, perceived bureaucracy) play a critical role in shaping human decisions (Jager 2006). Figure 2 illustrates this point: The left graph depicts the total installed power of photovoltaic plants in a region while the right figure shows the trend of national incentives. There is no clear relation between the two, indicating the presence of other factors influencing the adoption of photovoltaic technology.

Figure 3 depicts our partial implementation of the general architecture. It considers both the strategic and tactical levels. An optimization model is used for the strategic component, while the tactical decision-making module is implemented through mechanism design. Finally, a multi-agent simulation is used for predictive modeling in the tactical layer, capturing both economic and social influence.

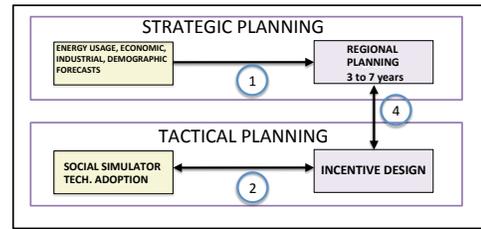


Figure 3: Decision Support for Designing Energy Policies.

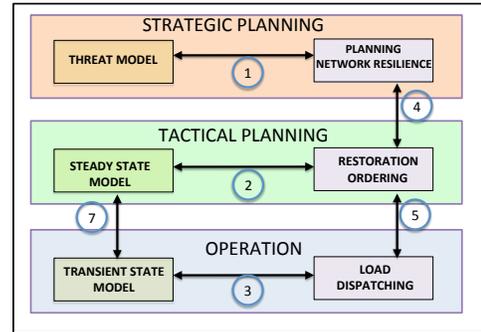


Figure 4: Decision Support for Minimizing Blackouts.

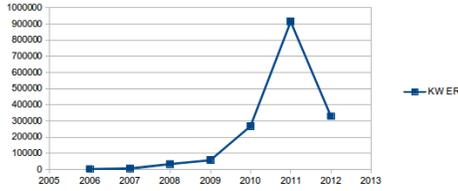
Minimizing Blackouts

Blackouts are a major source of human suffering and economic losses. Figure 4 depicts our instantiation of the emerging architecture to mitigate their effects. At the strategic level, an optimization model uses a threat model (e.g., a hurricane simulator from the National Hurricane Center) to decide where to reinforce the network and stockpile resources (Coffrin, Van Hentenryck, and Bent 2011). When a hurricane hits a region, a tactical optimization model uses the steady-state power flow equations to dispatch repair crews in order to fix damaged components and minimize the size of the blackout (Van Hentenryck, Coffrin, and Bent 2011; Coffrin and Van Hentenryck 2014). An operational model then must dispatch generators and chooses which loads to pick up, while ensuring transient stability (Mak et al. 2014; Hijazi, Mak, and Van Hentenryck 2015).

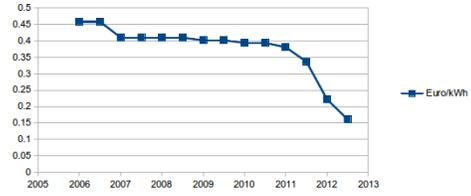
The strategic, tactical, and operational models consider radically different time horizons (from months to a few seconds). They also focus on different abstractions of the power grid (e.g., steady states versus rotor dynamics). Yet, it is critical in the strategic planning model to capture the steady-state behavior in planning for resilience and system dynamics in sequencing the repairs. Observe also that the dynamics of the power system is typically described by systems of partial differential equations. The computational issues raised by integrating static and dynamic aspects of power systems are substantial and require novel methodologies.

Planning and Scheduling Evacuations

Planning evacuation is a critical aspect of disaster management with significant consequences on human lives and welfare. It is also a wicked problem that typically involves a



(a) Installed PV Panels (kW) in Emilia-Romagna.



(b) Italian National Feed-in Tariffs Prices in Euro/kWh.

Figure 2: The Financial Incentives and the Photovoltaic Panels (in kW) Installed in Emilia-Romagna.

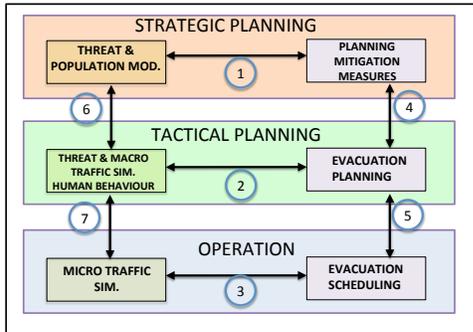


Figure 5: Decision Support for Evacuation Planning.

natural or man-made threat (e.g., a flood or a bushfire), the traffic network, a variety of data sources about population, mobility patterns, and background traffic, and human behavior in emergency situations. Figure 5 depicts an instantiation of the emerging architecture being deployed in the Hawkesbury-Napean region, a massive flood plain in the West of Sydney (Even, Pillac, and Van Hentenryck 2014; Pillac, Van Hentenryck, and Even 2014). A major break or spillover at the Warraganba dam would necessitate the evacuation of about 70,000 residents. The strategic level decides which mitigation measures are necessary to ensure safe evacuations: These measures may include road improvements, reshaping intersections, building levies, and raising dams. The optimization model must rely on predictive models for floods, population growth, mobility patterns, and background traffic. The flood extent is typically computed by hydro-dynamic models based on the Navier-Stokes equations. Choosing the “right” mitigation measures is computational challenging since it requires an integration of discrete optimization and hydro-dynamic models. The tactical level aims at choosing the best evacuation routes, while the operational level decides when to evacuate residential zones. Different (e.g., macroscopic and microscopic) traffic simulators can be used for tactical and operational predictions.

Evacuation planning however raises two fundamental issues. First, evacuation planning and scheduling operates on a time-expanded graph, making the optimization model particularly challenging to solve. Second, evacuation planning models must take into account human and driver behaviors

during such emergencies. For instance, anecdotal evidence from actual evacuations indicates that drivers slow down at forks, such as those introduced by contraflows. Optimization and simulation models ignoring such behavior are overly optimistic in predicting evacuation times and may produce unreliable plans. Many of the links in the current implementation of Figure 5 require tighter integrations and feedback loops, a key challenge in evacuation research.

Emerging Integration Patterns

This section reviews a number of interaction patterns for the general GSS architecture. The patterns are presented in abstract, simplified forms to crystallize the ideas, but they are linked to the case studies for grounding them in actual applications. They are not intended to be exhaustive, but to convey some opportunities and challenges in GSS research.

Vertical Integration of Decision Problems

This section outlines vertical integrations for a simple global model of the form

$$\min_{x,y} f(x) \text{ subject to } c^u(x) \wedge c^l(x,y)$$

which is assumed to be too large to be amenable to traditional solution techniques. Consider now the waterfall model of vertical integration, often used in logistics and supply chains. The upper-level model solves

$$\min_x f(x) \text{ subject to } c^u(x)$$

and transmits the optimal solution \bar{x} to the lower-level model

$$\text{find } y \text{ such that } c^l(\bar{x}, y).$$

This vertical integration has a fundamental issue: There may be no solution to the lower level when $x = \bar{x}$. In more general settings where the objective contains a term $g(x, y)$, the value \bar{x} may lead to severely suboptimal solutions. Tighter integrations address these issues.

Integration Through Benders Decomposition A two-way, weakly coupled, vertical integration of the upper and lower levels has the lower level generate Benders cuts for the upper level. When \bar{x} cannot be extended into a solution

to c^l , a Benders cut $\neg \bigwedge_{j=1}^k (x_{i_j} \neq \bar{x}_{i_j})$ excludes the solution \bar{x} and hopefully many others. Benders decomposition has the advantage that it also applies when the lower-level model c^l is not algebraic and is given by, say, a simulator. This vertical integration is used in numerous application areas, including in disaster management and policy design. A key research issue in this context is to find effective generalized Benders cuts for applications where the lower model captures a complex infrastructure.

Integration Through Corrective Actions This tighter vertical integration is motivated by the case study in power restoration in which the lower-level model performs a correction on the high-level model. The key idea is to sequence the restoration actions using a steady-state model of the power grid, while the lower level corrects the generator dispatches and load pickups using the transient model of generator dynamics. The variables $x = \langle x^a, x^b \rangle$ capture the sequencing decisions (variables x^a) and the generator dispatches and load pickups x^b in steady states. The variables y capture the generators rotor angles and the dispatch and pickup variables in transient states. The lower-level transient model then optimizes

$$L(\bar{x}, \epsilon) \equiv \min_{\epsilon, y} \|\epsilon\| \text{ subject to } x^b = \bar{x}^b + \epsilon \wedge c^l(\langle \bar{x}^a, x^b \rangle, y)$$

and the upper-level model can be thought of

$$\min_x f(\langle x^a, x^b + \epsilon \rangle) \text{ subject to } c^u(x) \wedge L(x, \epsilon).$$

This integration provides a tractable direction to integrate discrete optimization and partial differential equations, which is becoming ubiquitous in global system research. How to generalize this pattern for more complex feedback between the layers is one of the fundamental open research issues in the context.

Integration Through Aggregation This vertical integration has numerous applications, including in evacuation planning and scheduling where it is used to compute convergent plans effectively. Its key idea is to abstract the y variables into a smaller set of variables z and the constraint c^l into its abstract version \tilde{c}^l that satisfies $c^l(x, y) \Rightarrow \tilde{c}^l(x, z)$. For instance, when the lower-level variables $y = \langle y^1, \dots, y^k \rangle$ are partitioned over time, the z variables, which are now time-independent, can be thought of as $z_i = \sum_{t=1}^k y_i^t$ and the upper-level optimization becomes

$$\min_{x, z} f(x) \text{ subject to } c^u(x) \wedge \tilde{c}^l(x, z).$$

The upper level model then captures some fundamental aspects of the lower level. The two models can then be integrated through the architectures discussed previously. Choosing the right aggregations, e.g., temporal, spatial, or constraint-based, is one of the fundamental research issue raised by this pattern.

Integration of Predictive and Prescriptive Models

We now turn to the horizontal integration of predictive and prescriptive models.

Exogenous Uncertainty When the predictive model is exogenous and does not depend on the decision variables, the integration of predictive and prescriptive models naturally gives rise to stochastic optimization models such as

$$\min_x \mathbb{E}_\xi [f(x, \xi)] \text{ subject to } c(x, \xi)$$

where the distribution of ξ is given by predictive model \mathcal{M} .

Endogenous Uncertainty When deciding mitigation measures, ensuring transient stability, scheduling high-performance computers, the prediction of model \mathcal{M} depends on the values of the decision variables. Indeed, the flood extent is affected by the mitigation measures, the generator dispatches influence transient stability, and the thermal heat of CPU cores depends on the job schedules. A tight integration of predictive and prescriptive models

$$\min_x f(x, y) \text{ subject to } c(x, y) \wedge \mathcal{M}(x) = y$$

when \mathcal{M} is a pointwise predictive model which can be expressed analytically. Discretizations of partial differentiable equations, neural nets (Bartolini et al. 2011), decision trees, and regression models (Borghesi et al. 2013) can all be adapted to satisfy this requirement. One significant benefit of this integration is the ability to prune the search space through the predictive model which is now a constraint in the optimization model. The approach can be generalized to the case where \mathcal{M} returns a distribution, in which case stochastic modeling techniques such as chance constraints and risk minimization can then be used. It is also useful to point out that this integration can be combined with Benders decomposition when model \mathcal{M} is not algebraic.

Human Behavior Capturing human behavior is critical in GSS applications. Model \mathcal{M} can predict aggregate human behavior, learned from historical data and digital traces (Pentland 2014). However, it is often important to be more proactive and design incentives to influence human behavior as illustrated in the case study about energy policies. The integration of mechanism design and optimization is a critical and ubiquitous area for GSS and the underlying computational challenges are tremendous. The other extreme of the spectrum is to remove human decision making entirely for some applications. This is the approach taken in designing convergent evacuation plans, i.e., plans that avoid forks which requires human decisions and often create congestion (Even, Pillac, and Van Hentenryck 2015).

Conclusion

The opportunities and technical challenges underlying GSS are tremendous. We have reviewed some emerging architectures which represent some small steps in this direction. There are numerous other computational architectures to be discovered and even more open questions to answer. In particular, it is critical to develop active models for global system science that are resilient, learn over time, and reconfigure themselves.

Acknowledgements

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