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PREDICTIVE VISION OF PHYSICS OF DECISION : MODELISATION OF VIRUS PROPAGATION WITH FORCE FIELDS PARADIGM

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ABSTRACT

This paper introduces a novel method for simulating complex system behaviors using a specific geometric space and force fields within that space. The approach considers the system's performance as a physical trajectory defined by its performance indicators and environmental attributes, which can be deviated by force fields representing risks or opportunities within the system. The primary contribution of this work is the proposal of a method that uses multiple trajectories of a defined system to identify force fields that accurately represent the system.

1 INTRODUCTION

Today, complex systems, whether biological, technical, organizational or social, pose a major challenge in terms of modeling and understanding. Their dynamics emerge from nonlinear interactions between a multitude of variables, often in noncontinuous evolution, and in an uncertain environment. This complexity makes it difficult to develop robust, generalizable and interpretable predictive models.

In this context, an emerging approach proposes to renew our way of conceiving system dynamics: the Physics of Decision (POD). Inspired by theoretical physics, POD proposes to model systemic behavior as trajectories in a multidimensional space, influenced by force fields representing external or internal factors (such as risks and opportunities) (Benaben et al. 2019). These fields are defined as potential gradients and act as attractors or repellents on the system's trajectory. The trajectory of our system depends on its position in the a multidimensional space (which dimensions typically are Key Performance Indicators (KPIs) of the system, characteristics of the system's environment and attributes of the system), and a perturbation of the system can be seen as a forced displacement of our system in this multidimensional space, resulting in a different trajectory. Risks and opportunities can be seen as physical forces pushing our system towards or away from its objectives in its space.

The idea behind POD is to help decision-makers perceive the consequences of risks and opportunities on the system's trajectory. One of the strengths of POD lies in its ability to link descriptive and predictive approaches to performance: on the one hand, it enables us to track and characterize system trajectories (Bellepeau et al. 2024), and on the other, it opens the way to an understanding of structural influences that enable us to anticipate the consequences of risks or opportunities.

The paper is structured as follows. Section 2 focuses on the current research for modeling complex system using several approaches (simulation based, data-driven...) and the POD fundamentals. Section 3 first introduces the POD framework, then tunes the sparse identification of nonlinear dynamics (SINDy) approach to that and presents the proposition for finding the force fields. Section 4 provides SIR model to present the work's significance and the validation of the model. Section 5 proposes a discussion and the perspectives of the future works.

2 LITERATURE REVIEW

2.1 Modeling Complex System

Modeling complex systems poses substantial challenges due to their high-dimensional, nonlinear, and frequently stochastic nature. Various established methodologies have been developed to tackle these challenges, each offering a balance between flexibility, interpretability anc computational cost.
Simulation-based approaches, such as discrete-event simulation (DES) and system dynamics (SD), are widely used to investigate emergent phenomena and dynamic interactions without requiring closed-form analytical models (Ben Rabia and Belladaoui 2022). SD, in particular, enables macro-level modeling via feedback loops and stock-and-flow structures, making it well-suited for strategic planning (Forrester 1987). Recent works have extended SD to model cascading disruptions in supply chains (Olivares-Aguila and El Maraghy 2019). However, these methods often suffer from high computational costs and depend heavily on expert-driven assumptions to define the model structure, which can hinder its scalability and adaptability in highly complex, data-rich systems.

Machine learning models, especially deep neural networks, offer powerful tools for capturing complex nonlinear relationships from high-dimensional data (Abdullahi et al. 2025). Nevertheless their "black-box" nature raises concerns around transparency and interpretability (Lipton 2018). This lack of transparency can hinder trust and acceptance among stakeholders, particularly in fields where understanding the rationale behind decisions is crucial, thereby constraining their applicability to systems necessitating a physical comprehension (Linka et al. 2022).

Physics-Informed Neural Networks (PINNs) represent a flexible framework that facilitates both data-driven predictions and the identification of governing equations within intricate systems. By incorporating physical laws into the learning process, PINNs ensure that the model adheres to known system dynamics (Li 2025; Ganga and Uddin 2024). While this method is effective for systems where the physical laws are completely understood, it encounters limitations when dealing with systems whose dynamics are only partially known or when modeling novel phenomena. An alternative application of PINNs focuses on uncovering the underlying equations governing the system. By employing symbolic regression methods in conjunction with neural network architectures, it becomes possible to discern the simplest mathematical expressions that accurately describe the observed dynamics (Cranmer et al. 2020). Despite its potential, symbolic regression can be computationally demanding and susceptible to noise, necessitating meticulous model tuning.

Sparse Identification of Nonlinear Dynamics (SINDy) seeks to identify the governing equations of dynamical systems directly from data. Proposed by Brunton et al (2016) (Brunton et al. 2016), SINDy utilizes sparse regression techniques to discover a parsimonious model that captures the dynamics of the system. By emphasizing sparsity, SINDy effectively identifies the most relevant terms in a library of candidate functions, allowing for the extraction of interpretable models from high-dimensional data. The strength of SINDy lies in its ability to bridge the gap between data-driven and physics-based modeling. By providing interpretable models that retain the essential features of the underlying dynamics, SINDy has been successfully applied to various applications, including chaotic systems demonstrating its versatility and effectiveness (Rudy et al. 2017).

2.2 Background of POD framework

In today's increasing dynamic and uncertain global environments, instability is becoming a structural feature of decision-making environments (Benaben et al. 2022). Within this context, uncertainties are conceptualized as potentialities, classified as risks when leading to adverse outcomes, and as opportunities when associated with beneficial effects (Benaben et al. 2022). This raises the question: could Newtonian physics provide a conceptual foundation to enhance management science by revealing the underlying dynamics governing organizational behavior? POD framework responds to this challenge by interpreting decision-making dynamics as physical forces acting upon an organization's trajectory in a multidimensional space (Moradhkani and Benaben 2024; Moradhkani and Benaben 2022).

The innovative Decision Support System (DSS) proposed by POD employs the principles of physics to address these quantifiable potentialities that emerge from incomplete information, knowledge gaps, and experimental data. The fundamental elements of the POD framework following the three crucial phases of decisions as Simon (1960) described them :

- **Intelligence** : Understand system performance (KPIs), internal parameters and context (Bellepeau et al. 2024).
- **Design** : Analyze vulnerabilities and dynamics using tools like neural networks and clustering.
- **Choice** : Select optimal actions through heuristic optimization to steer the system effectively.

The proposed methodology has been integrated within the POD framework, which has been investigated across various domains. These include crisis management scenarios such as the COVID-19 pandemic (Moradkhani and Benaben 2022) and its impact on air pollution (Bellepeau et al. 2022). Additionally, it has been applied in operational management contexts such as road traffic management (Moradkhani et al. 2022) and polling place management (Moradkhani et al. 2020). Moreover, the methodology has been utilized in efficiency management scenarios, specifically project management (Le Duff et al. 2022).

This article is part of the "Design" section of the POD framework. In fact, the aim of this article is to analyze the trajectories of a complex system in order to find potentials that characterize a multidimensional space (which dimensions typically are KPIs of the system, characteristics of the system's environment and attributes of the system). To effectively model the system dynamics within the POD framework, it is crucial to derive explicit, interpretable equations that govern system behavior.

3 THEORETICAL FRAMEWORK

3.1 Formal description of the POD framework

3.1.1 Foreword, essential definitions, and notations

The POD framework conceptualizes a system as an object evolving along a trajectory (Figure 1) within a multidimensional space called the *Extended Characterization Space*, composed of quantitative **KPIs**, system **attributes**, and environmental **characteristics**. A **KPI** reflects system performance over time; an **attribute** describes internal properties of the system; and a **characteristic** pertains to contextual variables from the system's environment.

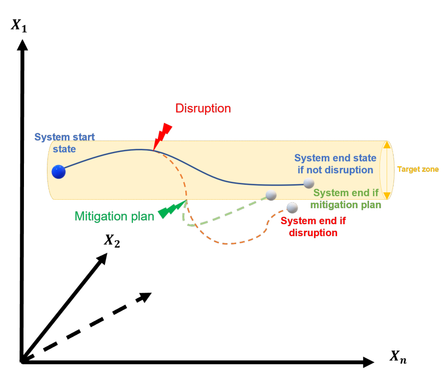


Figure 1: Representation of the POD approach

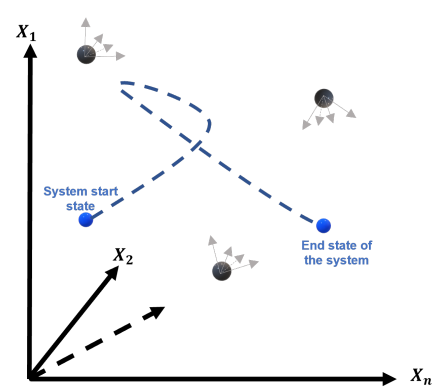


Figure 2: System trajectory in performance space

The POD approach adheres to a force-based vision for evaluating system performance. In this framework, a system is conceptualized as an object, with its trajectory represented within the extended characterization space. This trajectory may deviate due to internal or contextual disruptions, interpreted as risks and opportunities, which are analogous to physical forces acting upon the object (Figure 2).

3.1.2 Notion of force field in the POD framework

System characterization and identification are essential challenges in systems theory. The mathematical representation of a system lies at the heart of the characterization challenge. The method of representing time-dependent systems by differential equations is well established in systems theory and applies to a fairly large class of system, for example the differential equation:

$$\frac{dX}{dt} = \phi(X)$$

Our system evolves in a multidimensional space and is influenced by force fields that have a position in this space. Figure 2 shows an example of any trajectory influenced by 3 fields in the extended characterization space.

We define a force field with the following characteristics:

- **Force field original position:** $\{X_{1,m}, X_{2,m}, \ldots, X_{n,m}\}$
- **Force field laws of physics:** $F_{m \twoheadrightarrow \text{sys}}(r)$
- **Force field intensity:** $F_{m \twoheadrightarrow \text{sys}}(r) = \alpha_m F_{m \twoheadrightarrow \text{sys}}(r)$

with m the number of fields, n the number of dimensions and r an Euclidean distance between the force field and the system.

3.2 Detailled presentation of SINDy-POD

3.2.1 Presentation of the Sparse Identification of Nonlinear Dynamics

SINDy (Sparse Identification of Nonlinear Dynamics) is a data-driven method for discovering the underlying differential equations of a system directly from time-series data. It operates in three main steps:

(a) **Library construction** — A set of candidate functions (e.g, polynomials, delays) is assembled into a feature matrix $\Theta(X)$

(b) **Sparse regression** — Each state variable's derivative $\dot{x}_i$ is fitted as a sparse combination of these features using techniques like STLS (Brunton et al. 2016), LASSO (Tibshirani 1996), or modern optimizers such as *ADAM* (Siva Viknesh and Younes Tatari and Amirhossein Arzani 2025), keeping only the most relevant terms.

(c) **Model identification** — The resulting sparse coefficients define an explicit, interpretable model, which can be simulated for validation.

SINDy is valued for its transparency, efficiency, and extensibility. By capturing only the dominant mechanisms, it yields compact models that are physically meaningful and computationally lightweight, making it a powerful tool for system discovery and analysis.

3.2.2 Presentation of SINDy-POD

The SINDy-POD method extends classical SINDy by modifying the library of candidate functions to rely on distance-based potentials. Instead of a polynomial library, the candidate functions are based on inverse distances to reference points in the extended characterization space. This reflects an experimental choice aimed at preserving physical consistency.

Given a trajectory $X(t)$, we define a set of m reference points $y_i \in \mathbb{R}^n$ with n the number of dimensions. The library is constructed as:

$$\Theta(X) = \left\{ \frac{1}{\|X - Y_i\|^2 + \varepsilon} \right\}$$

where ε is a small regularization term.

The predicted dynamics are:

$$\dot{X} = \Theta(X) \cdot \Xi \tag{1}$$

where Ξ contains the learned intensities associated with each potential field.

This formulation captures the influence of "attractive" or "repulsive" zones in the extended characterization space, enabling a physical interpretation aligned with the POD framework. The fields may be attractive in one dimension and repulsive in another.

The training involves minimizing the loss:

$$\mathscr{L} = \frac{1}{|X|} \sum_t |\dot{X}_{\text{pred}}(t) - \frac{d}{dt} X(t)|^2 \tag{2}$$

with reference points y_i, and coefficients Ξ.

Algorithm 1 Learning Force Fields with SINDy-POD (Distance–Based Conditional SINDy)

Input: trajectories $(X(t), \dot{X}(t))$; dimension n; number of reference points m; number of training epochs N; threshold τ; interval k; patience P; learning rate η

Output: coefficients Ξ and reference points y_i defining the field $\dot{X} = f(X)$

```
Initialization  sample y_i ~ N(0,1) ⊂ R^n for i = 1,...,m   Ξ ← 0_{m×d}
for e ← 1 to N do
    foreach mini-batch (X, Ẋ) do
        Θ(X) ← [1/(‖X − y_1‖² + ε), ..., 1/(‖X − y_m‖² + ε)]
        Ẋ_pred ← Θ(X) Ξ
        L ← (1/|X|) ∑ ‖Ẋ_pred − Ẋ‖²
        (y_i, Ξ) ← (y_i, Ξ) − η ∇L                          // gradient descent
    end
    if e mod k = 0 then
        Ξ_{|Ξ|<τ} ← 0                                       // sequential thresholding
    end
    compute validation loss L_val
    if no improvement for P epochs then
        break                                               // early stopping
    end
end
return Ξ, y_1,...,y_m and f(X) = Θ(X) Ξ
```

3.3 Description of the proposition

The objective of this study is to discover the force fields governing system behavior within the POD framework. To achieve this, we propose a three-step methodology.

First, we collect a diverse set of trajectories from the system of interest representing a broad range of differents scenarios.

Second, we apply the SINDy-POD to this trajectory dataset. By leveraging distance-based functions within the extended characterization space, the method learns both the location and intensity of the underlying force fields. These force fields represent the key influences that shape the system's evolution over time.

Finally, we visualize and analyze the resulting force fields and predicted trajectories to interpret the physical behavior of the system. This step allows us to identify regions of attraction or repulsion in the multidimensional space and to evalute the model's ability to generalize across different initial conditions and parameter configurations.

4 EXPERIMENTAL RESULTS AND VALIDATION

4.1 Use Case: SIR Model for Epidemic Dynamics

To demonstrate the accuracy of the model we applied SINDy to a well-known nonlinear dynamical system, the *SIR* epidemic model (Kermack and McKendrick 1927).

$$\dot{S} = -\alpha SI, \qquad \dot{I} = \alpha SI - \beta I, \qquad \dot{R} = \beta I$$

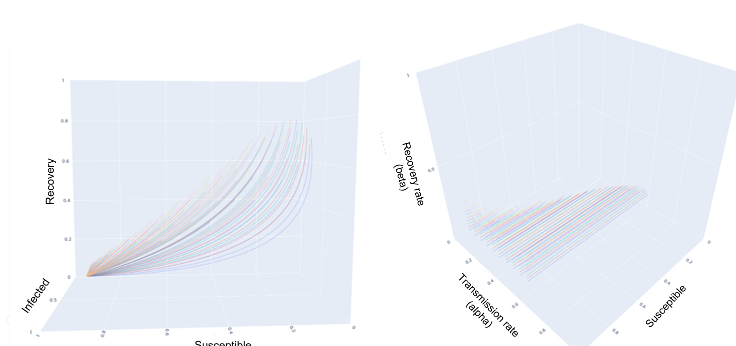
where $S, I, R \in [0,1]$ denote the fractions of *susceptible*, *infectious* and *recovered* individuals, α is the transmission rate (probability to be infected) and β the recovery rate (inverse of disease duration). Based on the previous section, we can consider S, I, R as KPIs of the system, α as a characteristic of the system and β as an attribute of the system. Because the true right–hand side is explicitly known, the SIR system provides an ideal test-bed for assessing the accuracy and robustness of sparse identification.

Synthetic data set. We generated **100 independent trajectories** of the SIR model by randomly sampling the parameters within the following ranges: the *transmission rate* $\alpha \in [0.1, 0.6]$, capturing a wide spectrum of infectious diseases, and the *recovery rate* $\beta \in [0.1, 0.3]$, corresponding to disease durations ranging from 1 to 10 days. The initial conditions were fixed for all simulations, with the initial susceptible, infectious, and recovered population fractions set to $S_0 = 0.95$, $I_0 = 0.04$, and $R_0 = 0.01$, respectively. Each trajectory was numerically integrated over a total simulation time of $T = 20\,\mathrm{s}$ and sampled at $n = 200$ uniformly spaced time steps. This setting yields a moderately coarse resolution that realistically reflects typical experimental data quality and granularity.

Protocol.

1. *Trajectory pool* — generate 100 independent SIR realizations with a combination of α, β in the above-mentioned intervals. Each trajectory is sampled at $p = 200$ uniformly spaced instants. The 100 trajectories are shown in different dimensions in Figure 3.
2. *Inverse problem* — feed the state matrix $X = [SIR, \alpha, \beta]$ to SINDy with a library enriched by inverse-square distance $\theta_j(r) = 1/r_j^2$. The sparse regression returns:
   - the *locations* y_i of the force field,
   - the *coefficients* c_i such that the total forcing term reads $F(x) = \sum_i c_i/(x - y_i)^2$.
3. *Out-of-sample test* — integrate the identified model under *new* parameter pairs $(\alpha^\star, \beta^\star)$ drawn in the same intervals and compare the simulated trajectories against ground-truth SIR solutions.

This three–step protocol allows us to (i) quantify POD-SINDy's ability to retrieve both the epidemiological bilinear terms and the hidden $1/r^2$ interaction, and (ii) assess generalization by predicting dynamics for unseen transmission and recovery rates.



(a) (b)

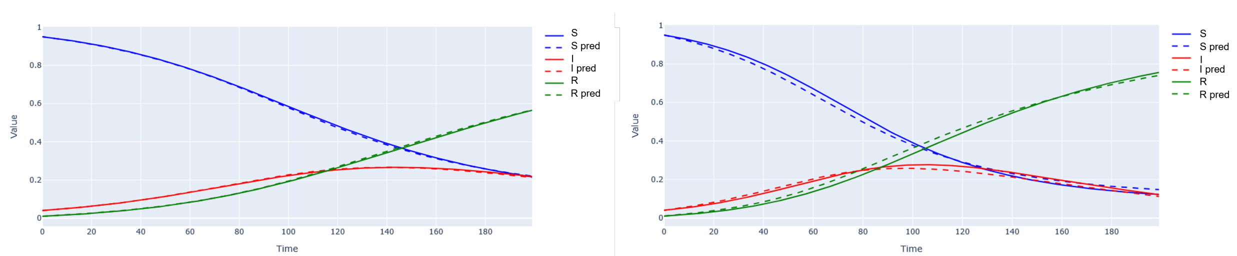
Figure 3: (a) Trajectory of S, I and R. (b) Trajectory of S, α and β

Given the Figure 1, we observe the various trajectory of a system from different perspectives, depending on the observed dimensions (for our model: S, I, R, α, and β). Figure 3 a) illustrates the evolution of the system's KPI, where each trajectory reflects distinct behaviors driven by different transmission and recovery rates. In constrat, Figure 3 b) represents the system's evolution in a space defined by the number of susceptible individuals (considered a KPI), the transmission rate (a characteristic), and the recovery rate (an attribute). For a given set of initial conditions, S_0, I_0, R_0, α, and β, the system follows a specific trajectory within this space. The next section presents the training of our model on 100 such trajectories to characterize the space defined by S, I, R, α, and β, enabling decision-makers to anticipate disease dynamics under given scenarios.

4.2 Identification of the force field and physics interpretation

To train the model, we used the dataset generated according to the parameter ranges specified in previous section. The training process was conducted using a set of predefined hyperparameter explained in the Algorithm 1, including a learning rate $\eta = 10^{-3}$, a total of $N = 5000$ epochs, a patience threshold of $P = 300$ for early stopping, a sparsity threshold $\tau = 10^{-5}$, and an update interval $k = 10$ for sequential thresholding. We consider here the number of force fields (m) equal to 5.

Figure 4 shows the evolution of a disease for an initial population of $S_0 = 0.95$, $I_0 = 0.04$, $R_0 = 0.01$ and two scenarios: first scenario with $\alpha = 0.40$ et $\beta = 0.15$ and second scenario with $\alpha = 0.55$ et $\beta = 0.20$.

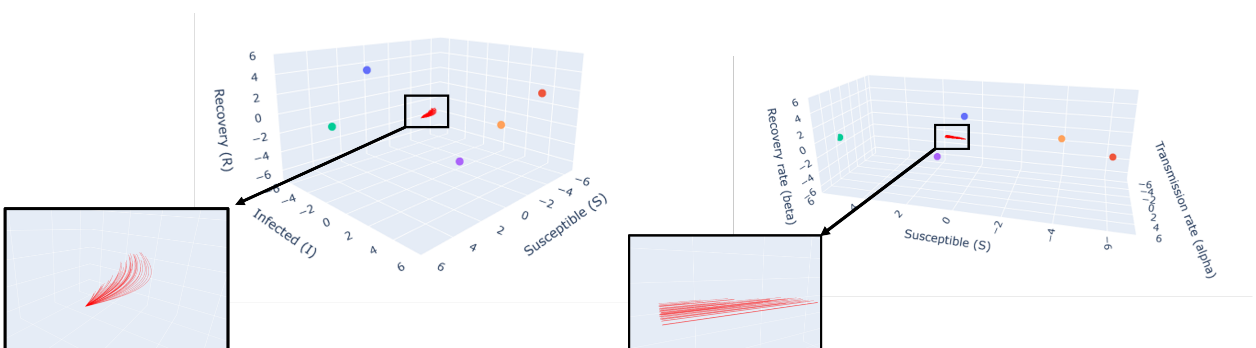


(a) with $\alpha = 0.40$ and $\beta = 0.15$ (b) with $\alpha = 0.55$ and $\beta = 0.20$

Figure 4: Trajectory of S, I and R

To evaluate the generalization of the capability of the learned force field, we generated 50 new trajectories by randomly sampling the transmission rates ($\alpha \sim \mathscr{U}(0.1, 0.6)$) and recovery rates ($\beta \sim \mathscr{U}(0.1, 0.3)$). Figure 5 illustrates how the POD-SINDy model captures the overall dynamics of the system, even for these previously unseen configurations. This suggests that the model has identified dominant force fields acting as attractors or repellents within the extended characterization space.

From a decision-making standpoint, Figure 5 b) provides a practical tool for anticipating the evolution of the susceptible population (S) based on transmission (α) and recovery (β) parameters. By locating a scenario in this space, one can forecast epidemic trajectories and support strategic decisions such as targeted interventions or resource allocation.



(a) (b)

Figure 5: (a) Trajectory of S, I and R. (b) Trajectory of de S, α et β

Figure 5 illustrates that the extended characterization space has been explored across a wide range of disease families, with varying transmission rates and disease durations. By enforcing five fixed force fields, we obtain a representation based on the concept of force fields, capturing the dynamic of this entire class of disease families.

5 DISCUSSION AND PERSPECTIVES

Discussion. The work presented introduces a novel approach to modeling complex systems by drawing an analogy with classical mechanics through the POD framework. Systems are represented as dynamic points in a multidimensional space, subject to perturbations modeled as force fields. This analogy with Newtonian mechanics aims to address the interpretability limitations often associated with neural network models while enhancing predictive accuracy by embedding strong physical constraints into the modeling process. This representation allows for anticipating system responses, such as a population's competence in facing disease outbreaks, without relying on traditional simulations. By coupling a SIR model with POD-SINDy, dominant force fields governing behavior can be identified. These fields offer actionable insights, paving the way for an interpretable and exploitable decision-support tool grounded in physically inspired dynamics.

Nevertheless, several unresolved questions remain. First, the choice of the physical law governing these forces must be further explored. In this study, we adopted an inverse-square law, akin to gravitational or electromagnetic forces, but this choice warrants critical examination in future research. Additionally, the optimal number of force fields required to characterize a given system family remains an open question. This issue is closely tied to the interpretability of the model, central to POD's goal of empowering decision-makers. Understanding the intensity and direction of force fields provides insights into the system's trajectory within the space, including zones of attraction or repulsion.

Perspectives. Future research directions should focus on identifying organizational conservation laws, which may reveal invariant quantities in system evolution. Another critical avenue is the integration with Agent-Based Models (ABM) to enrich macro-dynamics with micro-level interactions. Furthermore, deeper exploration of latent space topologies, such as attractors, bifurcations, and decisions-relevant regions, is essential to enhance interpretability and visualization, providing more intuitive decision-support tools for decision-makers.

Conclusion. As complexity continues to reshape the landscapes of science, industry, and society, the POD framework stands as beacon for new era of modeling, one where understanding precedes prediction, and insight powers action. Through the development and validation of SINDy-POD approach applied to epidemiological dynamics, this study demonstrates the potential of uncovering hidden force fields that govern system behavior. By revealing the invisible structures steering system evolution, this approach aspires not merely to forecast the future, but to illuminate the pathways by which it can be shaped.

REFERENCES

Abdullahi, I., H. Larijani, D. Liarokapis, J. Paterson, D. Jones, and S. Murray. 2025. "A Data-Intelligence-Driven Digital Twin Framework for Improving Sustainability in Logistics". *Applied Sciences* 15(2):601.

Bellepeau, C., H. Bergere, C. Thevenet, N. Moradkhani, T. Cerabona, and F. Benaben. 2022. "Use of Physics of Decision to assess how COVID-19 impacted air pollution". In *International Conference on Information Systems for Crisis Response and Management*, 887–894.

Bellepeau, C., V. Romero, G. Martin, C. Courrèges, B. Montreuil, and F. Benaben. 2024. "Enhancing decision-making and production monitoring in assembly lines: visualizing performance evolution using KPI trajectories". In *2024 10th International Conference on Control, Decision and Information Technologies (CoDIT)*, 1981–1987: IEEE.

Ben Rabia, M. A., and A. Belladaoui. 2022. "Simulation-based analytics: A systemic literature review". *Simulation Modelling Practice and Theory*.

Benaben, Frederick and Faugere, Louis and Montreuil, Benoit and Lauras, Matthieu and Moradkhani, Nafe and Cerabona, Thibaut and Gou, Juanqiong and Mu, Wenxin 2022, June. "Instability is the norm! A physics-based theory to navigate among risks and opportunities" https://doi.org/10.1080/17517575.2021.1878391.

Benaben, F., B. Montreuil, J. Gou, J. Li, and M. Lauras. 2019. "Framework for Risk and Opportunity Detection in A Collaborative Environment Based on Data Interpretation". In *Hawaii International Conference on System Sciences*.

Brunton, S. L., J. L. Proctor, and J. N. Kutz. 2016. "Discovering governing equations from data by sparse identification of nonlinear dynamical systems". *PNAS* 113(15):3932–3937.

Cranmer, M., A. Sanchez Gonzalez, P. Battaglia, R. Xu, K. Cranmer, D. Spergel *et al*. 2020. "Discovering symbolic models from deep learning with inductive biases". *Advances in neural information processing systems* 33:17429–17442.

Forrester, J. W. 1987. "Lessons from system dynamics modeling". *System Dynamics Review* 3(2):136–149.

Ganga, S., and Z. Uddin. 2024. "Exploring Physics-Informed Neural Networks: From Fundamentals to Applications in Complex Systems". *arXiv preprint*.

Kermack, W. O. and McKendrick, A. G. 1927. "A Contribution to the Mathematical Theory of Epidemics".

Le Duff, C., J. Gitto, J. Jeany, R. Falco, M. Lauras *et al*. 2022. "A physics-based approach to evaluate crisis impacts on project management". In *Conference on Information Systems for Crisis Response and Management*, 134–143.

Li, Z. 2025. "A Review of Physics-Informed Neural Networks". *Applied and Computational Engineering*.

Linka, K., A. Schäfer, X. Meng, Z. Zou, G. E. Karniadakis, and E. Kuhl. 2022. "Bayesian physics informed neural networks for real-world nonlinear dynamical systems". *Computer Methods in Applied Mechanics and Engineering* 402:115346.

Lipton, Z. C. 2018. "The mythos of model interpretability: In machine learning, the concept of interpretability is both important and slippery". *Queue* 16(3):31–57.

Moradhkani, N., and F. Benaben. 2024. "A force-inspired paradigm for performance-based decision support". *Journal of Industrial Information Integration*.

Moradkhani, N., and F. Benaben. 2022. "Multi-Criteria Performance Analysis Based on Physics of Decision". *IEEE Transactions on Services Computing*.

Moradkhani, N., F. Benaben, B. Montreuil, A. Barenji, and D. Nazzal. 2020. "Physics of Decision for Polling Place Management: A Case Study from the 2020 USA Presidential Election". In *ICMS 2021 - 15th International Conference on Modeling and Simulation*, 440–448.

Moradkhani, N., H. Dolidon, and F. Benaben. 2022. "Persistent physics-based crisis management framework: A case study of traffic in the Nantes city due to flood exposure". In *Hawaii International Conference on System Sciences*, 2481.

Olivares-Aguila, J., and W. El Maraghy. 2019. "System dynamics modelling for supply chain disruptions". *International Journal of Production Research*.

Rudy, S. H. *et al*. 2017. "Data-driven discovery of partial differential equations". *Sci. Adv.* 3:e1602614 https://doi.org/10.1126/sciadv.1602614.

Simon, H. A. 1960. *The new science of management decision*. Harper and Brothers https://doi.org/10.1037/13978-000.

Tibshirani, R. 1996, January. "Regression Shrinkage and Selection Via the Lasso". *Journal of the Royal Statistical Society: Series B (Methodological)* 58(1):267–288.

Siva Viknesh and Younes Tatari and Amirhossein Arzani 2025. "ADAM-SINDy: An Efficient Optimization Framework for Parameterized Nonlinear Dynamical System Identification".

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