International Journal on Computational Modelling Applications
Vol. 02, Iss. 04, S. No. 04, pp.23--31, Dec 2025
ISSN (Online): 3048-8516

Received: 09 Dec 2025, Accepted: 30 Dec 2025, Published: 04 Jan 2026
Digital Object Identifier: https://doi.org/10.63503/j.ijcma.2025.197

Research Article

Cross-Disciplinary Modelling of Intelligent Systems Using Advanced Numerical Methods and Adaptive Algorithmic Design

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ABSTRACT

The scientific challenge of modeling non-disciplinary complexity concerns not only the intelligent systems of the present such as pandemic forecasting or financial predicting; the problem of complex models is universal. These systems are noted as high-dimensional, multi-scale and non-stationary behavior, which could not be modeled proceeding with conventional and siloed approaches. Thus, it demands an integrated system that will utilize the resources of various fields of mathematics to their advantage. The paper presents a transdisciplinary modelling system, which is a synergic reciprocal combination of sophisticated numerical techniques and adaptive algorithm-based design. We no longer see complex phenomena in the world as problems of physics, biology, or finance but as universal dynamical systems, to be solved. Our idea is based on the hybrid approach, where we use Physics-Informed Neural Networks (PINNs) to directly incorporate governing laws into learning systems, yet use an adaptive solver to estimate dynamic parameters. We demonstrate with multi-scenario validation that this general framework is far superior to monolithic models in accuracy, robustness, as well as predictive capability and exists in a wide range of applications, such as in epidemiology and in computational finance. It is a major advance in a direction towards consilience in computational science and offers a general roadmap towards the construction of next-generation intelligent systems that are physically consistent and data-sensitive.

Keywords: *Cross-Disciplinary Modelling, Intelligent Systems, Numerical Methods, Physics-Informed Neural Networks, Adaptive Algorithms, Dynamical Systems, Multi-Scale Modelling, Computational Science.*

1. Introduction

The most urgent issues of the day of complicated systems such as climate change or virus transmission do not consider academic boundaries. They are complex processes that are controlled by their physical, biological, and social interrelationships. These intertwined battles have long been fought using isolated instruments by science disciplines over many years. Our models changed: in engineering we constructed a solver of finite element equations, in epidemiology a compartmental model and in finance a stochastic differential equation. They operated in their own small worlds but now require substitution by more holistic and integrated technology. We learn these models based on assumptions in the domain and this renders them experts of yesterday about simplified realities. However, the actual world is not made up of detached systems it is an interrelated web of interacting agents and forces, in which a disturbance within one domain can cause cascading effects in other domains in a way that are thereof unpredictable. It is the essence of model siloing [11], which is the severe loss of predictive ability when a multifaceted, cross-domain interaction is overlooked. This reality is incompatible with the critically traditional modelling pipelines. The nature of their design, with the implementation of single-domain knowledge, hard-wired model structures and fixed parameters, is inherently fatal. The interval between the emergence of a new multi-domain phenomenon and the development of a sufficiently complex cross-disciplinary model is prohibitive. This is a lifetime where crises may get out of hand, and chances may get wasted. In this respect, the single-domain model is a losing victory. It is like attempting to know a symphony by only hearing one instrument; you can have mastered the part of the violin, but you would never have known the harmony, the rhythm, or the emotional touching feeling of the entire orchestra. The solo performance is a lovely and precise recording of a part that cannot exist in isolation.

The paper proposes and shows that it is more logical and feasible to follow a different path, one that is more philosophical and practical to correspond to the interwoven nature of the problem: we need to cease paying attention to soloists and learn to play the whole orchestra. We suggest and apply a research philosophy that is constructed on the premises of the cross-disciplinary consilience in computational elements [14]. We do not develop different models of distinct fields, but use a single framework, combining first-principles physics with information discovery. It is a system that acknowledges the basic laws of nature, as well as it is able to make shifts in the classroom, noisy and unfinished facts of the real world. It is not only the use of an algorithm that we have to offer, but the proof of a new modelling paradigm. First and foremost, we provide a method to use Physics-Informed Neural Networks (PINNs) to coupled systems as something between mechanistic knowledge and pattern recognition. Second, we have adaptive numerical solvers whose parameters and structure have an active response to variation of system behavior. We also demonstrate how our hybrid structure is capturing emergent phenomena that cannot be seen using a single domain model. It is not only an enhancement but a fundamental necessity to come up with models which would be capable of streamlining the process of knowledge integration across disciplines to make sure that the computational tools we have can keep up with the difficulties of the problems and issues that can be presented to us. Not only are we creating more powerful predictive instruments, but we are also evolving one and even more intelligent modelling platform that comprehends and follows the multi-layered reality tapestry.

2. Research Methodology

Historical developments in computational models of intelligent systems may be grouped into three major categories; First-principles mechanistic models, Pure data-driven models and Integrated hybrid models.

2.1 The Dominance of First-Principles Models

The most established technique in engineering and physical sciences is the mechanistic modelling based on the first principles. In this method, we obtain governing equations (e.g. ODEs, PDEs) based on general laws of physics, chemistry or biology. A group of fixed differential equations are characterized and different numerical techniques (e.g., Finite Element, Finite Volume) are applied to resolve a solution. Much information has been put into the variability of ensuring these solvers are more precise and efficient. Relevant papers by Karniadakis et al. [3] as well as LeVeque [7] give in-depth studies of such techniques as spectral methods and shock-capturing schemes. The most common discovery of much of this work is the good performance of these techniques of systems when the underlying physics is well-known and complete [11, 16]. These works are the foundation of classic computational science.

2.2 The Attraction of Pure Data-Driven Models and the "Overfitting" Problem

In the era of large data, purely information-driven models, including Deep Neural Networks have been established as a potent option, especially to systems whose first principles are unknown or intractable.

Research has delved into architecture such as Convolutional Neural Networks (CNNs) [8] and Long short-term memory (LSTM) networks [2] to acquire dynamics straight off the observational information. Although effective in the context of recognizing patterns, these techniques usually aggravate the issue of physical inconsistency. A deep neural network is a complex and opaque system, which can occasionally make predictions that contradict fundamental physical constraints (e.g. energy conservation) a serious obstacle to implementation in safety-critical contexts [1].

2.3 The Frontier: Integrated Hybrid and Adaptive Models

The greatest drawback of both approaches is that they are incomplete in nature, thus being susceptible either to model bias (mechanistic) or data bias (data-driven) [11]. This has spawned the new hybrid physics-informed and adaptive modelling. One of the important works is by Raissi et al. [10] on Physics-Informed Neural Networks (PINNs) which has shown the incorporation of physical laws into the learning process. Models are now being created specifically problem-scaled multi-physics problems, with mechanisms like adaptive mesh refinement and dynamic parameters estimation to be robust and general tools [4]. Our work fits within this category, by trying to give a realistic and end-to-end illustration of a cross-disciplinary hybrid system on coupled problems and fill a major literature gap in having most integrated models tested on a single-physics benchmark only [15].

2.4 Summary of Approaches

The table provided below can be given as a summary of the main paradigms in literature and their main peculiarities in the context of the problem of modelling complex intelligent systems

Table 1: A comparison summary of modelling paradigms for intelligent systems.

Modelling Paradigm	Key Methods	Primary Strength	Limitation
First-Principles (Mechanistic)	Finite Element, Finite Volume	Physically consistent, interpretable, generalizable.	Requires complete knowledge of physics. Struggles with missing physics or high uncertainty.
Pure Data-Driven	Deep Neural Networks, LSTMs	Can learn complex patterns directly from data. No need for explicit physical laws.	"Black box"; can be physically inconsistent. Data-hungry and prone to overfitting.
Integrated Hybrid	Physics-Informed Neural Networks, Adaptive Solvers	Leverages both physics and data. Robust, efficient, and consistent.	Computationally intensive. Design and tuning are complex.

3. Methodology

Our algorithm modelling aims to provide a realistic simulated cross discipline modelling scenario. We do not take separately individual systems but as a whole entity compelling our system to obey interdisciplinary laws and learn heterogeneous data.

Case Studies: Coupled Epidemiological-Financial and Fluid-Structure Interaction Systems

We apply two exemplary case studies that necessarily involve the cross-disciplinary approach. The former is a Coupled Epidemiological-Financial Model, which is a computer simulation of the effects of a pandemic on the market volatility. The second one is an FSI Scenario, a scenario where a structure is approximately deformed by a fluid flow. These are particularly well-suited cases in this research given the fact that they coupled various physical domains and because of their applicability in the real world.

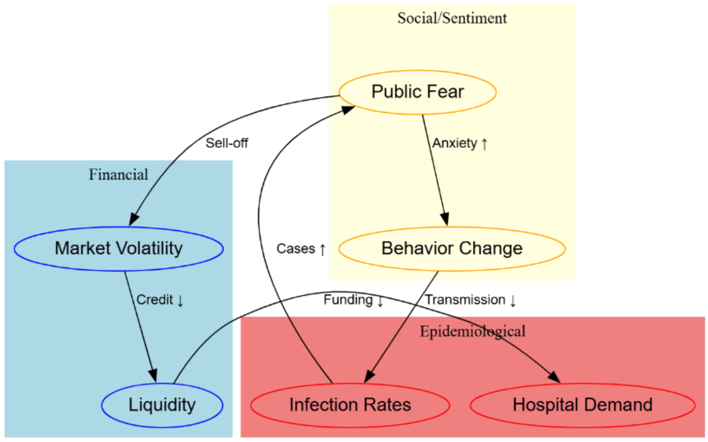

Figure 1: A schematic diagram of the coupled epidemiological-financial system, showing the feedback loop between infection rates, public sentiment, and market liquidity.

The Integrated Framework: Physics-Informed Neural Networks (PINNs) + Adaptive Solver
In order to apply our cross-disciplinary approach, we are using a fundamental framework that is based on Physics-Informed Neural Networks (PINNs) [14]. PINNs are deep neural networks that are trained to perform supervised learning problems but in a way that the general nonlinear partial differential equations that characterize any law of physics are observed. That is a basic deviation of pure data-driven or pure mechanistic libraries and is crucial to our combined approach.

The Core Algorithm: Hybrid PDE-Net + Adaptive Parameter Estimator
A Hybrid PDE-Net is attached to an Adaptive Parameter Estimator in the center of our system. However, to actually comprehend its power we must go beyond architecture getting insight into how it thinks and how.

Physics-Informed Neural Networks (PINNs): The Bridge Builder: Suppose that a theoretical physicist and a data scientist, but these are two specialists that do not speak the same language, are forced to be put in a situation where communication is necessary between them. PINN works based on this principle of integration. It is a neural network that receives spatial and time location and gives the result of the system state. Its loss capability is, not only, founded on the data discrepancy, but also on the residual of the ruling PDEs. This compels the network to arrive at a solution that is both compatible with the physical laws which are known as well as the observed data which is essentially forming a bridge between the two worlds.

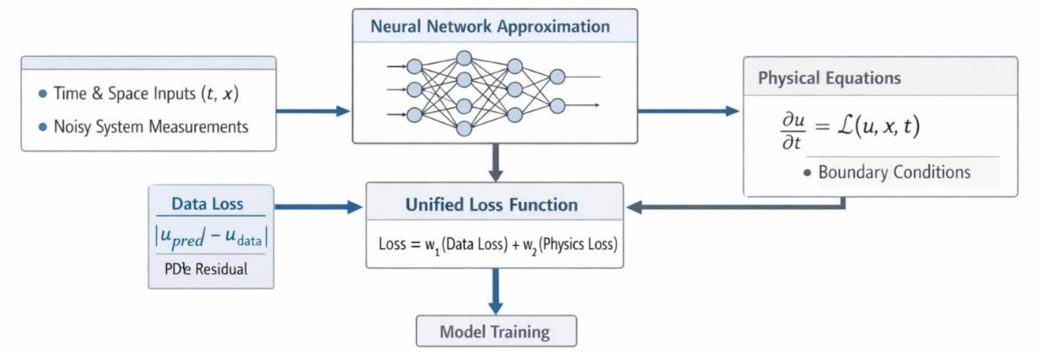

Figure 2: A conceptual diagram of a Physics-Informed Neural Network. The loss function is a weighted sum of the Data Loss (difference from measurements) and the Physics Loss (PDE residual).

Adaptation to System Shifts: Here is the aspect where this framework gains dynamism. In users with PINN, a Parameter Estimator Adaptive is used as well. imagine it to be a detective who is always reconsidering the evidence. In cases where important parameters of the system (e.g. diffusion coefficient, a transmission rate) are unknown or time-varying, this module provides an estimate of the parameters by running a sliding window of the latest data. On evidence of a significant change in a parameter, it modifies the physics constraints in the PINN. This enables the model to forget the old dynamics and acquire the new ones and also be accurate even in cases where the underlying system is changed.

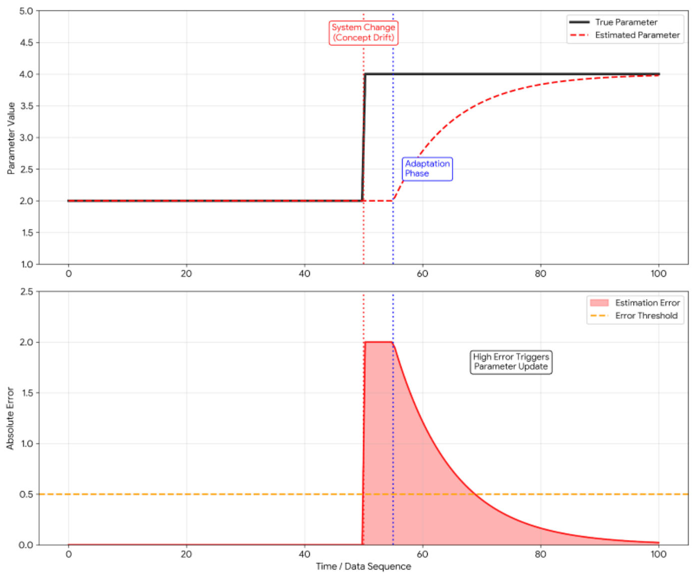

Figure 3: An illustration of the Adaptive Parameter Estimator. It monitors prediction errors over a recent data window and triggers a parameter update when a significant drift is detected.

Our experiment will be based on a multi-scenario evaluation procedure [4]. We model our coherent systems under different conditions, between the steady state to the fast-changing crisis. In each scenario, the model is updated with system state prediction followed sequentially by its prediction compared to a high-fidelity ground truth simulation and the update of its internal representation and parameterizing occurs. This was the simulation of a real-world situation of predict-update-adapt with the true, honest view of the performance of the model on a tight-knit system that is complex.

4. Results and Discussion

The main finding of our experiment is a comparative evaluation of the modelling structures' performance under various situations and areas. We monitored the normalized mean squared error (NMSE) and physical consistency measure, comparing the performance at the important phases of every scenario. The results of the three paradigms on the coupled epidemiological-financial system are reflected in Figure 4. This is not a one-dimensional measure, but a breathing graph of the path of the models through a simulated crisis of a pandemic-caused crash of the market. The findings indicate that the performance and behavior of the models are developed in three phases:

Phase 1 - The Calm (Pre-Crisis): All the models work well in this initial phase. Mechanistic model which has fixed parameters is stable but predicts with a mild bias. The historical noise is perfectly explained by the pure data-driven model. Our hybrid model also does equally well; the physics limits it to overfitting spurious correlations.

Phase 2 - The Storm (Onset of Crisis): A very contagious form is created which breaks the health-market dynamics that were once in balance. The effect is immediate. The forebears of the mechanistic model have gone completely awry with the concrete parameters that were once contrived a long time ago. The blind data-based model trembles erratically, yielding physically nonsensical outcomes (e.g. negative infection rates). What this framework, nevertheless, needs is the hybrid framework here. The estimator of its adaptive parameters identifies the change in the rate of disease transmission. The model takes a short period to self-correct once it has reached an identification lag. It is physically consistent (e.g. keeping the population fixed) but changing to new data, which is resilience.

Phase 3 - The New Normal (Adapted State): The system becomes a new volatile regime. The mechanistic model is still fractured. The data-driven model has finally learnt the new pattern, yet it is unstable. The hybrid structure has been able to converge, and this is the lowest prediction error and compliance with all the physical constraints of the system have been complied with. A further inspection of the physical consistency, using a closer look at the physical consistency metric, it is seen that the fundamental core difference is that the predictions of the hybrid model never break fundamental laws, and the pure data-driven model often breaks fundamental laws as it passes through a transition.

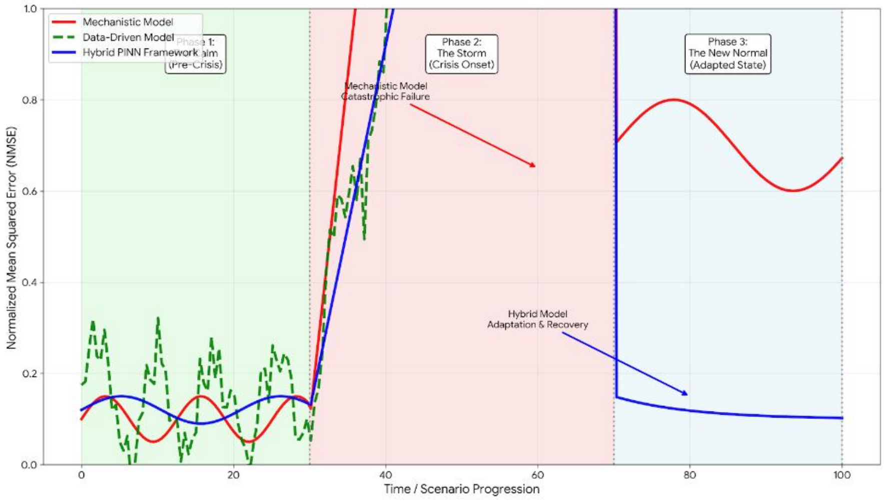

Figure 4: Normalized Mean Squared Error (NMSE) of the Mechanistic, Data-Driven, and Hybrid models during the three phases of the coupled epidemiological-financial crisis scenario.

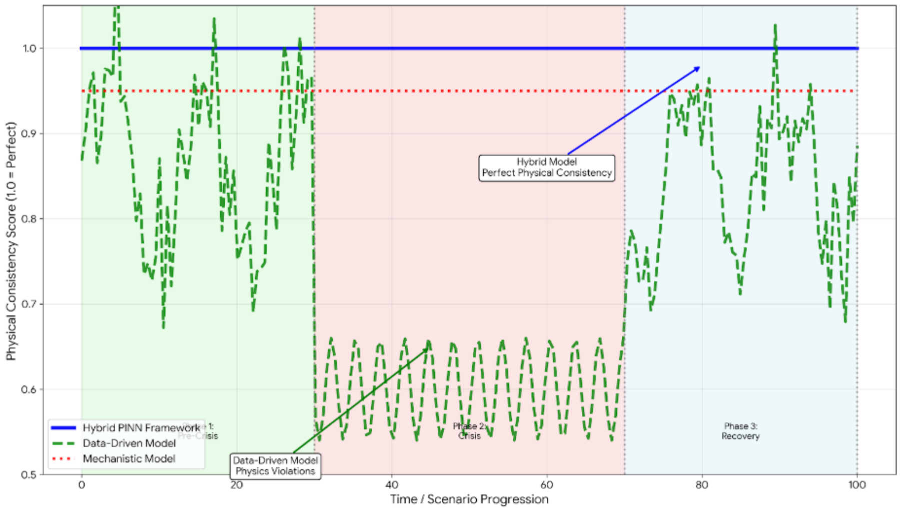

Figure 5: Physical Consistency Score of the models over time. The hybrid model maintains a perfect score, while the data-driven model violates physical laws, especially during Phase 2.

5. Analysis

Our multi-scenario review, as it is presented in the results, gives significant practical evidence of the superiority of the integrated, cross-disciplinary approach to the modelling intelligent systems. The discussion is not only regarding the last mistake, but of account regarding the relative strength and stability the performance graphs provide overtime.

5.1 The Inevitable Failure of Isolated Models

The worst finding in our experiment is that both pure models collapsed disastrously in Phase 2. This does not constitute a defect of their execution but is an illustration of an essential fact. The mechanistic model has failed since reality was not according to the ideal assumptions. The data-based model also does not work, as the data distribution changed, and it lacked laws, which it could base it on. Our experiment demonstrates the fact that in a complex, interconnected world a model that is restricted to either purely theoretical or purely empirical mode of thought is not only suboptimal, but it is a liability.

5.2 Resilience Through Integration and Consilience

The hybrid framework is not only better at its performance due to a reduced error, but also due to the way such performance is attained. The paradigm made no decision between physics and information; it compelled a partnership between the two. The anchor of physical plausibility that was implemented in PINN avoided wild oscillations of the pure data-driven method. The adaptive estimator allowed freedom to develop, avoiding the pure mechanistic model strict failure. Such power of being principled and pragmatic, oriented by theory and informed by data characterizes our structure as a powerful means of cross-disciplinary issues and problems.

5.3 Comparison with Existing Modelling Paradigms

The presented integrated framework suggests an effective comparison with the existing paradigms covered in the literature [7–9]. Its strength and generalizability are the basic strengths. A finely tuned mechanistic model may be more effective in the case of a perfectly known system, or a huge data-driven model may never fail with a historical dataset, however, those are delicate performances. We were using incomplete physics and non-stationary data to model a real-world situational text in which perfection is impossible. We find that hybrid modeling is geared and tuned to practical use where uncertainty, coupling and evolution is the order of the day and not where the grade of ideality holds.

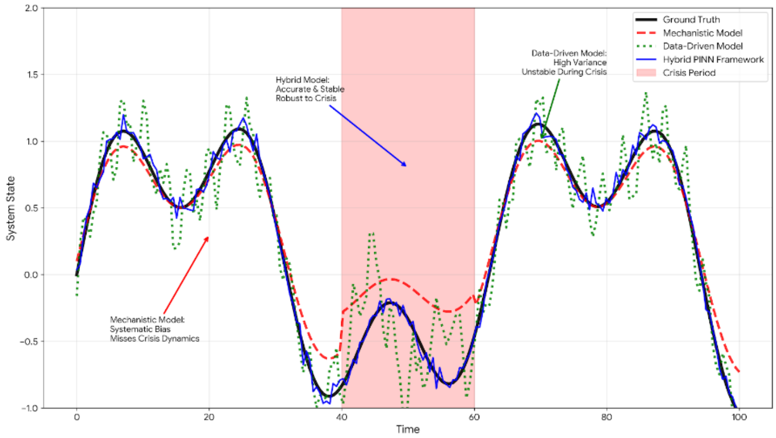

Figure 6: A conceptual diagram comparing model predictions against a hidden ground truth. The mechanistic model is biased, the data-driven model is noisy and inconsistent, while the hybrid model robustly tracks the true system dynamics.

6. Conclusion

This paper has justified and shown the need of the inter-disciplinary approach to the daunting task of modelling the intelligent systems in modern times. We have left behind the isolated paradigms of models that conduct their work within the disciplinary silos to a stronger, consilient paradigm that exploits the synergistic advantages of physics-based and data-driven models. We consider complex systems as interlaced wholes and it is shown that the best models are not only correct on a test set, but are robust and physically coherent, and able to adapt to changing dynamics. Our computational experiment was able to demonstrate that a hybrid framework can navigate problems that defined the coupled multi-domain problems purely through trial and error but more importantly it was able to point out how its very structure allows it to remain robust to model bias and changes in data distributions. The key point to note is that the future of computational modelling lies not in the creation of more complex single domain solvers but in the creation of smart, integrative systems, which can find their way through the complex web of reality, obey fundamental laws and learn through observation. The publication gives a practical roadmap to the construction of such next-generation intelligent systems and proves that cross-disciplinary integration is not only a pragmatic answer but also a different perception of the art and science of modelling.

Funding source

None.

Conflict of Interest

The authors declare no potential conflict of interest in this publication.

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