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DESIGNING EVOLVING CYBER-PHYSICAL-SOCIAL SYSTEMS:
COMPUTATIONAL RESEARCH OPPORTUNITIES

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ABSTRACT

Cyber-Physical-Social Systems (CPSS) are natural extensions of Cyber-Physical Systems (CPS) that add the consideration of human interactions and cooperation with cyber systems and physical systems. CPSS are becoming increasingly important as we face challenges such as regulating our impact on the environment, eradicating disease, transitioning to digital and sustainable manufacturing, and improving healthcare. Human stakeholders in these systems are integral to the effectiveness of these systems. One of the key features of CPSS is that the form, structure, and interactions constantly evolve to meet changes in the environment. Designing evolving CPSS includes making tradeoffs amongst the cyber, the physical, and the social systems.

Advances in computing and information science have given us opportunities to ask difficult and important questions, especially those related to cyber-physical-social systems. In this paper, we identify research opportunities worth investigating. We start with theoretical and mathematical frameworks for identifying and framing the problem – specifically, problem identification and formulation, data management, CPSS modeling and CPSS in action. Then we discuss issues related to the design of CPSS including decision making, computational platform support, and verification and validation. Building on this foundation, we suggest a way forward.

KEYWORDS: Systems Engineering, Cyber-Physical-Social Systems, Research Opportunities

1.0 FRAME OF REFERENCE

The rapid increase in computational capabilities makes it possible to pose questions, the answers to which necessitate the creation of knowledge. Both the National Academies of Engineering[2] and the

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[2] http://www.engineeringchallenges.org/challenges.aspx

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National Science Foundation[3] have identified grand challenges. The United Nations has identified sustainable development goals. We suggest that addressing issues associated with grand challenges requires coordination of cyber systems, physical systems, and social systems. In this paper, we use the most basic definition of a cyber-physical-social system, “A Cyber-Physical-Social System (CPSS) is a system comprising cyber, physical and social components, which exists or emerges through the interactions between these components….” [1]; as shown in Figure 1. We further restrict our discussion to *engineered* systems with a designed function or functions and do not consider un-designed emergent properties. When making engineering decisions about progress, considering social issues is more complex than using traditional Design for X (DfX) methods. In this paper, with a view to fostering dialog, we present some challenges and opportunities for dealing with grand challenges. To address grand challenges, we assert that *engineered* cyber-physical-social solutions are required. Machine learning and artificial intelligence, and multiple advances in computing as well as advances in engineering design have made it possible for the design community to tackle more ambitious projects: the current application areas for cyber-physical-social systems are shown in Figure 2.

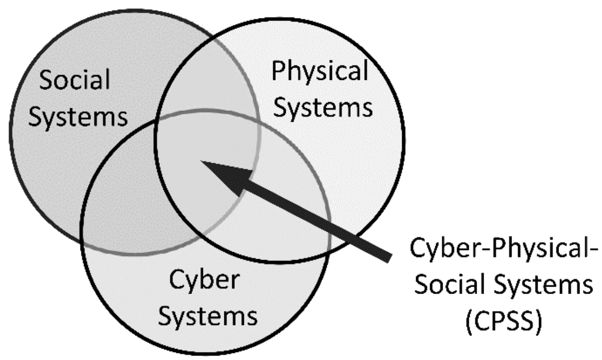

Figure 1. The relationship the components of cyber-physical-social systems (CPSS)

In this paper we highlight some critical research challenges by drawing on recent reviews. Our emphasis is on those issues that are particularly acute when dealing with CPSS. In Section 2, we discuss theoretical and mathematical/computational frameworks for identifying and addressing evolving CPSS, namely, problem identification and formulation, data management, CPSS modeling and CPSS in action. In Section 3, issues related to decision-making, computational platforms and uncertainty, verification and validation are discussed. This is followed in Section 4 with an overview of the problems facing CPSS designers and a discussion of a way forward. Each sub-section of this paper is organized as follows: a general description of the issue, followed by sub-subsections in which we describe the background/state of the art followed by a description of research opportunities and challenges related to that issue.

[3] https://www.nsf.gov/cise/oac/taskforces/TaskForceReport_GrandChallenges.pdf

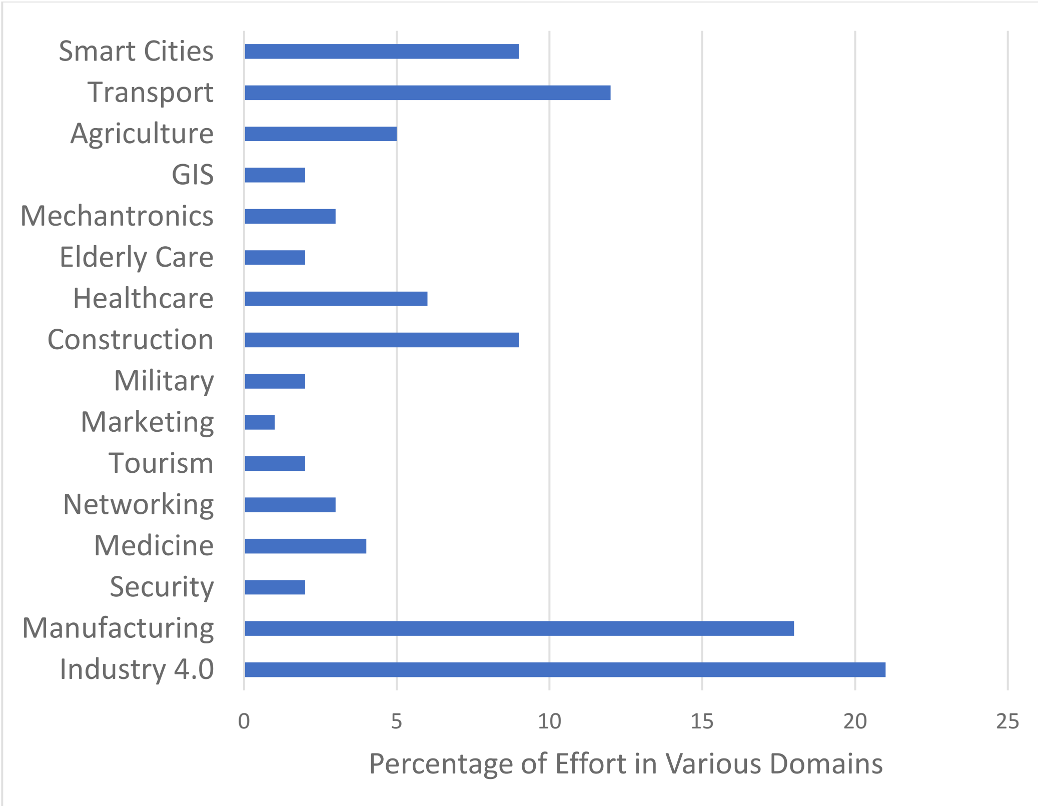

Figure 2. Application areas in which the idea of CPSS have been used. [1]

2.0 THEORETICAL AND MATHEMATICAL/COMPUTATIONAL FRAMEWORKS FOR IDENTIFYING AND COMPUTATIONALLY ADDRESSING EVOLVING CYBER-PHYSICAL-SOCIAL SYSTEMS

To understand CPSS and their current limitations, in this section we focus on limiting and barrier issues.

2.1 CPSS Problem Identification and Formulation

In complex situations where there are multiple issues, identifying and framing the problem is difficult. Many CPSS problems are wicked problems which Horst Rittel describes as being "ill-formulated, with confusing information with many clients or decision-makers with conflicting values, and where ramifications in the whole system are thoroughly confusing," see editorial by Churchman [2]. Further, in many cases, resources are not available to completely address all issues at once and progress must evolve in a way that is both systematic and organized.

2.1.1 CPSS Problem Identification: Background/State of the Art

To identify a problem, it is necessary to define a boundary between the problem and its surroundings – this may be determined by defining the system's function, behavior and structure. Of course, within the system are multiple subsystems that contribute to the function, behavior and structure and the interactions among the subsystems can be complex. Charles Schwenk points to the importance and difficulties of cognitive understanding of problems that require strategic decisions [3-4]. Building on this notion, Bhalerao and co-authors propose a method for framing wicked problems through evidentiary and interpretative analysis [5].

2.1.2 Problem Identification: Challenges

After careful study, Elbanna and co-authors propose the following challenges and opportunities: i) study the evaluation of complex relationships rather than simply main effects, ii) carefully evaluate the personality of the CEO and other top managers, iii) perform longitudinal studies rather than cross-sectional research, iv) perform studies with a joint focus on problem formulation and implementation – most studies focus on one or the other, v) study the psychological rather than the demographic characteristics of tops managers, vi) combine overarching constructs form strategic decision making from various fields of research such as new product development, alliance formulation, mergers, etc. and vii) develop a comprehensive review synthesizing the literature on strategic decision-making [6-7].

2.2 CPSS Data Management

As we increasingly rely on data for decision-making, reliability is critical. When combining – or using data – often critical issues are overlooked or not transmitted with the data set. Accurate representations and fairness become critical issues. In addition, issues remain in managing uncertainty, these are further discussed in Section 3.3. Combining information from multiple data sets also contributes to data unreliability and is often left to the experimenter's judgment. However, this could be automated if extensive metadata is associated with each data set and evaluated before use.

2.2.1 CPSS Data Management: Background and State of the Art

If data from the physical or social systems is unavailable, synthetic data may be created using simulations or theory. Synthetic data can be based on simulations or on assumed distributions of appropriate samples and their anticipated statistics [8] or with accepted behavior [9]. Methods for generating synthetic data are in the literature. For example, Buttfield-Addison and co-authors offer methods for creating synthetic data [9]. El Amam and co-authors, 2022, discuss procedures for using synthetic data in machine learning [8]. Further, Lu and co-authors review machine learning methods for synthetic data generation [10]. A critical issue is whether these methods are adequate for use in the design of evolving CPSS.

In addition to sparse data, there are additional reasons to generate synthetic data. For example, synthetic medical data, defense, or industrial data may be generated to maintain confidentiality or the data may be of low quality. Synthetic data might also be created for use in a generative adversarial network (GAN). In addition, synthetic data can also be used to maintain fairness. Both Lu and co-authors [10] and Mehrabi and co-authors [11] review data fairness and offer methods to mitigate it.

2.2.2 *CPSS Data Management: Challenges*

Knowledge graphs link heterogeneous data sources; Hogan and co-authors [12] and Ji and co-authors [13] review this topic. A key issue is that the construction of knowledge graphs requires a great deal of human input, automating this process would be helpful. Further, when entities and relations are extracted from data sources to form a knowledge graph, data loss or distortion can occur.

2.3 CPSS Modeling

Although determining suitable architectures for modeling CPSS in evolving environments may present challenges, perhaps the most difficult issue for CPSS modeling and design is predicting social or human behavior.

2.3.1 CPSS Modeling: Background/State of the Art

Social systems are an important part of CPSS. However, human/social behavior is often irrational and unpredictable [14], and modeling it accurately is virtually impossible. For social groups, agent-based modeling partially alleviates this problem, but this is problematic even when the agents are ascribed human characteristics such as personality and emotion [15-16]. Individual behavior is even more problematic to model. Puentes and co-authors suggest that, in part, behavior can be predicted from historical data [17]. Online Amazon and Walmart take advantage of this by recommending purchases based on their past purchases. Further, Thaler and Sunstein suggest that the environment be designed to “nudge” the system toward the desired behavior [18].

2.3.2 CPSS Modeling: Challenges

Although some methods for modeling human behavior appear in the literature, the methods are far from accurate. A possible approach is to add layers of additional information about the society or individual in order to improve behavior predictions. For example, information about cultural norms can be added to alter the probability of specific behaviors. Also if more accurate predictions are required, then information about psychological characteristics can be included to improve accuracy [19]. Alternatively, for specific cases, modeling all possible outcomes as different scenarios and developing strategies for guiding the system toward the desired behavior.

2.4 CPSS in Action

Remembering that the system is that which satisfies the designed function, and the environment is everything else, the environment itself may be designed to facilitate the desired system behavior, as mentioned in Section 2.3. If the environment is unchanging, of course, a CPSS evolves toward an equilibrium state. Alternatively, it responds through changes in environmental stimuli. For convenience, we define that for discontinuous changes in the environment results in the system between stages in the system and continuous environmental changes result in changing systems states.

2.4.1 CPSS In Action - Evolution: Background/State of the Art

Our focus is on *engineered* CPSS. These engineered systems evolve, according to a plan, using information from the changing environment. In other words, evolution is controlled based on the recursive processing of incoming data. There are various ways of determining the way the system will respond to changes – some of the more popular methods are managing evolution based on rules, trees, neurons or graph nodes as surveyed by Leite and co-authors [20], as shown in Figure 3.

Decentralized control / decision-making is inevitable when designing large scale CPSS such as healthcare, educational systems, or manufacturing systems. At least part of a system must organize itself without intervention, especially in response to changing environments or changing tasks. Khani and co-authors discuss the effects of rule-based social structuring and the number of agents on the ability to self-organize when faced with tasks of increasing complexity [21]. The dynamic adaption of centralized and decentralized behavior is discussed by Barber and co-authors [22] as well as van der Vecht [23].

Decentralized decisions can be analyzed with game theory. Advanced game theory models, such as Mean Field Games (MFG) are used to study Nash equilibria among a large population of rational players [24]. The agents in these games have preferences about their state, for example, they may prefer wealth and capital. Evolutionary games are used for dynamic strategy changes [25] and the population’s competing strategies [26]. Fro accurate results, the best reply correspondence in Game Theory must be perfect. This is difficult when computational models that are abstractions of reality are used. One way to circumvent this limitation is proposed by Xiao and co-authors [27], they recommend using design capability indices to develop ranged sets of solutions, rather than providing specific solutions.

There is also the possibility of using multi-agent reinforcement learning to study centralized and decentralized behavior [28]. Multi-Agent Reinforcement Learning (MARL) is used to model multiple agents that learn by dynamic interactions with the environment and includes all of the agents' actions and their behavior. This considerably increases the complexity of MARL computations.

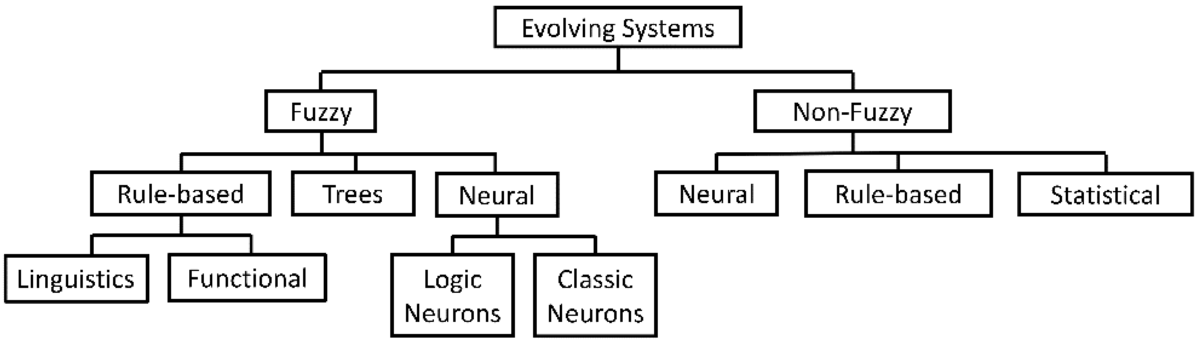

Figure 3. Categories of evolving systems (based on [20])

2.4.2 CPSS in Action – Evolution: *Challenges*

One of the most critical areas for evolving CPSS systems is ensuring effective communication procedures among the different parts of the CPSS and with the environment. This includes achieving effective multidisciplinary knowledge exchange among all parts of the system, whether they are social, physical, cyber or all of these.

3.0 DESIGNING CPSS

Given the information about the desirable properties of CPSS in Section 2, we consider some of the tools we have to design them. This includes tools to support decisions by designers and the functionalities embodied in computational platforms. Importantly, we discuss the relationship between uncertainty and validation and verification.

3.1 Decision Making for CPSS

There is extensive published literature on decision-making. Our focus is on methods for decision-based design processes that are independent of the domain of application [29-30]. This is important as it is known that the instantiation of different design processes will inevitably result in different designed products although the design may satisfy the design requirements, the outcome from one process may be preferred over others. Further, as CPSS are complex, frequently identifying a path forward involves multiple coupled decisions, so the consideration of decision trees and decision networks is essential. This modularity in decision-making also allows "test" decisions to be made and the effects observed before proceeding with the remainder of the process.

3.1.1 *Decision Making for CPSS: Background/State of the Art*

Schlenoff and co-authors propose a Process Modeling Language (PSL) [31-32]. In ISO10303[4] a standard is proposed for Process-Engineering Data. Mistree and co-authors also have focused specifically on the process of domain-free decision-making. Bert Bras laid the foundation for designing design processes, in the early 1990's, by proposing a "design guidance system" [29-30]. Subsequently, Panchal and co-authors propose a method for managing processes based on a value-of-information approach [33-34] and Ming and co-authors propose decision-based modules for process design and templates that can be linked to form hierarchies and networks [35-38]. Wang and co-authors describe how process-based knowledge is used in a design guidance system [39].

The stakeholders in CPSS include humans, machines, and virtual agents. Gilles and Bevacqua describe desirable characteristics of virtual agents [40]. The interests of each stakeholder are typically different and often conflicting. The information available to each and their levels of intelligence (or cognitive abilities) may also differ. Therefore, a decision-making framework or mechanism for these stakeholders to deal with conflicts and reach a consensus is critical. Typically research on consensus in CPSS is classified into four categories, i) human-human consensus, ii) machine-machine consensus, iii) human-machine consensus, and iv) large-scale human-human-machine-machine consensus. Large-scale consensus building is complex and involves cases i-iii in situations where many humans and machines work together to make collaborative decisions [41-43] and foundational to the challenges highlighted in the next section.

3.1.2 Decision Making for CPSS: Challenges

Tools for representing design-process chains is insufficient – we need to be able to design these design-process chains. What follows are research opportunities and challenges identified by Panchal and co-authors [44-45]. A way of introducing process constraints and objectives is needed as well as a way to improve or compare process instantiations. Decision-chains for processes could be integrated with other value-related decision chains, such as supply chains. Storing and retrieving these chains will allow their reuse – thus preserving intellectual capital [34]. These process chains should be reconfigurable and extensible. Some questions that merit investigation include: How can the impact of design processes on the products being designed be assessed? How can the design process and the product be design concurrently? How can the various sources of uncertainty in designing design processes be accounted for and managed? Nellippallil and co-authors [46] address these requirements by proposing a robust co-design framework for the concurrent design of design processes together with products with a focus on exploring a ranged set of design solutions that are relatively insensitive to uncertainty. We discuss the aspect of managing uncertainty in Sections 3.3.1 and 3.3.2.

3.2 Computational Platforms for CPSS Design

Decision makers at all levels of responsibility in the enterprise are required to make decisions by synthesizing information with input from experts, rules and regulations, information about infrastructure and IoT systems, performance and diagnostic information, input based on experience, and information from the market, supply chains and other business units, etc. Ideally all applicable information must be secure, yet accessible, usable for multiple purposes, and manageable yet not entangled with irrelevant information. At the same time multiple human stakeholders with different agendas must communicate and make decisions building the future [47]

[4] ISO10303 http://www.nist.gov/sc5/soap/

3.2.1 Computational Platforms: Computational Background/State of the Art

Although computational platforms of various sorts exist today, some of their limitations include: i) generally they only support siloed knowledge based on various viewpoints, each with its own body of knowledge, assumptions, and capabilities, for example, business, operations, markets, etc. ii) the available information may not be easily accessible to those with different interests and needs, so supportive ontologies must be developed, and iii) often information is not contextualized – it is important to know the information source, assumptions on which it is based, and factors considered. [47].

3.2.2 Computational Platforms: Challenges

From the industrial viewpoint, Swaminathan and co-authors [47] identify the challenges with developing computational platforms. These include enabling the reconciliation of different systems viewpoints, capturing the assumptions inherent in each viewpoint and guiding the reconciliation among these different viewpoints. Can we capture and utilize both tacit and formal knowledge. Most importantly, How do we capture (and support) "each activity that contributes to the decision, including information gathering, options analysis and recommendations associated contextual frames, in terms of inputs considered, capabilities available, assumptions about contextual factors, goals, priorities and available degrees of freedom, and the contextual impacts on the accuracy and validity of the results?" [47].

3.3 Uncertainty, Verification and Validation of CPSS Design Methods

There is an integral relationship between uncertainty and verification and validation. If the input and the mathematical models are inherently uncertain, then it is inevitable that the output will also have some associated uncertainty. It is then difficult to verify or validate the results. In the presence of uncertainty, a user may not trust results, regardless of how transparent the design process is.

In this paper we use the IEEE definitions of verification and validation:

> Verification is ""… the process of providing objective evidence that the system, software, or hardware and its associated products satisfy requirements allocated to it … satisfy standards, practices, and conventions …" [48]
>
> Validation is "… the process of providing evidence that the system, software, or hardware and its associated products conform to requirements … solve the right problem…and satisfy intended use and user needs." [48]

In other words, the act of verification ensures that the results are correct and the act of validation ensures that the solution obtained is useful.

In Section 3.3.1, we address uncertainty and follow this with a discussion of verification and validation.

3.3.1 CPSS Uncertainty, Verification and Validation: Background/State of the Art

When considering the sources of uncertainty in modeling CPSS, first and foremost is that models are abstractions of reality. This is further complicated by the fact there we need to deal with both quantitative and qualitative information. Further, the modeling is complex and we have to resort to the notion of bounded rationality thereby limiting our ability to deal with the complexities involved [49].

Bar-Yam suggests that complexity, by itself makes projects unmanageable [50]. Morales and co-authors [51] offer interesting insights into how one could deal with engineering complexity.

There are two types of uncertainty – aleatory and epistemic uncertainty. Aleatory uncertainty is due to natural or intrinsic variability. Epistemic uncertainty is due to lack of knowledge. Uncertainties can also be classified based on their use in models, i) Type I - variations due to noise factors [52] , ii) variations due to control factors (design variables) [53], iii) variations due to uncertainty inherent in models [54] and iv) Type IV – uncertainty due to a combination of Types I-III [54].

Several methods have been used to reduce or eliminate uncertainty in individual variables or modules, Zhang and co-authors review basic methods of managing uncertainty by uncertainty quantification (UQ) [55], that is, by seeking to eliminate uncertainty everywhere and propose a framework for uncertainty evaluation in which both the input to the system and the output of the system is evaluated, Figure 4. Instead, we recommend selectively managing uncertainty and focusing on modeling it only where the presence of uncertainty results in changes in decisions of important model variables or parameters. Oberkampf and Roy discuss code verification including software development, version control, software quality and reliability, code verification, and approximate/exact solutions. They also discuss solution and model verification and prediction, as well as the design and execution of validation experiments, the assessment of model accuracy and predicitive capability as well as offering suggestions for planning, and managing procedures for verification, validation and uncertainty quantification. [56].

Huang and co-authors recommend managing uncertainty by focusing on the uncertainty in factors that have the greatest impact on results by using dimensionality reducing techniques such as those discussed by Huang and co-authors [55]. Several methods for uncertainty reduction by retaining factors that have the greatest effect on solutions are shown in Figure 5, for further information, please see [55]. However, computational efficiency and robustness are problems for high dimension data sets with sparse data. To solve these problems, Huang and co-authors mention that new methods are being developed with combinations of technologies, but problems still remain. Methods have been proposed for dealing with sparse data – but they have shortcomings. Some of these shortcomings can be overcome by using data characteristics to improve penalty functions or design new penalty functions. Thus, these approaches begin to merge into methods for creating synthetic data.

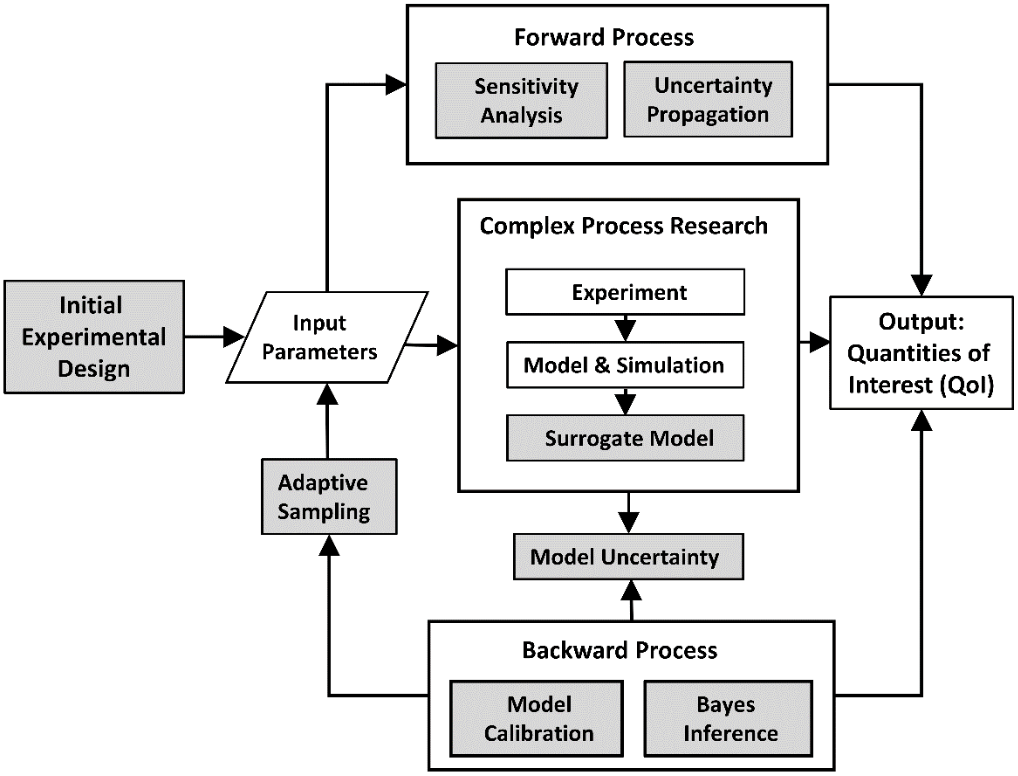

Figure 4. A framework showing the main processes of uncertainty quantification which are in the shaded boxes. [modified from 55]

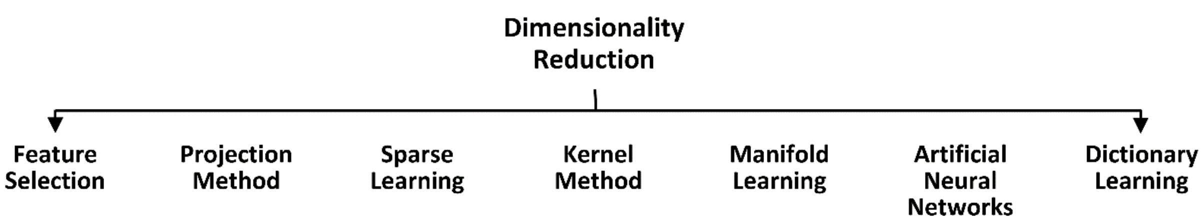

Figure 5. Overall categories of dimensionality reduction techniques [modified from 59]

Typically, the focus of UQ is on both the Types I and II uncertainty in noise factors and variables. However, it is important not to neglect uncertainty introduced by computational models, Type III uncertainty. Computational models are abstractions of reality and are frequently simplified in order to speed computation. In this context, the idea of value of information becomes important. There is often a tradeoff between desired accuracy and the cost of obtaining information [33-34]. This leads directly to one of the major problems in verification. In the presence of uncertainty, the predictions of CPSS systems are likely to be uncertain and unreliable, and the results may not be trustworthy. Solution processes for Types III and IV which are effective for early-stage top-down design exploration are presented in [54, 60-62]. Nellippallil and co-authors illustrate how to manage all four types of uncertainty when co-designing materials, products and manufacturing processes [46, 60]

The design literature tends to be focused on the sequential exploration in different modules instead of a concurrent (or co-) realization of systems, especially those from different disciplines [62-68].

The multidisciplinary optimization (MDO) [69-71] community has proposed methods for optimizing multilevel systems. However, many MDO methods use optimization techniques that result in point solutions on the boundary of the solution space; the boundary itself may embody uncertainty. Usually in the early stages of design, it is important to determine satisficing regions for design rather than single point solutions [72, 73]. Robust design can be used to determine these satisficing regions, this offers another avenue for dealing with uncertainty. Robust designs are relatively insensitive to uncertainty in parameters [53, 74]. In a recent effort, Baby and co-authors [75], propose a framework, 'FRoMCoDE', that supports multilevel robust co-design. Simultaneous robust co-design visualization and exploration is achieved by integrating interpretable Self Organizing Maps (iSOM) [76] with standard decision-based robust design constructs. Using this framework, designers are able to i) model the multilevel decision-making and their interrelations for systems under uncertainty and ii) visualize and carry out co-design exploration of the multilevel design and solution spaces simultaneously.

Verification and Validation

Clearly the accumulated uncertainty in data, calculation methods, and assumptions can increase verification and validation in uncertainty. Both "black box" validation methods as well as "white box" validation procedures for large systems have been proposed, however the inherent complexity of CPSS makes it difficult to assess their validity. The situation is particularly critical for strategic decision making in which decisions about the future are required – usually some assumptions about the future decision environment are required and, of course, this may be beyond the decision-maker's ability to predict. The risk tolerance of the decision maker is also a consideration, although as far as possible, a reasonably accurate assessment of the degree of uncertainty and the associated risk and a knowledge of its sources is desirable.

Three organizations have recommended standards for verification and validation– IEEE, AIAA and ASME. Of these, IEEE is by far the most complete [48]; their risk-based level of integrity combines assessment of the system and its environment as well as the potential consequences of system behavior [48]; see Figure 6. ASME has published standards for verification and validation for computational solid mechanics, computational fluid mechanics and medical device applications[5]. AIAA offers a guide to verifying and validating computational fluid dynamic simulations[6]. For large, complex CPSS, verification may not be either black or white – there can be degrees of validation – and this may depend on potential consequences of the decisions being made, Figure 6.

Integrity Level	**Description**
4	Behavior of the system, in combination with its environment, causes the following: - Catastrophic consequences for which the likelihood of the behavior occurring is at most occasional or - Critical consequences for which the likelihood of the behavior occurring is at most probable
3	Behavior of the system, in combination with its environment, causes the following: - Catastrophic consequences for which the likelihood of the behavior occurring is at most infrequent or

[5] https://www.asme.org/codes-standards/publications-information/verification-validation-uncertainty

[6] https://arc.aiaa.org/doi/book/10.2514/4.472855

	- Critical consequences for which the likelihood of the behavior occurring is at most occasional or - Marginal consequences for which the likelihood of the behavior occurring is at most probable
2	Behavior of the system, in combination with its environment, causes the following: - Critical consequences for which the likelihood of the behavior occurring is at most infrequent or - Marginal consequences for which the likelihood of the behavior occurring is at most probable or - Negligible consequences for which the likelihood of the behavior occurring is at most reasonable
1	Behavior of the system, in combination with its environment, causes the following: - Critical consequences for which the likelihood of the behavior occurring is at most infrequent or - Marginal consequences for which the likelihood of the behavior occurring is at most occasional or - Negligible consequences for which the likelihood of the behavior occurring is at most probable

Figure 6. The IEEE categorization of integrity levels of system behavior [48]

3.3.2 CPSS Uncertainty, Verification and Validation: Challenges

Given an understanding of the degree of verification finding ways to improve trust in CPSS designs is challenging. One possibility is to partition the problem, and proceed in a step-wise manner to verify each step. If possible, it is even more effective to have ongoing observation or communication with the system and take steps to avoid undesirable situations; see [75]. Another possibility is to identify potential scenarios which the CPSS may encounter and plan appropriate responses [76], thus reducing the degree of risk. The question that needs to be addressed is - How can we hard-code systems to deal with changing circumstances?

4.0 CPSS: THE WAY FORWARD

Recent advances in computing and information science make it possible to explore avenues of investigation which were not possible earlier. These advances give rise to tremendous possibilities for designing CPSS to address critical social, environmental, health, education, manufacturing problems, etc. As is shown in Figure 1, many researchers have already begun to design CPSS. However, it is unclear to what extent the methods are generalizable. In this paper we point to research challenges and opportunities to establish an intellectual foundation for this area of inquiry.

Based on the considerations raised in the body of the paper, the research challenges and opportunities are aggregated into three categories: i) standards and procedures to be generally accepted, ii) methods to be developed, and iii) theoretical/mathematical/computational issues.; see Table 1. Although there are challenges, both the standards and procedures and the methods needed are likely to be easier to accomplish than to overcome the theoretical/mathematical barriers. Some of these issues can be dealt with by extending the current state of the art as described above, others will need to be considered from entirely different perspectives.

Table 1. A summary of opportunities and barrier issues important for the development of Cyber-Physical Social Systems.

Standards and Procedures to be Generally Accepted

Generally agreed definitions of terms, e.g. cyber-physical-social systems, Section 1.0

Standardize metadata for searchable databases, Section 2.2.2

Accepted open interface standards for plug and play modules, Section 3.2.2

Methods to be Developed

Ways to capture, combine and support all activities contributing to decision-making, Section 2.4.2

What are methods for minimizing human intervention when creating and updating databases, knowledge graphs and models, Section 2.2.2

Extended methods to manage uncertainty for dealing with multi-module systems, Section 3.3.2

Theoretical/Mathematical/Computational Barriers for Further Developments in CPSS

How can a CPSS problem be identified and partitioned to make the solution process manageable? Section 2.1.2

What are the theoretical foundations needed for dealing with product and process evolution? Section 2.1.2

How can social/human behavior be predicted, modelled, and assessed? Section 2.3.2

What is a desirable degree of autonomy in specific CPSS? Section 2.4.2

How can the process of design be captured, designed, and managed? Section 3.1.2

How should a CPSS environment be designed? Sections 2.1.2 and 2.3.2

Taken together, it is clear that with increased computational power comes the possibility of automating a greater portion of design processes. With developments in AI, such as ChatGPT, there will be major changes both in what we are capable of doing and how we can accomplish it. Our coverage in this paper is by no means complete. In this paper, we sow the proverbial seen to foster a dialog on challenges and computing research opportunities related to the design of cyber-physical social systems. We invite members of the JCISE community to reflect on what is presented and contribute to furthering the dialog. Let the dialog begin.

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