A Causal Bayesian Network Model for Resolving Complex Wicked Problems

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***Abstract*—Wicked problems are a specific class of complex problems that emerge from complex adaptive systems (CAS) and stakeholder disagreements on the definition and character of these problems and their possible resolution. Attempts at resolving wicked problems through integration and use of formal methods such as ontologies, Bayesian networks (BN), and complex systems dynamic (CSD) models have been attempted recently but wicked problems continue to defy resolution. This paper argues that this is the result of a lack of ontologically precise causal Bayesian models that adequately represent the hierarchical, dynamic, emergent characteristics and multiple perceptions of CAS and their emergent wicked problems. This paper's contribution is the incorporation of complexity systems theory concepts, namely: perspective, granularity and context, as explicit ontological constructs in a high precision ontological causal BN model, the Granular Contextual Perspectives (GCP) causal Bayesian Network model, using Hidden Markov Model (HMM) formalism to address this shortcoming. Using an illustrative example this conceptual paper shows that the (GCP) causal Bayesian Network model performs better than baseline Bayesian Network models at the visual representation, compact and retractable inference, and machine learning of CAS and their emergent wicked problems. The model is useful at supporting the exploration of possible effects of proposed alternative interventions or prototypical design strategies for resolving a given wicked problem.**

***Index Terms*—Hidden Markov Models, Causal Hierarchical Dynamic Bayesian Networks , Ontology engineering, Wicked problems, Complex Adaptive Systems, Design Science strategies**

I. Introduction

Wicked problems, which have been described as specific class of ill-defined complex problems that emerge from complex adaptive systems (CAS) and stakeholder disagreements on the definition and character of these problems have, and continue to be difficult to resolve [1]–[4].

Wicked problems include ill-defined problems like pandemics, climate change effects, traffic jams, rapidly changing business environments, and financial market crashes. While these problems have not always been recognised or defined explicitly as wicked problems, attempts at resolving this class of complex problems has been receiving a lot of attention recently [2], [3], [5]–[7].

Resolving wicked problems has proved to be elusive primarily because of their complex and dynamic nature, the difficulty faced in defining them and disagreements on how to resolve them, especially where multiple stakeholders with divergent perspectives of a given problem are involved. The lack of recognition of these complex problems as "wicked", is in itself part of the problem as inappropriate tools suitable for resolving "tame", well defined static problems as puzzles are then applied incorrectly to resolve these non linear wicked problems [8].

Complex Systems Dynamic (CSD) models [9], Ontologies [10], [11], Hierarchical Bayesian Networks (HBN) [12], Hidden Markov Model (HMM) [13] and combinations of these have increasingly been used to try and solve wicked problems. The promise of these various efforts lies in the integration of the advantages provided for by each of these approaches into an integrated modeling framework.

While some effort at such integration has indeed been attempted in the recent past, [14]–[17], challenges still remain. This paper argues that this is the result of a lack of ontologically precise causal Bayesian Network (BN) models that adequately represent the hierarchical, dynamic, emergent characteristics, and multiple perceptions of CAS and their emergent wicked problems. This paper proposes a novel ontologically precise casual Bayesian model to address this shortcoming.

The paper's contribution is the incorporation of complexity systems theory concepts, namely: perspective; granularity; and context, as explicit BN model ontological constructs to develop a high precision ontological causal BN model, the Granular Contextual Perspectives Bayesian (GCP) causal Bayesian model. The model uses Hidden Markov Model (HMM) formalism to: i) enhance the visualisation of the character of CAS and their emergent wicked problems; ii) extend the scope of Bayesian inference to answer wicked problems' specific queries; iii) refine Bayesian machine learning of the structure and parameters of given wicked problems.

The rest of the paper is structured as follows. Section II gives an account of related work. Section III provides a broad overview of the character of wicked problems. In section IV the key complexity theory kernel concepts (granularity, context, and perspectives) incorporated in the GCP causal Bayesian model as modeling constructs are introduced and defined. In section V, using the COVID19 pandemic as an illustrative example, a further exploration of the character of wicked problems is carried out through the lens of the systems theory kernel concepts identified as useful in modeling the character of wicked problems.

Section VI provides the formal definition of the GCP causal BN model and details of the model architecture. In section VII the superiority of the (GCP) causal BN model to baseline Bayesian models in addressing wicked problems is demonstrated using the COVID19 pandemic as an illustrative example. In section VIII a discussion of the implications of the (GCP) causal BN model and its utility claims on modeling wicked problems is carried out. Section IX provides a conclusion and the way forward with respect to empirical experimentation using the GCP causal BN model.

II. Related work

The character of wicked problems as viewed through a systems paradigm lens appears in [1], [7], [18], [19]. Work on modeling CAS using CSD models from which wicked problems emerge is detailed in [9]. Systems thinking and design thinking disciplines having contributed to a better understanding of the systemic character of wicked problems and ways to address such problems [19]–[22].

[23] define an ontology as "a formal, explicit specification of a shared conceptualization". The application of ontology engineering to model the structure of complex phenomena to generate formal human and machine readable artifacts called domain ontologies is found in [11], [24]–[26]. The utility of ontologies as representing the structure of domain knowledge is well documented in [24], [26]–[28]. The application of ontological theory based on logical and philosophical principles to enhance clarity and precision in abstracting complex reality has been proposed in [11], [24], [26].

Bayesian networks, as graphical probabilistic models have been developed to compactly represent and reason over linked complex phenomena using computation techniques [29], [30]. Various attempts to integrate dynamic systems models, ontology engineering methods and Bayesian networks to model CAS are detailed in [16], [31], [32].

While these various disciplines have contributed to a better understanding of complexity and how to handle complexity through visualization and computation, attention to their integration for the purpose of addressing wicked problems emerging from CAS and multiple stakeholder perspectives of such problems has been fragmented and inadequate.

As highlighted in [33] Causal Bayesian Models CBMs need sound knowledge of causal big data generating processes to effectively support useful prediction, inference, and structure, parameter learning applications. CSD models provide insights into CAS dynamic and delayed feedback processes, their causes and effects. CBMs and their formalism in particular, as articulated in [34] hold much promise as the basis for integrating CAS' ontological constructs and processes to adequately represent and provide the computational mechanism to reason about, and resolve wicked problems.

Recent accounts in literature point to the inadequacy of ontological constructs in existing conceptual models to support the conceptual modeling of CAS to resolve wicked problems [35], [36]. Incorporation of highly precise ontological structures as Causal Bayesian Models (CBM) constructs representing CAS and emergent wicked problems' knowledge are thus necessary for such purposes. The GCP causal BN model provides a novel way to addresses these inadequacies.

III. The character of Wicked problems

The term "wicked problem" attributed to Churchman [37], was popularised by [38], and has been used to describe ill-defined, very difficult problems to solve [39]. A summary of the original ten characteristics of wicked problems as outlined in [38] are summarised in [40] as follows: i) non-solubility, i.e., inability to break the problem into parts; ii) non-definitiveness in problem resolution i.e., that there is "no single or definite computational formulation or a set of valid solutions or right answers, but only answers that are better or worse from different angles" [41]; iii) indeterminacy, i.e., conflicting perspectives of the problem and possible solutions emanating from different experiences, knowledge, goals; iv) irreversible consequentiality, i.e., trial and error strategies do not work [40]. Wicked problems include pandemics, inequality, poverty, traffic jams, rapidly changing business environments, and financial market crashes. Recent literature refers to super wicked problems which not only exhibit the characteristics of wicked problems but an added dimension of urgency in resolving them because time to resolve their irreversible effects is running out [42]. Global climate change effects fit into this category [6].

Wicked problems have been closely linked to CAS that are characterised by: non-linearity; positive and negative feedback loops between multiple interacting entities and across multiple dimensions [43]. These characteristics need to be grasped to fully appreciate the complexity of the interacting variables and the pathological emergent structures and behavioural patterns which are refereed to as wicked problems [3], [5], [43], [44].

Wicked problems can thus be viewed as a class of pathological effects that emerge from complex interactions between agents in bounded, albeit open, natural or artificial CAS manifest at varying granular levels of observation or engagement, whose definition for a given context / sub-context is contested by stakeholders with multi-dimensional perspectives of the problem [43]. Emergence is central to the characterisation of wicked problems. [45] provide a useful formal framework for defining emergence:

> Let $\{S_i\}_{i\in I}$ be a family of general systems or "agents". Let Obs^1 be "observation" mechanisms and Int^1 be interactions between agents.
> The observation mechanisms measure the properties of the agents to be used in the interactions. The interactions then generate a new kind of structure $S^2 = R\left(S_i^1, \mathrm{Obs}^1, \mathrm{Int}^1\right)$ which is the result of the interactions. This could be a stable pattern or a dynamically interacting system. We call S^2 an emergent structure which may be subject to new observational mechanisms Obs^2 [45].

A wicked problem is thus where S^2 is a pathological emergent structure with related behavioural patterns arising from the numerous dynamic interactions of related entities within natural or artificially defined bounded CAS, and observed at Obs^2.

Wicked problems manifest at two levels. The first level, which in this paper shall be referred to as level I, is about the ontological aspects of the problem, that is, what the problem is, what relationships characterize the problem, and where and how it manifests. The second level, level II, is about the epistemological aspects of wicked problems, that is, how and at which granular level wicked problems are perceived, explored, known, and understood, at say Obs^2, and how candidate solutions are conceptualised. At level II multiple divergent stakeholder contextual perspectives from varying granular levels of observation or abstraction of a level I wicked problem are explored.

[46] identify dynamic complexity, finitude, and normativity as the summary key factors that cause wicked problems. Complexity, they define as a feature that arises from interactions between system variables and feedback loops which make natural and engineered systems unpredictable. Finitude refers to cognitive ability limitations, experience and knowledge. Normativity is about different norms and values held dear by different stakeholders, the major source of conflict that makes consensus difficult to reach [46]. Complexity factors belong to level I, while finitude and normativity belong to level II.

The numerous interactions among variables, (the causes), and the unpredictable patterns of change, (the effects), make it difficult to make effective interventions to resolve wicked problems. Interventions can easily become the source of other problems. As a result these problems are notoriously difficult to abstract, represent in conceptual models and solve using existing computational models in information systems.

Systems theory and systems thinking as a practice have been applied to identify prototypical pathological patterns that emerge from such interactions and unintended consequences that arise from the inappropriate of use of deterministic [20], [47], [48].

IV. Granularity, Context, and Perspective

For any given context or sub-context complex phenomena is abstracted cognitively and described at different levels of granularity and from a specific perspective. [35] captured this phenomena thus:

> "There is only one Herbert (the frog) that we and the molecular biologist apprehend, but, depending upon our interests and our focus, we may each apprehend him from different granular perspectives" [35].

Granularity is a concept relating to the cognitive, spatial, or temporal level of abstraction of a phenomena from an observer's point of view [36], [49], [50]. It is also used to define the coarseness of an observation or an investigation [51].

The important factor about granularity with respect to complex phenomena is that the observer's interest and hence level of abstraction is a key determinant in what is defined, 'seen' and investigated [26]. [52] argues that to study and understand complex phenomena fully "we need to be able to keep an eye both the tree and the forest", that is, atomic elements, micro sub-systems that emerge from their interactions, and the macro system that result from the linkages between sub-systems.

Context in modeling systems is important. Natural and artificial systems are said to have a translucent boundary which defines what is inside of a system and what is outside, determined by the focus of interest [53]. [34] demonstrates the importance of context in deciding what is considered endogenous and exogenous to the system under review, and the impact this has on the modeling process.

Perspective refers to enduring beliefs by a person or a group of people with similar mental models of the world, a product of our knowledge, past experience, uncertainty, incomplete information and societal norms. Perspectives influence the definition, and proposed solution spaces for wicked problems and are a source of bounded rationality, that is, restricted understanding and explanation of the state of the world we live in and its problems [54].

Different perspectives of a given problem are the source of disagreements between stakeholders about the definition of a given common problem. The divergence in belief systems is typically driven by one or more of the following: local context; various scientific philosophical standpoints about complex phenomena; the related methods of studying them; experiences; culture; divergent stakeholder interests and biases [3], [6], [40].

Veridical partitioning is the essence of representation of some aspect of reality in a model for a given purpose [35]. [35] advocate embracing realist perspectivalism, a view that knowledge can be obtained by means of veridical granular partition integration. The GCP casual BN model is about exploring veridical partitions and promoting veridical integration as a way of promoting ontological commitment to a common view of a given wicked problem and its solution. It is thus important, given this objective, to explicitly represent multiple perspectives in ontologies and BNs to support the sharing of knowledge and gain wider understanding of a given wicked problem.

V. The COVID19 Pandemic as a Wicked Problem

In this section the Coronavirus Disease 2019 (COVID19) pandemic is used as an illustrative prototypical wicked problem example to further explore the character of wicked problems applying the key identified key systems theory modeling concepts: granularity; context; and perspective.

At the micro granular contextual sub-system level interactions between the Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2), the lung cells and the human immune system take place. At the individual human granular contextual level, the COVID19 disease manifests (observed) as a complex clinical ailment that emerges from micro granular level interactions.

The problem is wicked for the following reasons. The problem is non-soluble, that is, it cannot be easily broken into parts that can be analysed and dealt with separately. The ailment is an emergent phenomenon from a wide range of interacting variables at the micro granular contextual sub-system level, i.e., the SARS-CoV-2, the lung cells, the human immune system, and pre-existing health conditions, which interact in both known (deterministic) and uncertain (unknown) ways. The solution to the ailment is non definitive. While development of specific vaccines provide a solution, such a solution is likely to be temporary. The coronavirus is subject to mutations, a result of the virus adapting to its dynamic ever changing environment, thus making it difficult to find a singular clinical solution to its eradication. At coarser granular contextual level, say the community level, large gatherings, the so called "super spreading events" lead to exponential spread of the coronavirus through close contact between those infected and those not yet infected, leading to surges or "waves" of community level infections. This phenomenon, as systemic pattern, is typical of pandemics, the 1918 H1N1 influenza 'Spanish flu' pandemic being a case in point. Here, consequences of inappropriate actions or behaviours are irreversible.

While the pandemic is broadly understood to be a health problem of level I 'wickedness' more complexity, level II complexity, is brought on by conflicting perspectives on the nature of the broader economic and social impacts of the level I health problem, and how these should be defined and resolved, a case of indeterminacy of the wicked problem. Non clinical solutions implemented in different countries like 'lock-downs' to limit the movement of people as a measure to stop the spread of the coronavirus have been contested by stakeholders with varying perspectives of the problem and with different specific interests.

Stakeholders with an interest in preserving economic activity argue that lock-down impositions threaten jobs and livelihoods. Travel restrictions have resulted in the collapse of businesses in the airline, hospitality and tourism sectors across the world, highlighting another characteristic of wicked problem, irreversible consequentiality, where decisions and their consequences cannot be reversed. Other interest groups argue that restrictions on movement impinge on their rights of freedom of movement, and this has led to riots in some countries. This is a classic character of wicked problems, where a solution to a given problem becomes the cause of another problem [38]. The divergent perspectives represent level II characteristics to do with finitude and normativity [46].

The foregoing represents a wide range of complex interactions between CAS at different levels that make the problem non-soluble, non-definitive, non-determinate, and subject to irreversible consequentiality [40]. CAS exhibit dynamism, emergence, counter-intuitiveness, inter-connectedness between interacting agents within systems at various granular contextual levels, which lead to non-linear, unexpected outcomes. These outcomes or impacts are emergent at at various granular levels of observation for given contexts and perspectives.

It has been argued in [55] that the hierarchical dynamic complexity of complex adaptive systems means that wicked problems cannot be solved in a deterministic kind of way, that is, by analysing the character and behaviour of the problem, and developing interventions at the same level of the problem observation. Interacting variables are different for each granularity, context, and perspective delineated sub-system, and thus have to be represented in models as such. Further, the inter-connectedness of these sub-systems, driven by the fact that they represent multiple perspectives of the same wicked problem have to be represented as such in ontologies to support the sharing of knowledge and perspectives.

It has been suggested in [43] that there is "an engaging symmetry between complexity and wicked problems, where complexity is both the source of intractable wicked problems, and a way to trace the pathway out". This is the approach taken in this paper in building a high ontologically precise casual hierarchical and dynamic Bayesian Network model to represent and support the resolution of wicked problems through Bayesian inference, structure, and parameter learning.

VI. The Granular Contextual Perspectives Causal Bayesian network model

Figure 1 shows a high level architecture of the GCP causal BN model depicted as a 2 time step unrolled dynamic HMM representation of two separate Granular Contextual Perspectives (GCP) systems and sub-systems A and B and an integrating GCP system C.

Each GCP system is modeled as a template, where the key ontological notions of granularity, context, and perspective are incorporated as template variables, see [56] for a detailed definition of templates as representational model frameworks.

Within each GCP sub-system entities and their attributes are modelled as observable, semi-observable and latent random variables and values, after [57]. Observable variables are colored grey. The relationships between the variables represent causal links between world entities concepts and their conditional probabilities.

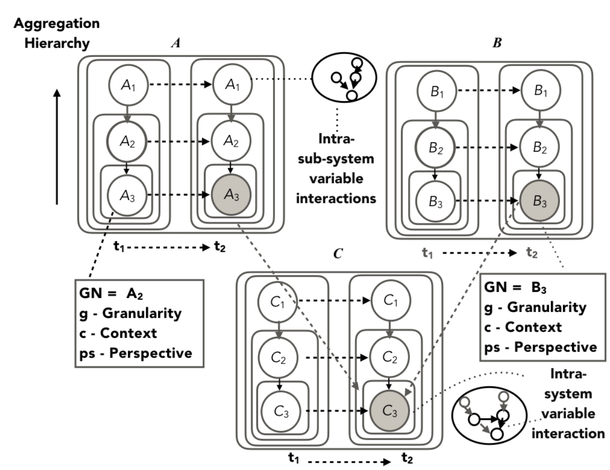

Fig. 1. Granular Contextual Perspectives Architecture

The major difference between typical dynamic HMMs, and the GCP causal BN model, wherein lies the novelty of the GCP causal BN model, is that while the variables propagated and observed over time are the same for dynamic HMMs, represented by a single GCP sub-system, say GCP A in the GCP causal BN model model, each GCP template contains a set of interacting random variables which are either different for each GCP or interact in a unique way as their existence and behaviour is determined or influenced by the parent sub-system meta-properties: granularity, context, and perspective. Each variable in a GCP subsystem is essentially an entity playing a role defined by the GCP sub-system.

Further, intra - GCP sub-system variable interactions produce emergent patterns and properties at the sub-system level which are greater or smaller than the sum of their parts. In the COVID19 example provided this could be the disease, an emergent outcome of the interactions of the coronavirus and the lung cells and immune system of the individual.

The formal definition of the GCP system ontological architecture, which adapts and extends the definition of granular niches in [58] follows.

Definition 1:

A GCP is defined as an 9-tuple *(*S,T,M,N,Gl,C,Ps,A,E) where:

- *(*S) is a spatial or virtual location occupied by this GCP;
- *(*T) is a time interval granularity;
- *(*M) is a non-empty set of member entities, present at location S for part of time interval *T*, each representing a role;
- *(*N) is a non-empty set of interactions between entity roles, the normal behaviour in that gcp;
- *(*Gl) is a hierarchical structuring of the entities, *M* based on relative granularity of abstraction /
- observation/ manifestation i.e. *Gl* is a function mapping every *m* in *M* onto a granular level*gl* i.e. *Gl(m) = gl*;
- *(*C) is a description of contextual character for a given granular niche;
- *(*Ps) is a description of the world view that holds for a given GCP, a product of stakeholder belief system, knowledge, experience and culture;
- *(*A) is a set of emergent attributes of the GCP sub-system which are not direct attributes of its members *M*;
- *(*E) is a possibly empty set of environmental parameters that hold at location *S* during time *T*

The following constraints are applicable for GCP sub-systems:

- If *m* $\in$ *M* then $Gl(m)$ *is unique i.e. every entity playing a specific role has exactly one granular level in a GCP.*
- *If* $m_1 \in M$ *and* $m_2 \in M$ *and* m_1 *is-part-of* m_2 *then* $Gl(m_1) \leq Gl(m_2)$
- *If* $m_1 \in$ *M,* $m_2 \in$ *M,Gl* $\in$ *N and Gl* $(m_1, m_2))$ *then* $\exists t$ $\in$ *T s.t. In*(s, t, m_1) *and In*(s, t, m_2) *i.e. for two entities to interact in a GCP sub-system they must exist in that sub-system at the same time.*
- *For all m* $\in$ *M,* $\exists$ *t* $\in$ *T s.t. In(s,t,m) = false i.e. an entity does not have to remain in a GCP sub-system throughout its existence.*

The GCP causal BN model is defined formally as as a plate model, after [56] as follows:

Definition 2: A Plate model M_Plate defines, for each template attribute $A \in \aleph$ with argument signature $U_1, ..., U_k$:

- *A set of* template parents $Pa_A = \{(B_1(U_1)..., B_l(U_l)\ \}$, such that for each $B_i(U_i)$ we have that $U_i \subseteq \{U_1.., U_k\ \}$. The variables U_i are the argument signature of the parent B_i.
- A template CPD P$(A|Pa_A)$

The set of template parents B_i, $A_{1..n}, B_{1..n}, C_{1..n}$, the template parents, in GCP causal BN model, and $\{granularity, context, perspective\}$, being instances of the argument signature, U_i.

The proposed GCP causal BN model artifacts are intended, on the one hand to specifically abstract an 'objective' ontological structure and stochastic processes character of a complex world, while on the other hand, surface, and lay bare, the various granular contextual perspectives and assumptions held by stakeholders about a given wicked problem. The GCP causal BN model is expected to support the design of model artifacts that more precisely represent complex reality and provide richer probabilistic reasoning and learning capabilities with respect to CAS and their emergent wicked problems than baseline Bayesian modeling frameworks.

A, for instance, using our illustrative example could represent the health services' perspective within the context of the COVID pandemic at different granular levels. A_3 then represents the micro granular contextual sub-system level. Here the variables of interest include the Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2), the lung cells, the human immune system, and pre-existing health condition present. A_2 then represents the individual person granular contextual perspective sub-system level. Variables of interest at this level include COVID19 status, access to quality health care, severity of symptoms if present, and levels of anxiety.

The GCP system B could represent the economic perspective within the context of the Covid19 pandemic at different granular levels. C represents an integrative architecture to visually explore the linked sub-systems and Bayesian graphical pathways to enable the exploration of the likely effects of an intervention, within a GCP system (e.g., A), at a GCP sub-system level (e.g., A_3), across GCP systems and sub-systems (e.g., B_3). GCP C represents multi-stakeholder ontological commitment to a wicked problem definition and a candidate design solution/s, arrived at through consensus using the model.

VII. Utility of the GCP causal BN model

Figure 2 shows the application of causal diagrams, after [33] to inspect the precision of causal representation and the effects of interventions using the GCP causal BN model.

The X in the edges between the variables indicate an intervention, an incision of an edge to control the pathways

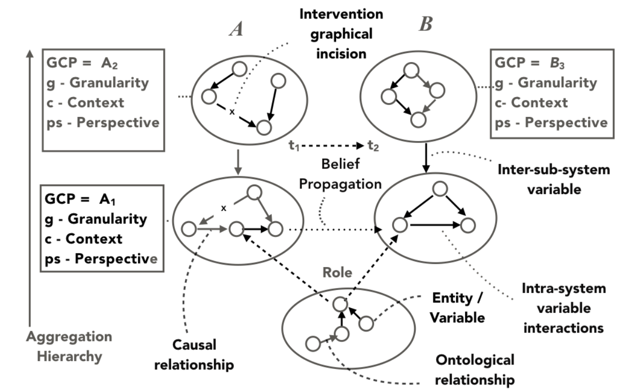

Fig. 2. Granular Contextual Perspectives causal graph showing an intervention

between interacting variables. For example, wearing a mask "deletes" the pathway through which the coronavirus is transferred from person to person.

A comprehensive account of how to identify causal inconsistencies, such as spurious non-causal confounding variables, and the problems brought about by conditioning on collider nodes, i.e., nodes in a causal graph representing a variable causally influenced by two or more variables is provided in [33]. [33] also outlines techniques applied to handle such issues in causal graphs, such as the back door criterion.

Causal diagrams provide the means to visually inspect cause and effects to: i) handle any conceptual inconsistencies; and ii) illuminate likely effects of proposed interventions [34]. The *do* calculus, after [34] is applied to determine causal inference of the form:

$$P(y|do(x), z) \tag{1}$$

which describes the conditional probability of y if an intervention on *x*, given knowledge of *z*, where *z* represents existing knowledge of the causal influence of the triple factors: granularity; perspective; and context.

By explicitly incorporating granularity, perspective, and context as top level ontological knowledge structuring constructs in a plate model representing GCP causal BN subsystems, the Markov conditioning assumption [56] can be utilised to extend the range of queries answerable by the model to address wicked problems.

The Markov conditioning assumption links graph and probability functions where each variable is probabilistically independent of its non-descendants, conditional on its parents, and is defined more formally after [56] as:

$$P(x_j|pa_j) = P(x_1, ...x_j - 1) \tag{2}$$

Conditional probability x_j is sensitive only to a small subset of predecessors PA_j., the ontological meta-properties, the argument signature U_i of the plate model representing a GCP sub-system, which considerably simplifies and reduces input information required [34]. Thus the application of the GCP causal BN model leads to reduction in computational complexity, given that Bayesian inference is NP Hard. NP hardness refers to computational complexity that increases exponentially with the size of the network making a problem unsolvable in non-deterministic polynomial time [59].

The possible effects of an intervention on inter-linked variables, given pre-existing knowledge of granular contextual perspectives encoded as conditional probability distributions, can be computationally simulated. Using the Covid19 pandemic example, this facilitates decision making on important questions such as, which granular hierarchical level to target with an intervention for a given Covid19 context (e.g., health, economic, and human rights contexts), to obtain the most desirable outcomes, with the least negative effects.

Queries of the following kind are enabled: "What is the likely effect of a statutory requirement for everyone to stay at home for 3 weeks on hospital *x* , located at location *l*, and the likely effect on employee *y*, an airline pilot who works for airline *z*, given the different perspectives and belief systems of the affected stakeholders?"

The GCP causal BN model also supports counterfactual queries by applying the following calculus, after [33]

$$P(y_x|x', y') \tag{3}$$

which describes a hypothetical situation that says, "was it *x* that caused *y*, and, what if I acted differently". The calculus extends the query space to address complex scenario planning queries of the kind:

"Imagine today is date *d*, 30 September 2022, *(representing temporal granularity in the GCP causal BN model)*, the pandemic has been brought under control through wide spread vaccination, and people are free to travel to *l* locations *(representing sub-context in our model)*. Airline company *x* finds out that its most lucrative market segment *b* of business travellers *(representing a granular sub-context in the model)* has adapted to doing business online *o*, and business people do not travel as much as during *bc*, the pre-COVID19 era, *(representing a sub-context, and temporal granularity in the model)*.

What could company *x* have done to prepare for such an eventuality *e a*ffected by multiple perspectives *ps* in the model, given evolving knowledge *k* of changes in business cultural practices, such knowledge being fragmented and subject to divergent beliefs *db* of company executives of how the future could pan out?".

The foregoing inferential and counterfactual queries are essential for the exploration of possible effects of proposed alternative interventions or prototypical design strategies for resolving a given wicked problem, and it is argued in this paper, that such queries cannot be handled efficiently and effectively through existing baseline Bayesian models as they do not have the systemic meta-properties as modeling constructs.

VIII. Discussion

Wicked problems are emergent features of CAS and while modeling of emergence in CAS is provided for in some research work such as [60] the specific modeling of the epistemological elements of CAS and wicked problems from an observers view point, level II of wicked problems in this paper, is not represented in such models. By incorporating granularity, context, and perspective as constructs delineating CAS subsystems the GCP causal BN model, using HHM conditioning, the model provides the mechanism to compactly represent both levels, I and II of wicked problems to support tractable inference computation. While some baseline Bayesian models do utilise HHMs to compactly model hierarchy and systems nestedness as elaborated in [12] such Bayesian models are not able to simulate the effects of interventions across granular contextual perspective sub-systems through Bayesian belief propagation.

The use of a common formal ontological modeling language promotes semantic inter-operation between collaborating stakeholders and helps eliminate bounded rationality between divergent perspectives about a given wicked problem. The model can thus be used to support multi-stakeholder group learning and understanding of the ontological and stochastic character of a given wicked problem, paving the way for improved collaborative exploration, and solution design.

The GCP casual BN model further refines machine learning capabilities with respect to learning the structure of wicked problems. The argument is that the incorporating of granular contextual perspectives as ontological knowledge constructs in the model provides a causal model that supports an estimand that refines statistical classification of data to more precisely recover the structure, and learn about parameters of a given wicked problem than baseline Bayesian models. The need for such high precision estimands is well articulated in [33]. The constructs provide the means to model data generating structures and processes missing from models without the representational complex systems constructs.

IX. Conclusion and the Way Forward

The GCP causal BN model outlined in this paper provides a novel high precision ontological representation of wicked problems in dynamic, hierarchical, Bayesian networks, problems that emerge from complex adaptive systems, and stakeholder context, perspectives and granular level of observation.

The incorporation of granularity, context, and perspective of kernel complexity theory notions as Hidden Markov Model modeling constructs in the GCP causal BN model architecture extends the scope of queries answerable using baseline Bayesian models to specifically handle inference and counterfactual queries that support the understanding and resolution of wicked problems. The constructs further serve to refine machine learning of a given wicked problem structure and its parameters. To the best of our knowledge no such model has yet been developed to enhance understanding of wicked problems and their resolution through Bayesian reasoning and causal graphical logic.

By providing a modeling architecture that links sub-systems as multi-domain ontology / perspectives of bounded linked sub-systems the proposed GCP causal BN model architecture reduces computational complexity. The model also simplifies representation of the complex relational interactions for a given wicked problem for visual inspection and discussion by stakeholders with different perspectives and beliefs about the status of the wicked problem, and to arrive at informed consensus based solutions.

While a single prototypical example was used to illustrate the utility and novelty of the model, the model is equally applicable in resolving other wicked problems exhibiting similar challenges of dynamic complexity, finitude and normativity, which include market crashes, urban development, and negative climate change effects.

The intention, as a way forward, is to carry out empirical experiments to benchmark the GCP causal BN model against baseline Bayesian models to further validate the veracity of the model for Bayesian inference reasoning and machine learning of wicked problems. This is to be carried out using synthetic ground truth data, applying the Kullback–Leibler KL divergence method as applied in [13] for structure and parameter learning in dynamic environments.

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