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Attempting to Understand the Progress of Software Architecture Decision-Making on Large Australian Defence Projects

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***Abstract*—This short paper details exploratory research into architecture knowledge management (AKM) at the very early stages of architectural design. This is a departure from traditional AKM; instead of a focus on decisions, the focus shifts to decision making. Additional decision theories and decision-making philosophies are needed to supplement the ubiquitous normative decision theory and its associated rational decision-making, which is assumed by AKM to-date as the *de facto* decision theory. Extensions to the agent model paradigm have been explored to portray the evolution of a set of architecture decisions according to multiple decision theories sourced from the human sciences of neurology, psychology, and sociology. Model Of Software System Architecture Decision-making (MOSSAD) uses agent-based modeling and simulation in an attempt to understand the dynamic complexity of interdependencies & interactions found in decision-to-decision relationships amongst hundreds of decisions and their asynchronous evolutions over time. If understanding is possible, this should lead to knowledge for legitimate progress of architectural decision-making. This in turn should lead to a new theory about the time period necessary for architectural design on a project.**

Keywords – software architecture; decisions; decision-making; agent-based modeling; simulation

I. Introduction – Exploratory Nature of this Research

According to a 1995 journal article in the publication Organization Science, no theory exists for decision-to-decision relationships [1, p.270]. More recently, a PhD thesis from MIT revealed design is virtually absent in the decision-making literature [2, p.6]. A 2008 reference text on decision making offers no theory on decision-to-decision relationships [3, p.427]. Even the most up-to-date reference text on decision making reveals "*Decision making is both complex to study and replete with conceptual and empirical dilemmas...Despite notable efforts, few have made headway in integrating this body of knowledge into coherent theory.*" [4, p.10].

Lack of theory is problematic; a typical research process has an early step of finding the appropriate theory:

- Developing the research question.
- Finding the theory or underlying frameworks.
- Finalizing the specific question or hypothesis.
- Choosing the research design.
- Choosing the method(s) of data collection

.... [5, pp.4-5]

The research question is simply "How much time is needed for all this decision making for a set of decisions?". Since normative decision theory is not the most appropriate theory considering the working environment in which the early stages of architectural design takes place [6, pp.254-257, p.271], [7, p.8], and considering the dilemmas just identified i.e. lack of other decision-related theories, the researcher is faced with "theory building". Fortunately, better understanding of decision-making phenomena essential for "theory building" comes from several human sciences.

II. A Multi-Discipline Subject

Architecture decisions are anything but sequential or decision tree-like.

Neuroscience reveals (i) an engineering design is a web of decisions, (ii) this web is formed in a massively parallel fashion [8, p.5]. How big the web is, and how fast it comes together is driven by several human factors, most notably by a designer's experience. The web structure itself changes over time, and to study the complexity of the decision-to-decision relationships "*boggles the mind*" [9, p,24].

Psychology reveals decisions are quite intangible (hard to pin down in time and space) [1, p.261], and yet humans have unconscious mechanisms for handling this. The decision-making process is unique for each individual [3, p.467]. A 'decision' is defined as "a construct" [1, p.261].

Sociology reveals decision making and decision processes to be a social phenomena [6, p1]. This is consistent with a field study of large software development projects in-situ wherein large-scale software design is described as a "*communication and collaboration process*" [10, p.1282]. The difference between 'good' and 'bad' decisions "*resides in the level of sponsorship.*" [11, p.190].

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The study of ecosystems [12] provides an apt determination for the rate of evolution of a species, dependent on a species position in a hierarchy. This is consistent to Kruchten's architecture decision ontology [13] which describes evolution of each and every decision as a state transition through several states. A hierarchy of decisions can be observed in Bredemeyer's three layers of architecture decisions [14].

The next part of the research process is choosing the right research design. Again, the human sciences point the way forward.

III. Complexity of Research Design

Most social scientists adopt a probabilistic or manipulative view of causation, and reject an essentialist view of causation [15, p.15]. Most social phenomena cannot be isolated in closed systems as is necessary to evaluate views of causality [16]. All social science can do is probe but not prove a causal hypothesis [4, p.547]. It is difficult to separate independent from dependent variables in social processes, because events are interrelated in a complex way.

Two of the well known research designs for preserving a multitude of variables in a software project-based work setting are large-scale case studies (e.g. [11]) and action research (e.g. [17]). However, PhD resources do not permit a large project be created just for the sake of research.

The nearest thing would be a model – a surrogate – of a real-life project where architectural design takes place. Treating architecting as a system, per Senge's systems thinking [18], was the initial basis for building MOSSAD [19]. This human architecting system has a systemic structure composed of decisions, interdependencies amongst decisions, decision making, decision makers, stakeholders and the decision-making environment. More recently, agent-based modeling [20] is used to model the architecting system, and simulation is used to visualize system behavior (i.e. decision evolution) over time

Only an agent-based model is able to handle multiple theories of decision making from the human sciences, and cater to a plethora of environment variables which will affect agent behaviors. For example, agent-to-agent interaction can occur according to a social theory, whereas individual agent behavior is determined by a theory of psychology.

IV. Model Description and Simulation Behavior

Much focus has been placed on how the model is initialized. A major part of design is realizing that design options exist [9, p.192]. (For most products, the range of design options is virtually limitless [21, p.653].) The majority of agents in the model are thus decision options / choices, not decisions. (This is a significant deviation from traditional agent modeling where agents usually make decisions based on sensor readings [22, Ch.11].)

One option for one decision is represented by one agent. If there are three alternative options for one decision, then three individual agents exist in this model. (If two of the 3 alternatives are non-suitable "non-starters" very early on, their evolution is going to be short lived.) At the time of writing, the model is populated with almost 1,000 decision option agents. The pattern of agent-to-agent interaction is analogous to the "web of decisions" described earlier in section II. A complex pattern of agent-to-agent interaction is expected because in real-life selecting one decision option is rarely independent of options for other decisions [9, p.194].

Maximum learning comes from observing how design evolves [9, p.186]. Our model attempts to simulate observable design evolution from Day 1 of a project by having a selected set / web of decision option agents (collectively equivalent to one architecture) each exhibit evolution from "Idea", through several intermediate states, and finally to "Approved" states as depicted in Kruchten's decision ontology [13]. (Selection of the set of agents is via on-going 'Discovery', due to the almost infinite number of design options.)

The following sub-sections describe some implementation details and one usage scenario of an agent model implemented with the Repast-Simphony tool [23] tool.

A. *Features of the Agent-Based Modelling & Simulation Tool (ABMS Tool)*

Table 1 lists features of Repast-Simphony and their uses.

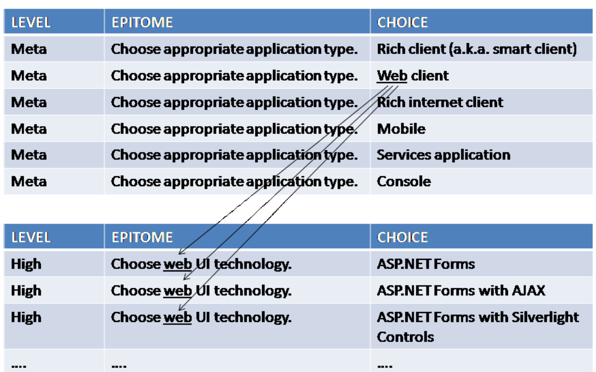
Table 1- ABMS Tool Features

Massive Storage	Many thousands of agents held in a "context".
	Multiple types of agents: Meta-level decision agents | High-level decision agents | Low-level decision agents | Generic decision agent | Stakeholder agents.
	Rich set of agent properties – static properties for decision discovery and dynamic properties which (i) determine rate of evolution (rate of state transition), (ii) trigger agent behavior when value of property changes.
Visualization (see Figure 2)	All Meta-level decision agents, High-level decision agents, Low-level decision agents, and Generic decision agent projected from context onto a grid; the "Decision Grid". One row for each of the Meta-, High-, and Low-level decision agent types. One grid location for one decision agent.
Animation / Simulation	Discovered decision agents relevant to a solution to the design problem at hand visually seen changing from dots to crosses.
	Decision agent evolution through state transition seen as increasing size of cross in grid location.
	Simulation paused at any time. An individual agent can be probed to examine values of agent's properties.
	Simultaneous animated charting of activity e.g. active agent count , by agent type.
Speed	Agent-to-agent interaction and state transition (change in value of 'State' property) of decision agents happen in $1/10^{th}$ of second. This is close to "massively

	parallel" decision making identified in section II.
Logging	For replay of simulation.

B. Use of the ABMS Tool for Discovering all Related Decisions and Decision Options

Initial decision discovery is based on a user entering a keyword (the user has, say, vague thoughts about a potential solution to the current architectural design problem). A search of the `Epitome` and `Choice` properties of all Meta-, High-, and Low-level decision agents in the decision grid is performed by the Generic decision agent. Where any match is found, the `State` property of that discovered agent is changed from "Idle" to "Idea". (Values of `ForwardLink` and `ReverseLink` properties are also set.) These matched agents are assumed to be part of the "web of decisions" that constitute the architecture. Figure 1 shows a partial schematic of discovery of one Meta-level Decision agent and 3 High-level Decision agents based on keyword "web". The Generic decision agent has oversight of all discovered & related decision agents. It is often referred to as a "super agent" for choreography of all evolving decision agents.



LEVEL	EPITOME	CHOICE
Meta	Choose appropriate application type.	Rich client (a.k.a. smart client)
Meta	Choose appropriate application type.	Web client
Meta	Choose appropriate application type.	Rich internet client
Meta	Choose appropriate application type.	Mobile
Meta	Choose appropriate application type.	Services application
Meta	Choose appropriate application type.	Console

LEVEL	EPITOME	CHOICE
High	Choose web UI technology.	ASP.NET Forms
High	Choose web UI technology.	ASP.NET Forms with AJAX
High	Choose web UI technology.	ASP.NET Forms with Silverlight Controls
....	....	....

Figure 1 – Searching for "web" in Agent Properties

C. Observing Decision Evolutuon In-Progress

Figure 2 shows (five) discovered decision agents change their shape from a dot to a much larger cross.

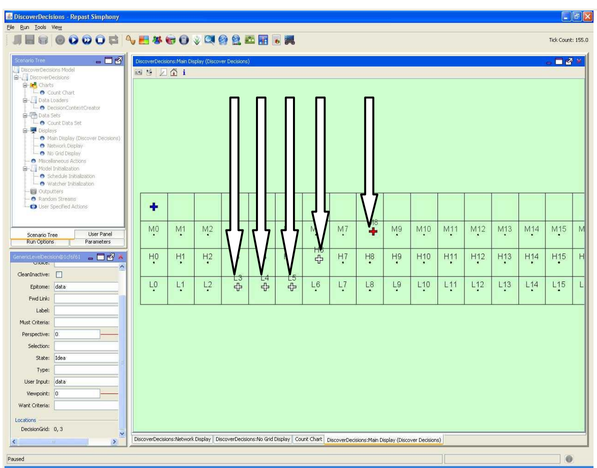


Figure 2 – Animated Decision Grid

When searching is exhausted, unrelated / undiscovered decision agents remain as small dots in the Decision Grid. An animated chart can plot the progress of discovered decision agents. Figure 3 shows a plot of the cumulative count of discovered Meta-, High-, and Low-level decision agents (Y axis) over time (X axis). Search exhaustion for Meta-level decision agents is indicated here by a flattening out of the bottom line – this is expected because the population of Meta-level decision agents is small compared to the population of High-level and Low-level decision agents. As the simulation engine clock ("tick count") advances, the chart scrolls to the left in order to display newer incoming data.

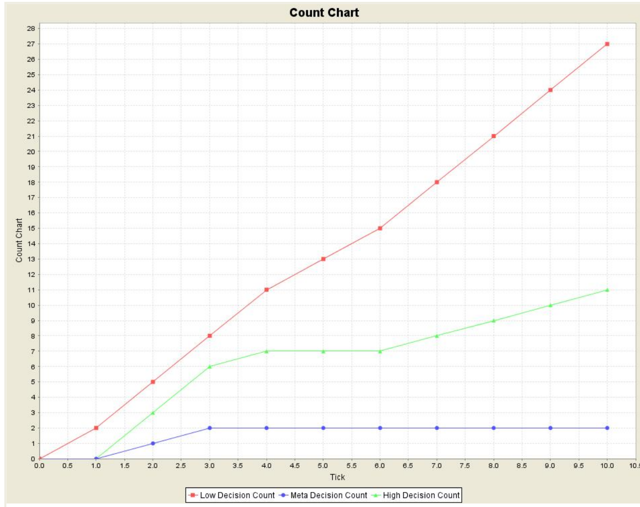


Figure 3 – Decision Agent Discovery over Time

Figure 4 shows decision agents projected onto a 'network' by Repast-Simphony, as an alternative to projection onto a 'grid'. Arcs are drawn from one discovered decision agent to the next discovered agent. (No analysis of network properties has been conducted yet.)

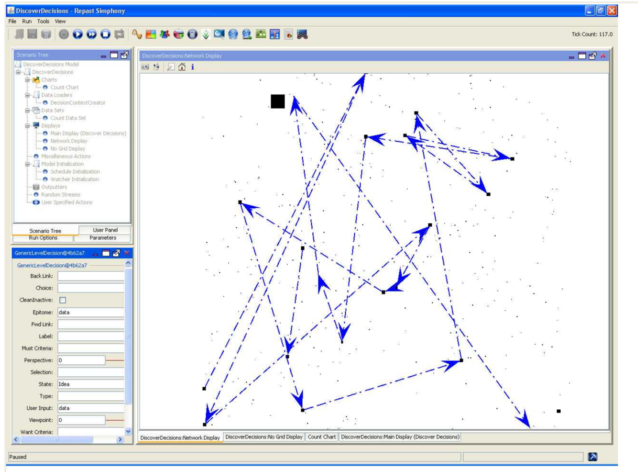


Figure 4 – Animated Decision Network

Decision discovery, and the changing of `State` property from "Idle" to "Idea", is thus the commencement of decision making. Continued (and rate of) state transition is determined by decision agents altering their own properties and those properties of other related decision agents.

V. Next Hurdle– Validation of Model

MOSSAD must handle a change in decision-making philosophies; progress of architectural design sees a switch in philosophies. Researchers of rational decision-making (RDM) – occurring towards the end of architectural design – have been more concerned with internal validity, whereas researchers of naturalistic decision-making (NDM) – occurring at the commencement of architectural design – have been more concerned with external validity [24, p.574]. By definition, NDM research is focused on decision makers in their natural settings, so it is not surprising that that NDM researchers stress the importance of ecological validity of field studies over the need for methodological rigor of surveys and experiments where conditions are under strict control.

Validation of simultaneous RDM and NDM within a synthetic, simulated project environment (a single simulation) poses a dilemma. This research will therefore be adopting the position of [25]; no model has ever been or ever will be thoroughly validated. "Useful", "illuminating", "convincing" or "inspiring confidence" are more apt descriptors applying to models rather than "valid" [25, p.846].

Specifically, this research will attempt to test MOSSAD for "Events Validation" and "Face Validity" [26]. Events validation occurs where events that have been observed in the model are compared to those of the real system. Face validity, where subject matter experts determine whether they believe that the model's behaviors output are reasonable. If the subject matter experts deem the model to be adequate, then it has achieved "face validity".

Simulations will need to be run hundreds, if not thousands of times, to build a range of possible decision-making scenarios and associated time periods.

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