Fuzzy-control models of service-system engagements

ABSTRACT

Purpose –

This paper presents conceptual models of client epistemology and decision-making in service engagements through the use of fuzzy variables and fuzzy relations. These models support more effective design and management of service. Motivating examples include, but are not limited to, service in education, consulting, health care, government services, KIBS and on-line intelligent services.

This research views a service system as a network of processes and resources, which are controlled by agents. The fundamental processes that make up this network can be generically defined as learning, decision and resource integration (a more parsimonious representation of Maglio et al's Interact, Serve, Propose, Agree, Realize (Maglio, Vargo et al. 2009)). The trajectory of an agent in a service-system network is determined by the agent's adaptive decision making in response to interactions and knowledge acquisitions. Consequently, service rejection and the levels of resource commitments are based on an agent's understanding of a proposed resource-integration process and the agent's perceived value of process outcomes.

In most cases, an agent must make engagement and resource-commitment decisions with incomplete knowledge of the resource requirements and the value of the outcomes of a proposed service process, which leads to perceived risk in the value creation of the service (Barile and Polese 2009). Stochastic models assume that uncertainty is associated with known variables and can be measured in terms of distributions and entropy (Barile 2009; Badinelli 2010). However, abductive and inductive reasoning (Barile), which are endemic to service engagements, involve vagueness and ambiguity.

The paper's modeling framework is based on the view of agents as fuzzy controllers. Fuzzy representations of variables represent vagueness through the mathematical representations of possibility and necessity instead of probability, and fuzzy relations capture ambiguity (Tsoukalis and Uhrig 1997; Liu and Lin 2006). All three of the fundamental processes of a service system are viewed in terms of fuzzy relations between inputs and outputs. Theoretical results and simulation studies illustrate the sensitivity of agent decisions to the forms of these fuzzy relations and prescriptions for service design and management are derived.

Methodology/approach –

The research derives representations of service processes through the model constructs of fuzzy variables, fuzzy relations and fuzzy controllers. Fuzzy control is used to model the engagement of agents in the three core processes of a service network

Computer simulation is used to provide experimental evidence of agent behavior and the performance of prescribed service designs.

Findings –

Key findings of this research include:

- A fuzzy systems approach to modeling service is a robust way to represent the abductive, inductive and deductive stages of service development.
- Assumed forms for relations between inputs and outputs of processes have strong effects on the decision making of agents.
- Client knowledge can be augmented by provider knowledge in ways that reduce the risk and enhance the value of a service process.
- Co-creation of knowledge, with the specific intent of reducing client ambiguity and vagueness about a proposed service process, improves the co-creation of value by that process.

Research implications –

The research argues for an approach to modeling service systems based on a robust and generic representation of service-system networks and service-system processes.

Practical implications –

This research responds to the challenge of endemic ambiguity and vagueness in the interactions of service clients and providers in a service system by providing robust and flexible models that can be applied to the design and management of service systems.

Originality/value –

The representation of a service client as a fuzzy controller is original.

The generic representation of the service-system network is shown to be robust and flexible.

Key words (max 5)

fuzzy systems, service engineering, knowledge management, co-creation, simulation

Paper type – Conceptual paper / Research paper /

Conceptual paper

1. Introduction and lit review

The purpose of this paper is the exposition of a robust approach to building models of service systems that are useful in supporting service design and management. This approach is based on the adaptation of fuzzy logic and fuzzy control to models of service-system engagements. We define a service-system engagement as a process of integrating resources from the service recipient and one or more other resource providers for the purpose of co-creating value. The integration can be managed by the service recipient, as in a self-service system, or by a service provider. In any case, the manager of the service must identify the most appropriate resources for the engagement, acquire access to these resources and utilize these resources in the context of the service engagement. Therefore, resource integration is the result of design and planning decisions by the manager of the service.

The research that is reported herein is part of a stream of model-development initiatives undertaken by the operations-research community in order to advance the modeling of resource planning in service systems. The vision of this community is to provide effective and practical model-based decision support to the design, planning and control of service in order to improve the efficiency and effectiveness of the service economy. More than 80% of the economies of industrialized countries are driven by service supply chains, and the quality and efficiency of service generally lags the performance of product supply chains. There is an obvious need for model-based decision support of the design, planning and control of service systems, which can bring the levels of efficiency and effectiveness to service enterprises that such support has brought to the manufacturing economy over the last one hundred years. Co-creation of value-in-context presents challenges to the modeler, which have only recently been broached by the operations-research community. New model constructs are needed, as it has become apparent that service cannot be viewed as an extension or modification of the models that have been developed for manufacturing supply chains.

Co-creation of value through resource integration is the fundamental process of service. The resources can be both tangible and intangible and are provided by both the service recipient and the service provider. This definition of service is not yet broadly adopted within the community of resource-management theorists, many of whom view service as a by-product of a product supply chain or a variation on the structure of a product supply chain. The reader is referred to Fitzsimmons (1985), Bettencourt et al. (2002), Lance et al. (2002), Sampson (2007) and Vargo and Akaka (2009) for clear and thorough explanations of the true definition of service as the co-creation of service outputs through the joint effort by the provider and recipient of the service. Tang & Zhou (2009) make an intuitive contrast between product supply chain models and service supply-chain models by introducing the word, *taktchronicity*, to represent the essential aspect of coordinated resource integration in service.

Modeling the integration of resources by service processes dates to the introduction of Data Envelopment Analysis (DEA). See Charnes et al. (1994), Fare and Grosskopf (2000) and Golany et. al.(2006). DEA produces rather crude and macroscopic descriptive models of service processes with the aim to compare multi-factor efficiencies of different service enterprises. However, the interest of service engineering, management and control requires more detailed models of service processes with the capability to predict the effects of manipulating combinations of resource inputs. An adaptation of DEA to a resource allocation decision model is provided by Korhonen and Syrjanen (2004). Like all DEA models, this model assumes a linear transformation of inputs to outputs or operand resources and is applicable to the re-distribution of such resources for higher efficiency. Gaimon (1997) provides a model for determining the aggregate workforce levels for IT and knowledge workers and broaches the issue of operant qualities of the workers, but allocates resources on the basis of the operand capacities of the workers. White and Badinelli (2009) optimize the allocation of operand workforce resources in which the relative contributions of service providers and service recipients affects the quality and efficiency of the service process.

Operant resources and the myriad ways of putting them to use has demonstrated that service tends to manifest hypervariety and complexity, leading many researchers to a systems view of service (Barile 2009; Barile and Polese 2009; Golinelli 2010; Ng et.al., 2011a). In the current paper we revert to a foundational view of the service system by focusing on a single service engagement. The larger service-system is a network of agents and interactions that integrate resources for value co-creation as suggested by Maglio et al (2009).

The current paper uses knowledge-based services as unit of study. However, this paper is not about information technology, but rather about the decision models of agents who must select and integrate knowledge resources for effective service. The reader is referred to Hsu (2009) and Qiu (2009) for up-to-date perspectives on the development of information-technology models for service support.

Of particular importance is the integration of knowledge resources in service engagements. Examples of knowledge-intensive business service (KIBS) include education, all domains of consulting, health care, government service, legal service, design service (e.g., architecture, engineering, advertising) and technology support. Revolutionizing these forms of KIBS is the use of knowledge-based intelligent service (KBIS), typically in the form of on-line knowledge resources. We note that the explosion in the use of KBIS for the provision of KIBS in the last decade has produced mixed results. Although on-line intelligent service in its many forms has produced huge benefits for the on-line community (more than one billion people by 2010), the use of this form of service has also engendered the widespread practice of routine and automated service rejection. For every successful use of on-line KBIS, a service recipient typically rejects scores of other offerings. Clearly, there is much room for improvement in the identification, access and integration of knowledge resources.

We note that the resources that are integrated are not necessarily owned by the service recipient or the service provider, but that these agents must have access rights to the resources. The separation of resource ownership from resource use is one of the many departures of the structure of service supply chains from product supply chains. In this paper we present a model of a service engagement for which the service manager has access to multiple sources of each of several categories of knowledge that are relevant to the service engagement. Selecting the most effective of these knowledge resources within a budget of time and perhaps, money is the challenging decision that the manager must make. Clearly, knowledge resources are complex objects that cannot be modeled as simply as material resources. Unlike the use of material resources in manufacturing processes, knowledge resources and the effectiveness of their use in a service engagement are not fully understood by any party to the service. A natural response by the modeler is to assume uncertainty in the parameters of a service process and to build a stochastic model of the service process. See Badinelli (2010).

However, a more realistic examination of the lack of understanding of participants in a service engagement reveals a more profound and intractable ignorance – vagueness about the definition of knowledge resources and ambiguity about the cause-effect relationships among knowledge resources and the value-adding capabilities that they produce in the service recipient. Fuzzy logic and fuzzy model constructs have been developed for providing model support to decisions that must be made in the face of such ignorance. See Tsoulakis and Uhrig, (1997), Ross etal (2002), Liu & Lin (2006)..

2. Framework

We place the service engagement in a generic framework for service which consists of a network of agents, resources, processes and decisions. The agents are the persons or systems that have access to resources and the ability to enter into a service engagement with those resources. Agents are independent, intelligent and willful, so that their participation in service engagements is the result of decisions that they make based on their pursuit of value and their understanding of the potential costs and benefits of the opportunities for service engagements of which they are aware.

Resources are objects that can possess both operand and operant properties. We depart from the restrictive view, conventional to SDL, of resources being either of the operand or operant type, in favor of a more realistic representation of a resource as an object with any number of properties, some of which may be operand in nature and some of which may be operant in nature. For example, a the information on a web page may be considered an operant resource, but the time and cost expended by an agent requires to download and present the web page book are operand resources. As all forms of this resource are bundled together, we can reconcile the co-involvement of these forms in a service engagement by considering the resource as a single object with multiple properties.

The service engagement then is a process that transforms a set of input resources into a set of output resources. After each engagement, each of the participants must decide on the nature and commitment of the next engagement. Through a sequence of resource-integrating engagements and engagement-commitment decisions an agent follows a trajectory through a service-system network. This trajectory reflects the adaptation of agents as they learn from the experience of their previous engagements. However, agent learning is generally incomplete, and the decision to commit resources to any potential engagement must be made with an understanding of a process that integrates vaguely defined resources in an ambiguously described transformation.

The adaptive decisions of many agents in the face of complex and poorly understood transformation processes creates a large, evolving system of interacting agents and resources which manifests several interesting behaviors that have engendered views of service-system networks. Due to the evolution of a service system through the interaction of numerous independent agents we can view these systems as ecosystems and terms such as service ecosystems, analytics ecosystems, data ecosystems, etc. have become popular among service researchers. (Lusch et al, 2010). Restricting the definition of agents to human beings leads to social network models for service ecosystems. The ability of some, but not all, service systems to adapt to changing conditions and continue to create value leads to the notion of viable systems. Under this view, a firm is not a set of assets or a system of entities, but rather an autopoetic network of processes. A view of agent decision making that is enabled by explicit learning processes that update the agent's estimates of uncertainty is the basis of models of Bayesian networks for service systems. The current paper does not attempt to clarify the descriptive or normative view of an entire service system. Instead, this paper probes the workings of the most basic unit of analysis of the service system – the service engagement. Our approach is reductionist. Through an understanding of the decisions by agents to commit to service engagements we hope to one day derive a satisfactorily accurate representation of an entire service system.

3. Model

What follows is an expose of the application of fuzzy-modeling principles to the description of a KIBS or KBIS service engagement. We model the service engagement as a process that transforms a set of input resources into a set of output resources for the purpose of co-creating value for the service recipient. The service integrator is the agent that plays the role of identifying and selecting the resources that are combined in the engagement. In making the selection decision the agent must construct a model of the transformation relation between resource inputs and resource outputs of the engagement. In previous work (Badinelli, 2010), we defined this relationship in terms of a technology function, a generalization of the term, production function. Generalizing further in the current paper, we represent the vagueness in the definitions of resources in terms of fuzzy numbers and the ambiguity in the technology function in terms of fuzzy relations.

Some mathematical definitions are in order. A crisp number is a conventional measurement that expresses the magnitude of a variable in terms of a single number. A crisp set is a collection of objects that can be accurately identified in terms of a precisely defined property that all of the objects have in common. An overly elaborate way to define a crisp set is with a membership function that assigns a value of 1 to every object in the universe of discourse that is in the set and a value of 0 to every object that is not in the set. A fuzzy set is a collection of objects that is defined in terms of an imprecise definition of a property. In the case of a fuzzy set, each object in the universe of discourse is assigned a membership value in the range, $[0,1]$, which indicates the degree of membership of the object in the set. Note that a membership function is not a probability distribution.

A membership function measures possibility, a measure of vagueness in the meaning or the specification of a parameter, instead of probability, a measure of ignorance in the value of a precisely specified parameter. For example, the set of somewhat tall people or the set of well-prepared students cannot be identified accurately due to the vagueness of the properties, “somewhat tall” and “well-prepared”. Data cleansing, unstructured data interpretation, context-based word interpretation, the specification of domain ontologies are all helpful assists to the agent that must interpret and define knowledge resources. However, even after the application of these technologies, KIBS and KBIS are ripe with vague interpretations of resource usages and the effects of these usages on the outputs of a service engagement. Fuzzy representations of resources become a necessity to the modeler of a service engagement.

We will derive a generic representation of a fuzzy algorithm for the control of a service engagement that requires several types of knowledge-resource inputs for the creation of several beneficial capabilities in the service recipient. A concept map can be used by a service integrator to identify the types of knowledge that the service engagement requires or can use as inputs and how they are connected to the output capabilities.

To begin, we define the knowledge artifacts of the input resources in terms of crisp numbers. A knowledge artifact is a precisely defined object such as a web page, a data table, a lesson plan, a blueprint, etc. The extent to which the service recipient studies a knowledge artifact is likewise a precisely defined measure such as the number of hours spent studying a web page, the performance on a lesson test, etc. The use of knowledge artifacts can be represented by either 0-1 integer variables or a continuous scale to represent the extent of effort in learning from the artifact – the use of the artifact. However, the actual knowledge that is acquired by the service recipient through engagement with a knowledge artifact cannot be not precisely known defined. Input resources can come from client or other integrated resource providers. In general, we assume that, for each ***type*** of knowledge, there can be multiple ***sources*** of artifacts. The resource integrator must decide which sources will be used in the engagement.

$a \in A =$ set of all agents

$i \in I =$ set of all knowledge artifact types

$k_{ia} =$ use (application) of knowledge artifact i provided by agent a

$K_i =$ domain of k_{ia} for every $a \in A$

$j \in J =$ the set of all capability types

$c_j =$ extent of capability type j that is co-created for the client by the service

A fuzzy statement is the assignment of a fuzzy property to an element of a domain of crisp objects. We say, "*a* is k " to mean that "element *a* is in the fuzzy set that is identified by the vague property, k ". This statement means that there is a membership function for a, $\mu_k(\text{a})$.

The possibility of the fuzzy statement is equal to the membership-function value of the crisp object in the statement.

Each type and source of knowledge has a membership function. Membership functions indicate the possible knowledge that is acquired from the use of the knowledge artifact – value in use. We assume monotonicity of value as a function of use, that is, more use leads to more knowledge. Membership functions are normalized to a range of $[0,1]$. Knowledge can be represented as a fuzzy number to indicate the degree of knowledge

$\mu_{iad}(k_{ia}) =$ membership function for degree or depth d of knowledge type i provided by agent a

$\mu_{jd}(c_i) =$ membership function for degree or depth d of capability type j

$(k_{ia}, \mu_{iad}(k_{ia}))$ or $\mu_{iad}(k_{ia}) / k_{ia}$ = notation for a singleton = a single object, k_{ia}, and its associated membership in the set defined by knowledge type i at degree d. Note that the line in this notation does not indicate division.

$\{(k_{ia}, \mu_{iad}(k_{ia}) \mid k_{ia} \in K_i\}$ = fuzzy set that represents knowledge type j at degree d

$\sum_{k_{iai} \in K_i} \mu_{iad}(k_{ia}) / k_{ia} =$ alternate notation for the fuzzy set, which indicates the entire membership distribution as the union of all singletons over the domain, K_i

$\int_{K_i} \mu_{iad}(k_{ia}) / k_{ia} =$ alternate notation for the membership distribution in the case of K_i continuous

A kernel is a basic form for a membership function that can be translated and scaled to represent the membership function of any given fuzzy set. For example, the triangular membership function over a standard interval of crisp values shown in Figure 1, can be translated and stretched or shrunk through simple mathematical scaling operations. Most fuzzy models adopt a kernel as a generic form for membership functions and then use scaling operators to construct membership functions for all fuzzy values. Furthermore, a set of membership functions for primary fuzzy properties such as $k =$ Small, Medium, Large can be used to construct a broader range of properties. Table 1 shows some common forms of scaling operators.

Figure 1a: Kernel for membership functions

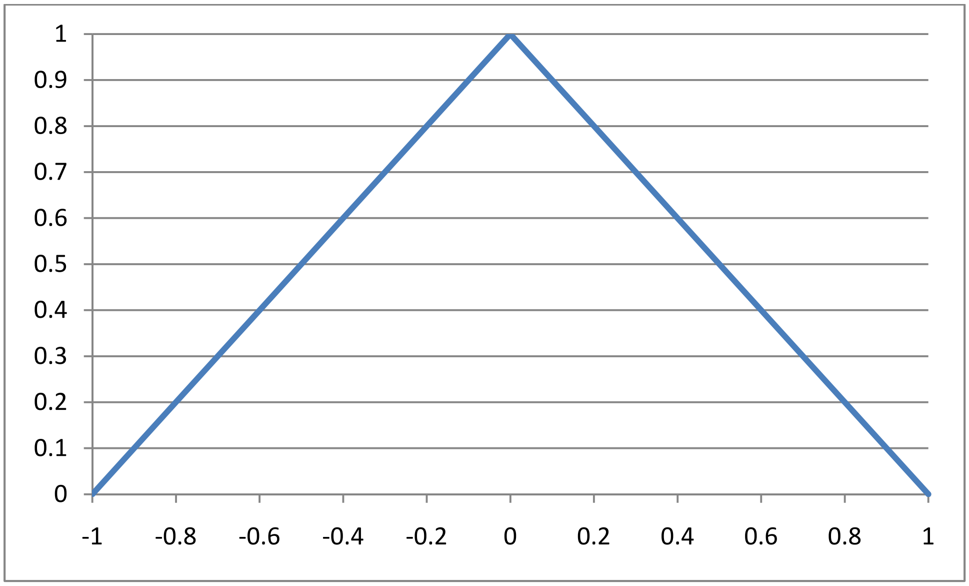

Figure 1b: Scaled Membership Functions

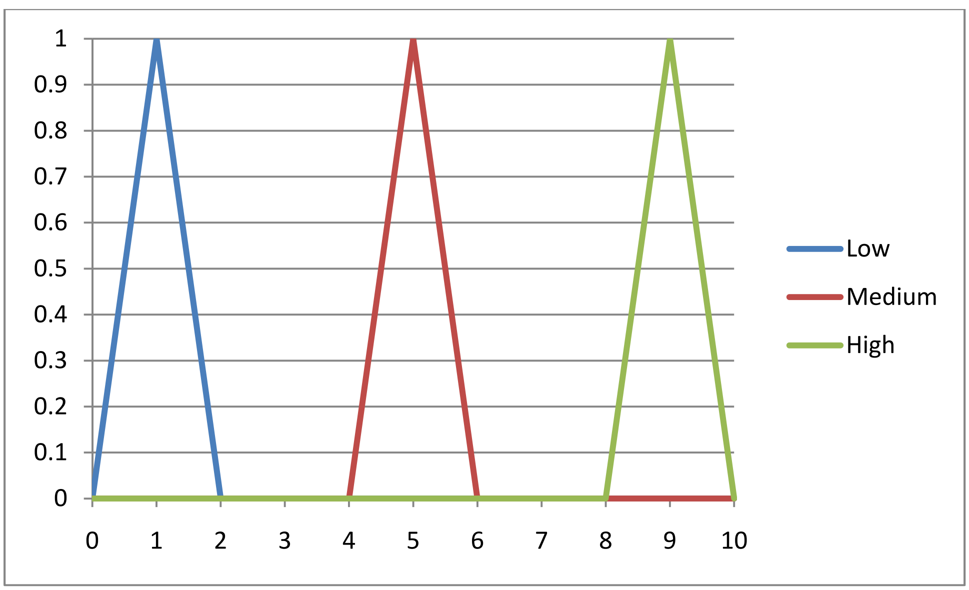

Table 1: Scaling operators

Fuzzy property	Operation	Formula
Very k	Concentration	$\mu_{VeryX} = (\mu_x)^2$
Somewhat	Plus	$\mu_{PlusX} = (\mu_x))^{1.25}$
More or Less k	Dilation	$\mu_{VeryX} = \sqrt{\mu_x}$
Approximately	Minus	$\mu_{PlusX} = (\mu_X)^{0.75}$
Indeed k	Contrast intensification	$\mu_{IndeedX} = \begin{cases} 2(\mu_X)^2, 0 \le \mu_X < 0.5 \\ 1 - 2(1-\mu_X)^2, 0.5 \le \mu_X \le 1.0 \end{cases}$
Not k	Negation	$\mu_{NotX} = 1 - \mu_X$
More than k	Over	$\mu_{MoreThanX} = \begin{cases} 1-\mu_X(x), x \ge max\{x\} \\ 0, x < max\{x\} \end{cases}$
Less than k	Under	$\mu_{MoreThanX} = \begin{cases} 1-\mu_X(x), x \le min\{x\} \\ 0, x > min\{x\} \end{cases}$

$\mu_o =$ a kernel for membership functions

$f_{kd}^S =$ a scaling function that transforms the kernel into a membership function for degree d of capability type j

$f_{iad}^S =$ a scaling function that transforms the kernel into a membership function for degree d of knowledge type i provided by agent a

$$\mu_{jd}(c_j) = f_{jd}^S[\mu_0(c_j)], j \in J, d \in D$$

$$\mu_{iad}(k_{ia}) = f_{iad}^S[\mu_0(k_{ia})], i \in I, a \in A, d \in D$$

A concept in a knowledge-based service engagement can combine more than one input knowledge resource in the creation of an output resource. If the input resources are fuzzy sets, then the combination of any two such resources requires a specification of a binary operation on the two membership functions that are involved. In fuzzy modeling there are many ways to map two membership functions into a third membership function that represents a logical connection of the first two. All such mappings are called norms. A norm operates on the space of the membership-function range.

Norm: $[0,1] \times [0,1] \rightarrow [0,1]$

The form of the membership function is irrelevant to the norm. The “AND” connection is represented by a T norm. The “OR” connection is represented by a T co-norm, also known as an S norm. Table 2 shows some commonly-used norms.

Table 2a: Norms for "AND" logical connections

T Norm	Formula
Min	$\mu_A T \mu_B \equiv \mu_A \wedge \mu_B = min\{\mu_A, \mu_B\}$
Algebraic Product	$\mu_A T \mu_B \equiv \mu_A \cdot \mu_B = \mu_A \mu_B$
Bounded Product	$\mu_A T \mu_B \equiv \mu_A \otimes \mu_B = max\{0, \mu_A + \mu_B - 1\}$
Drastic Product	$\mu_A T \mu_B \equiv \mu_A \dot{\wedge} \mu_B = \begin{cases} \mu_A, \mu_B = 1 \\ \mu_B, \mu_A = 1 \\ 0, \text{otherwise} \end{cases}$

Table 2b: Norms for "OR" logical connections

S Norm	Formula
Max	$\mu_A S \mu_B \equiv \mu_A \vee \mu_B = max\{\mu_A, \mu_B\}$
Algebraic Sum	$\mu_A S \mu_B \equiv \mu_A + \mu_B$
Bounded Sum	$\mu_A S \mu_B \equiv \mu_A \oplus \mu_B = min\{1, \mu_A + \mu_B\}$
Drastic Sum	$\mu_A S \mu_B \equiv \mu_A \dot{\vee} \mu_B = \begin{cases} \mu_A, \mu_B = 0 \\ \mu_B, \mu_A = 0 \\ 1, \text{otherwise} \end{cases}$

The cause-effect relation between the inputs of a service engagement and the outputs is represented by an implication, which is also a binary operation involving two membership functions, one for the antecedent (LHS) of the implication and one for the consequence (RHS). Hence, any relation can be represented by an implication. The binary operation that represents a logical implication in fuzzy logic can be expressed in many forms. Table 3 shows some of the more commonly-used forms.

Table 3: Implication operators for implication: "*If k is A, then c is B*"

Type	Formula
Zadeh Max-Min	$(\mu_A \wedge \mu_B) \vee (1 - \mu_A)$
Mamdani min	$\mu_A \wedge \mu_B$
Larsen Product	$\mu_A \mu_B$
Boolean	$(1 - \mu_A) \vee \mu_B$
Godelian	$\begin{cases} 1, \mu_A \le \mu_B \\ \mu_B, \mu_A > \mu_B \end{cases}$

$R_j =$ the set of implications or rules that make up the fuzzy algorithm for capability type j

$f_{rj}^{N2} =$ the operator for composing the consequent terms of implication rule $r \in R_j$ of the fuzzy model for capability type j

$f_r^{N1}=$ the operator for composing the antecendent terms of implication rule $r \in R_j$ of the fuzzy model

$\mu_{2r}(c_j)=$ membership function of the consequence of implication rule $r \in R_j$ of the fuzzy model

$\mu_{1r}(\{k_{ia}\})=$ membership function of the antecendent of implication rule $r \in R_j$ of the fuzzy model

$$\mu_{2r}(c_j)=f_r^{N2}\left[\{\mu_{jd}(c_j)\}_{d\in D}\right], r \in R_j$$

$$\mu_{1r}\left(\{k_{ia}\}_{i\in I, a\in A}\right)=f_r^{N1}\left[\{\mu_{iad}(k_{ia})\}_{i\in I, a\in A, d\in D}\right], r \in R_j$$

for all $j \in J$

$$\mu_r\left(\{k_{ia}\}, c_j\right)=f_r^m\left[\mu_{1r}(\{k_{ia}\}), \mu_{2r}(c_j)\right], r \in R_j, j \in J$$

A collection (union or intersection) of fuzzy implications is called a fuzzy algorithm. The union or intersection is represented by the word "ELSE" in the collection of implications. As each implication in an algorithm is represented by a membership function and the union or intersection connects two membership functions, the connection can be represented by a norm. The choice of union or intersection norm must be compatible with the choice of operator for the implication relations.

$$\mu_j(c_j)=f_j^G\left[\left\{\mu_r\left(\{k_{ia}\}_{i\in I, a\in A}, c_j\right)\right\}_{r\in R_j}\right], j \in J$$

Inferencing, drawing a conclusion from an algorithm from the input of crisp objects to the inferences, is made through the composition operation on the implications. For each inference in the makeup of an algorithm. The degree of fulfillment rules (DOF) shows the value of the membership function of the LHS of an implication by the input crisp object. We can represent these combinations of knowledge inputs to a concept process as DOF of an implication

In order to obtain a useful result from the application of a fuzzy algorithm as a model of a service engagement, the membership function of the output resource must be summarized in a way that indicates the most appropriate possible crisp output resource to represent the yield of the service engagement. The process of reducing a membership function to a crisp measure is called de-fuzzification.

$f_j^F=$ operator that performs de-fuzzification of the membership function of capability type $j \in J$

Then the final output of the fuzzy model is the set of crisp capabilities acquired by the service recipient,

$$\hat{c}_j=f_j^F\left[\int \mu_j(c_j)\big/ c_j\right], j \in J$$

The development above represents a general formulation of a KIBS or KBIS engagement that can be adapted to any context of the use of knowledge resources. The combination of all of the model elements provides a description of the cause-effect relationship from the use of specific knowledge artifacts to the de-fuzzified outcomes of value-generating capabilities. The main contribution of this paper is the setting of these foundational constructs for this kind of formulation for the purpose of supporting resource-integration planning.

4. Optimization

With a fuzzy algorithm defined for a particular service engagement we can consider the task of determining the optimal combination of resource inputs that will produce the best combination of resource outputs subject to a constraint on the time or financial budget for the using the resource inputs. We can formulate the optimization as follows,

Problem *P*:

$$\max_{k} v\left(\{\hat{c}_j\}_{j \in J}\right)$$

Subject to:

$$\sum_{iad} b_{iad} k_{iad} \le B$$

where,

$v =$ the service recipient's value function over the capabilities that are produced by the service engagement

$b_{iad} =$ the unit cost of input resource k_{iad} in terms of time or money

$B =$ the budget for the cost of input resources

Assuming monotonicity and additivity of the value function, problem *P* is a knapsack problem. For small numbers of options for input resources, dynamic programming can be used to obtain a solution. Even in cases of high dimensionality a service provider can develop partial dynamic programming solutions that specify the optimal combination of non-client resources for every state of remaining budget and then perform the final stage of the dynamic program when the client's resource options are known. In this way a solution can be generated immediately upon interaction with the service recipient and the resource integration can be optimized for the context of the engagement.

5. Conclusions

This paper has proposed three structural features of models of service. First, we view a service as a system that consists of a network of agents, resources and engagements. Second, agent decisions determine the trajectory of a service within the service system network. Third, the models of service engagements through which agents make resource-commitment decisions are necessarily fuzzy algorithms due to the vagueness and ambiguity of real KIBS and KBIS.

Through a generic formulation of a fuzzy algorithm we demonstrated that such models are robust in their ability to represent service engagements. Game theoretic models that require equilibrium conditions and stochastic models that require a crisp representation of all knowledge resources are not realistic enough to be of much use to a resource integrator. Fuzzy models not only embrace vagueness and ambiguity, but they do so with many options for implication functions and norms so that wide variety of context can be accommodated. The next stage of this research will be empirical applications and tests of fuzzy models for KIBS and KBIS.

References

Badinelli, R. (2010). "A Stochastic Model of Resource Allocation for Service Systems". *Service Science,* **2**(1/2) 68-83.

Barile, S. (2009). *Management Sistemico Vitale*. Torino, G. Giappichelli.

Barile, S., Polese, F. (2009), "Service Dominant Logic and Service Science: a contribute deriving from network teorie.", in E., Gummesson, C., Mele, F., Polese (eds), *The 2009 Naples Forum on Service: Service Science, S-D logic and network theory*, Napoli: Giannini.

Bettencourt, L. A., A. L. Ostrom, et al. (2002). "Client Co-Production in Knowledge-Intensive Business Services." *California Management Review* 44(4): 100-128.

Charnes, A., Cooper, W., Lewin, A., Seiford, L. (1994). Data envelopment analysis – theory, methodology and applications, Kluwer.

Fare, R., Grosskopf, S. (2000). "Network DEA", Socio-economic planning sciences 34, 35-49.

Fitzsimmons, J. A. (1985). "Consumer Participation and Productivity in Service Operations." *Interfaces* 15(3): 60.

Gaimon, C. (1997). "Planning Information Technology-Knowledge Worker Systems." *Management Science* 43(9).

Golany, B., Hackman, S., Passy, U. (2006). "An efficiency measurement framework for multistage production systems", *Annals of Operations Research*, 145, 51-68.

Golinelli, G. M. (2010). *Viable Systems Approach (VSA) Governing Business Dynamics*. Milan, Wolters Kluwer Italia Srl.

Hsu, C. (2009). *Service Science, design for scaling and transformation*. Singapore, World Scientific.

Korhonen, P., Syrjanen, M. (2004). "Resource allocation based on efficiency analysis", *Management Science* 50(8), 1134-1144.

Lance, A. B., L. O. Amy, et al. (2002). "Client co-production in knowledge-intensive business services." *California Management Review* 44(4): 100.

Liu, S. and Y. Lin (2006). Grey information: theory and practical applications. London, Springer.

Lusch, R F., S. Vargo, M. Tanniru (2010). "Service, value networks and learning", Journal of the Academy of Marketing Science, 38, 19 – 31.

Maglio, P. P., S. L. Vargo, N. Caswell, J. Spohrer (2009). "The service system is the basic abstraction of service science." *Information Systems E-Business Management*: 1-12.

Ross, T.J., J.M. Booker, W. J. Parkinson (2002). Fuzzy logic and probability applications, ASA SIAM.

Sampson, S. E. (2007). *A Customer-Supplier Paradigm for Service Science*. 2007 DSI Services Science Miniconference, Pittsburgh.

Tang, V., Zhou, R. (2009). "First-Principles for services and product-service-systems: an R&D agenda", International Conference on Engineering Design, ICED'09, 24 - 27 August 2009, Stanford University, Stanford, CA, USA.

Tsoulakis, L. H., R. E. Uhrig (1997). Fuzzy and neural approaches in engineering, Wiley.

White, S., Badinelli, R. (2009). Aggregate planning in complex, high-contact services, Working Paper, Virginia Tech, Blacksburg, VA, USA, June.

Qiu, R. G. (2009). "Computational thinking of service systems: dynamics and adaptiveness modeling." *Service Science* **1**(1): 42-55.

Vargo, S. L. and M. A. Akaka (2009). "Service-Dominant Logic as a foundation for service science: Clarifications." *Service Science* **1**(1): 32-41.