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Service Cost Estimation with Uncertainty Using Agent Based Simulation

John Ahmet Erkoyuncu*, Rajkumar Roy, Essam Shehab, Kalyan Cheruvu
Manufacturing Department, Cranfield University, Cranfield, Bedford MK43 0AL
{j.a.erkoyuncu, r.roy, e.shehab, k.cheruvu}@cranfield.ac.uk
+441234750111 Ext 5656

*Corresponding Author

This paper aims to contribute to the decision making in integrating uncertainty to service cost estimation by providing a novel approach through agent based modelling (ABM) for the early stage of bidding for Contracting for Availability. The paper presents the ABM architecture describing the agents that represent the customer and industry, which captures responsibilities in areas including failure, repair, supply and availability management. Furthermore, internal and external rules are defined to capture the interaction between the cost drivers. The major outcome relates to the robust and accurate "what-if" scenarios of the dynamic interplay among the many cost uncertain elements. The approach is a unique addition to the cost estimation literature by enabling to capture patterns and effects which have cost impacts during the service delivery. The developed approach has been validated through expert judgment. Also, a pilot case study is presented that reflects the increased understanding and precision in decision making regarding costs within a major company in the defence and aerospace industries.

1. Introduction

The business model in the manufacturing industry is experiencing a shift from selling products to delivering services (Takata et al., 2004). In the United Kingdom, this has typically been achieved by Contracting for Availability (CfA), which is a commercial process which seeks to sustain an equipment/system/part at an agreed level of readiness, over a period of time (e.g. equipment operational life, 30 to 40 years), by building a partnering arrangement. Within the manufacturing industry, defence and aerospace industry is taking a lead in CfA theme. The likes of Type 45 and Harrier provided by BAE Systems and Power by the Hour, or Total Care provided by Rolls Royce have commonly been cited as examples. In the example of Harrier, the contract requires the solution provider to ensure increased availability of Harrier fighter aircraft to support frontline forces. This has forced the company to grow its readiness and sustainment capabilities and support its customers through partnering arrangements. Such contracting approaches have been studied in the Industrial Product-Service System (IPS^2) domain, which combine products and services within the high net value and physical product core context (Roy and Cheruvu, 2009). Within these agreements the Original Equipment Manufacturer (OEM) or 'Solution Provider' typically receives income and incentives during project life as agreed at contracting stage by adhering to the agreed level of equipment availability and performance. Furthermore, it bears the risk of inaccurately predicting the service requirements and cost implications at the bidding stage.

Cost modelling is an essential part of the bidding process and uncertainties are a major source of challenges. Uncertainty, which refers to doubt, or hesitancy, is the situation where outcomes (e.g. cost) have several possibilities. It arises from lack of information and/or knowledge. On the other hand, risk is considered to be a sub-category of uncertainty, where the threat of outcomes can be probabilistically assumed (Erkoyuncu et al., 2010a); typically it is associated with loss or negative consequences. The dynamism refers to the continuous change in factors influencing the cost of CfA, while the financial burden requires adequate consideration of cost uncertainties in the estimation (Erkoyuncu et al., 2009).

Whilst there are many types of services that are offered including health check, obsolescence management, defect response, performance assessment, provision of spares and repairs is the most widely offered service within the defence and aerospace industry, which sets the context to this study. Also uncertainty is considered in association with service requirements early on during the bidding stage where limited information and knowledge exists. Some of the areas that influence the service cost estimation includes equipment usage rate, failure rates, repair turn around time, beyond economical repair, no fault found, obsolescence rate and labour efficiency as well as financial measures such as exchange and inflation/deflation rate. Considering that industry traditionally was not responsible for most of these engineering tasks, capturing the dynamism of these uncertainties has created challenges. The adoption of CfA, due to heavy financial responsibilities on the OEMs and growing complexities of the contract, has increased the importance of visualising maintenance costs under various scenarios in deciding the incentivisation scheme to follow. Given that CfAs are typically agreed based on incentive mechanisms, it is necessary to realise their cost implications early on at the bidding stage itself. Thus, there is a need for improved estimating techniques that can take account of the increased range and scale of uncertainties typical in CfA.

This paper contributes by modelling the dynamism in maintenance costs in a novel manner early on in the bidding stage of CfA, while focusing on a Target Price Performance Incentive (TPPI) mechanism. This incentive approach considers a fixed-price incentive contract which typically specify a target cost, profit, a price ceiling (but not a profit ceiling or floor), and a profit adjustment formula. In order to negotiate these elements it is necessary to be able to visualize cost estimates at the outset. For this purpose an agent based model (ABM) is used to reflect a typical service supply chain involving the customer, solution provider, spares supplier and resource supplier. Furthermore, within each agent a feedback scheme is considered using systems dynamic (SD) to trigger interaction with other agents. The granularity of the model is at a system or subsystem level. Rules and defined relationships between the agents enable to estimate costs for various scenarios based on risk sharing approaches between the solution provider and the spares supplier. The remainder of the paper has been organised as follows. Section (2) explains the adopted methodology. Related research in cost uncertainty modelling for CfA is described in Section (3). The validation through expert judgment and a case study is presented in Section (4). Sections (5) and (6) present discussion and conclusions.

2. Methodology

This paper advances the cost estimation literature by integrating a systematic approach across uncertainty identification, assessment, range definition and simulation for maintenance cost estimation specifically for the early stages of bidding. Using agent based modelling for this purpose sets a novel approach due to its limited use in the cost estimation literature. The methodology for this study consists of four key steps, including (1) understanding context, (2) developing research protocol, (3) framework development and (4) validation. Figure 1 illustrates the activities that took place in each step.

Understanding context phase combined literature review and learning through industrial conferences that have been attended. In the literature review key areas included: uncertainty, cost estimation/modelling, spares and repairs delivery, maintenance, product-service systems, incentives, uncertainty modelling and simulation (e.g. ABM, SD and discrete event). Industrial conferences or workshops organised by the likes of Society of Cost Analysis and Forecasting (SCAF), the Association of Cost Engineers (ACostE), and European Aerospace working group on Cost Engineering (EACE) also supported. The major goal of this phase included understanding of research gaps and key challenges.

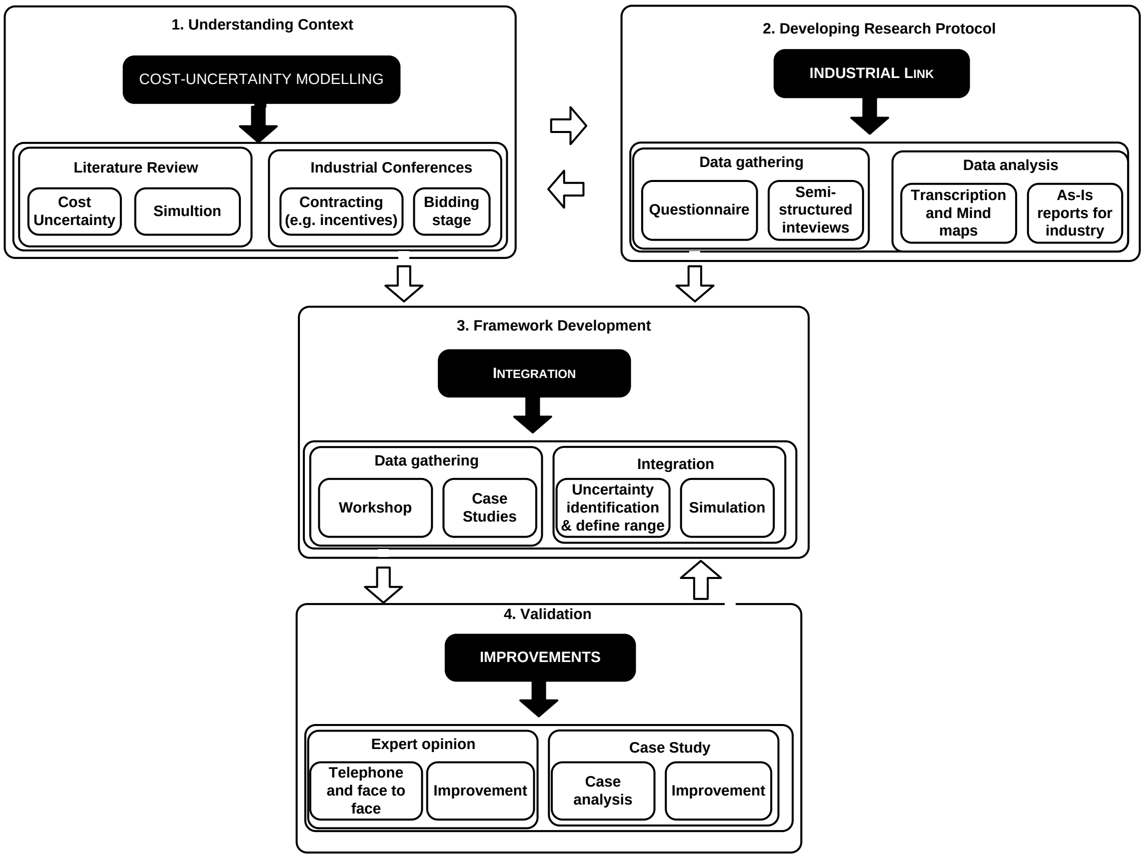

Figure 1. Research Methodology

The second phase involved the development of the research protocol through industry. The participants included three major companies and the customer in the defence and aerospace industries in the United Kingdom. Based on literature review, questionnaires were developed and piloted with one of the collaborating organisations. Subsequently the questionnaires were used in the semi-structured interviews. These totalled over 40 hours of industrial interaction with project managers, support managers, and cost engineers. The focus was on: identifying the types of uncertainties in CfA, methods to assess uncertainty and approaches to defining a range around a cost estimate early on, incentive schemes, and cost uncertainty modelling. Collected information was transcribed and analysed using MindMaps.

The third phase focused on framework development by integrating approaches in uncertainty identification, assessment, range definition and simulation. Initially, through two case studies (in the naval and air domain) and information gathered in the first phase supported to develop a comprehensive list of uncertainties and cost drivers for the bidding stage. This was followed with defining a process to assess uncertainties through the Numeral, Unit, Spread, Assessment and Pedigree approach (NUSAP Pedigree Matrix), which classifies uncertainty into three dimensions (e.g. basis of estimate, rigour in assessment, and level of validation) and a definition is provided for 4 scores for each dimension in order to achieve consistency across responses. And finally in this phase the scope of the simulation was decided and the rules and assumptions for the ABM was developed. This process involved three subject matter experts related to a case study in the naval domain. The rules and assumptions were defined to represent interaction between the considered agents, while focusing on the key sources of uncertainties and cost drivers. The model was constructed using AnyLogic, a Java based multi-paradigm software.

The final phase of the methodology involved validation. This was achieved through expert opinion and a pilot case study. The model used in the case study was validated in stages. Initially, the rules and assumptions were validated with three subject matter experts (participants of three different projects in the naval domain) whom on average had over 20 years of experience in maintenance cost estimation. Expert opinion from four participated of the research was also used to define the benefits, weaknesses and potential areas to use the model.

3. Service Cost estimation Approaches in Contracting for Availability

There is a wide selection of maintenance cost modelling approaches that are suitable for the CfA context. Approaches vary depending on two aspects: service life stage (e.g. design, delivery, and adaptation) and level of information available (e.g. low, medium, and hi) (Datta and Roy, 2010). Furthermore, within the bidding process cost estimation approaches vary driven by these two aspects as well. For instance, the context for the early stages of bidding varies from a mature phase of bidding where the available information is higher. The types of information that is essential in CfA include: user requirements, user budgets, supplier data, industry standards, historical data and expert opinion. These are used to define assumptions, risks and uncertainties, procurement, deployment and support. The context to this study is the bidding stage, where there is limited information, for the delivery stage of service in CfA. For this purpose, based on Datta and Roy (2010) the suitable approaches for cost estimation are expert opinions and various simulation approaches including systems dynamics, discrete event, and agent based modelling. Furthermore, at the early stages of bidding typically top-down approaches tend to be undertaken, which involves taking an abstract view of costs. The cost estimates have low reliability at this stage. However, as the amount of data increases, compared to the specified context, other estimating approaches such as parametric and analogy grows and a combination of top-down and bottom-up approaches can get used.

In developing any cost model, expert opinion plays a key role in integrating uncertainties to cost estimates. The integration may be achieved in a qualitative, quantitative or deterministic manner (Boussabaine and Kirkham, 2003). Examples of qualitative approaches include risk matrix, SWOT analysis, NUSAP pedigree approach, and brainstorming. Deterministic approaches include the net present value method, sensitivity analysis, and breakeven analysis. The risk and uncertainty analysis in the support stage is typically done through sensitivity analysis around the major cost drivers related to the operation and support of the system of interest (NATO, 2009). Quantitative approaches include probability distribution, simulation and artificial intelligence. Of the quantitative approaches the integration of uncertainty into maintenance cost modelling has mostly been considered through static models, which assume that the system operates in a certain fixed time instant (e.g. Monte Carlo simulation). On the other hand, stochastic models use random variables to reproduce or visualise the possible occurrence of events or disturbances that are unknown a priori. Thus, such models define a representation of stochastic phenomena, which is typically achieved through a set of probability distributions and/or a set of relevant statistical parameters to generate suitable values for the random variables over time. The supply chain literature has commonly applied stochastic techniques to represent dynamism in systems. Furthermore, three simulation approaches have typically been applied: discrete event simulation (DES), system dynamics (SD) and agent based modelling (ABM). Their applications have varied depending on the problem at hand whether it be at a strategic, operational or planning level (Chopra and Meidln, 2007). Strategic refers to issues such as deciding the structure of the supply chain over many years or modes of transport to be used. Planning, for instance involves consideration of which markets will be supplied from which locations. Finally, operational problems can be daily and the focus is on the supply chain configuration (e.g. allocation of inventory). In literature, SD and ABM have been used equally to address strategic and planning problems. On the other hand, the use of DES heavily focuses on planning problems, while it has also been used for the operational context (Owen et al., 2010). Figure 2, illustrates the areas of application of these simulation approaches. SD uses differential equations to model rates of change. Its use has typically been in causal loop diagrams where the relationship between the variables is explicitly defined. DE is a process centric simulation approach focusing on activities, such as queues and delays within a system. ABM involves bottom-up models where behaviour results from the aggregated activities of individuals. Thus, defining dependencies across agents is an important part of ABM. For strategic problems the use of ABM and SD has been a common approach due to their ability to capture different aspects of a system.

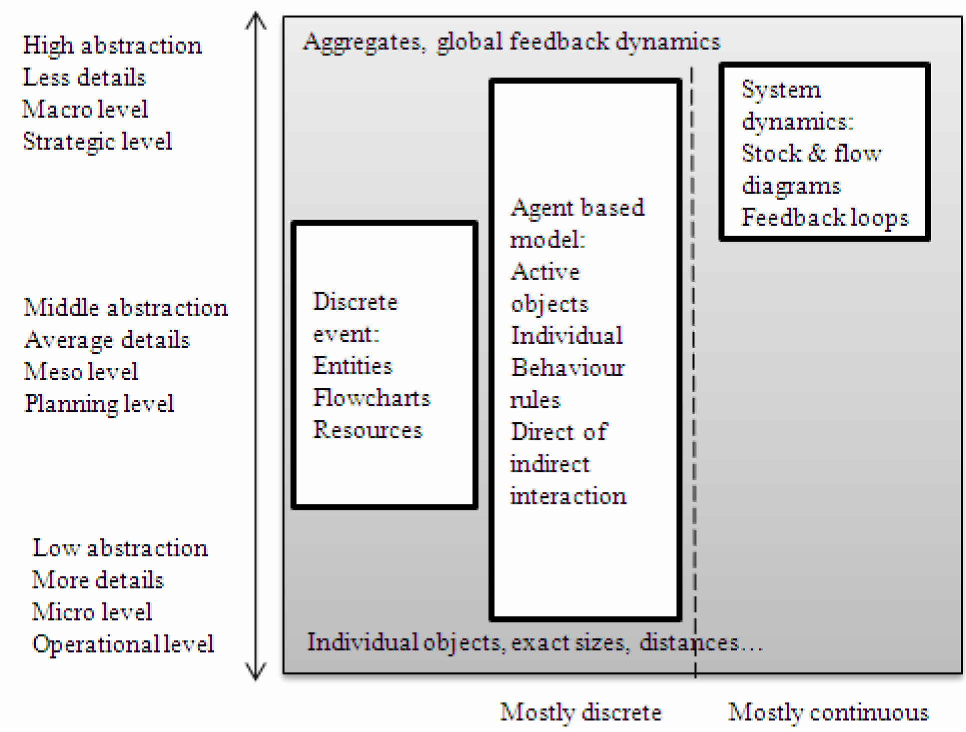

Figure 2. Simulation approaches for strategic, planning and operational problems

4. Uncertainty Based Service Cost Estimation Framework

The early stages of bidding for CfA in the defence and aerospace industry sets the context to the presented agent based model. The aim is to support understanding of the cost impact of incentive mechanisms. The model also considers different risk sharing approaches including (1) solution provider owns uncertainty, (2) spares supplier owns uncertainty, (3) solution provider and spares supplier share uncertainty. The model has the ability to replicate the evolution of maintenance costs for various time scales including the life cycle of equipment, a specific mid-term, or for the short term, however the minimum time scale of the model is a year. Furthermore, orders can be raised sequentially at different points of time. As for defining the agents the service supply chain is considered through four agents: customer, solution provider and two suppliers (spares and resource). The granularity of the model is considered to be the system or subsystem level due to the limited amount of information at the early stages of a bid.

Figure 3 illustrates the framework, which is composed of three phases including (1) assess cost uncertainty, (2) revise cost estimate, (3) agent based model. The first and second phases produce inputs for the agent based model. In the model, decision making within each agent is achieved through system dynamics simulation, whilst the ABM has been used to capture the interaction between agents.

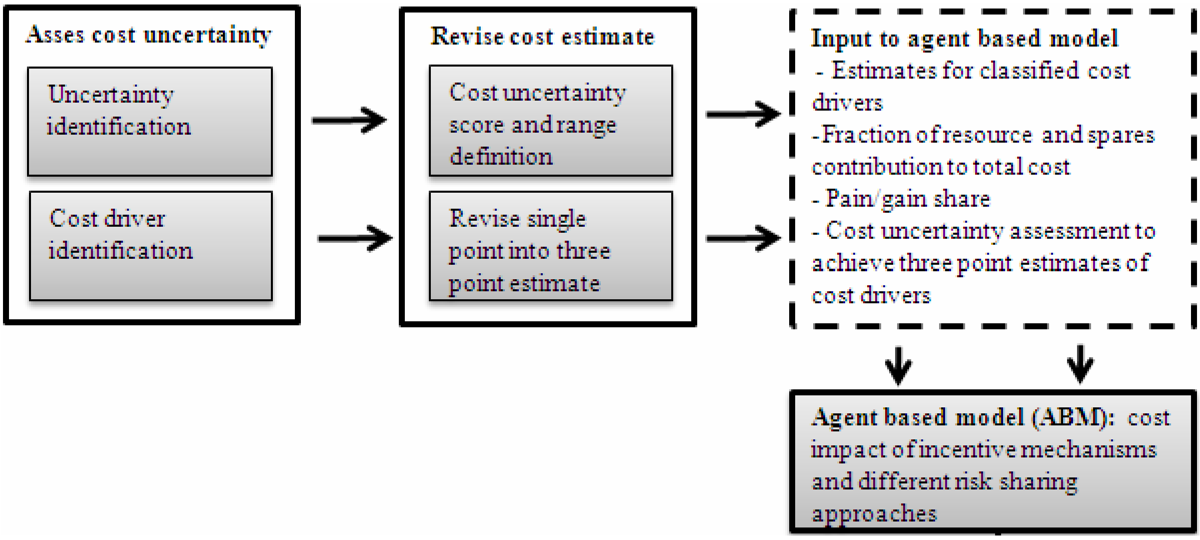

Figure 3. Uncertainty based service cost estimation framework

4.1 Assess Cost Uncertainty

In the initial phase, the uncertainties and cost drivers are identified and assessed. Figure 4 represents the activities that take place within this phase in a sequence. The uncertainty list has been developed to represent the typical service delivery in CfA (including spares, repair and training). Two case studies from the naval and air domains, along with results from the semi-structured interviews were used to develop this list. Briefly, the uncertainties have been classified in to commercial (e.g. contractual issues such as customer misuse), affordability (e.g. to customer-ability to spend), performance (e.g. of service delivery-key performance indicators), training (e.g. as a service delivered- number of students to attend), operation (e.g. activities in delivering service- complexity of equipment), and engineering (e.g. activities in planning service-obsolescence), where the full list of uncertainties can be found in Erkoyuncu et al., (2010b). Furthermore, the uncertainties are assessed using a qualitative approach, NUSAP Pedigree Matrix, to quantify the level of uncertainty using expert opinion. Three qualifiers including basis of estimate (e.g. level of data available), rigour in assessment (e.g. maturity of uncertainty assessment), and level of validation (e.g. validation of models and processes) are used where scores (e.g. 1, 3, 5, 7) for each qualifier is defined (Erkoyuncu et al., 2009b). The average of the scores of the three qualifiers represents the level of uncertainty for each uncertainty type.

Subsequently, the relevant cost drivers to the considered system are selected in order to understand how uncertainties influence cost drivers. The cost drivers considered in the ABM include failure rate, turnaround time, line replaceable unit cost, transport cost, packaging cost, repair cost, demand rate (spares), storage, emergent work, GFX supply, material availability, labour availability, customer estimate demand usage, customer actual usage, no fault found cost, beyond economical repair cost, number of students, number of trainers, facilities for training. These cost drivers were developed through a case study in the air domain and the list was validated in the naval domain with a view to establish a typical list of cost drivers in CfA. Direct relationships between uncertainties and cost drivers are considered in order to assign an uncertainty score for the cost drivers. This enables to understand the sources of uncertainties for cost drivers. For instance, the scores for uncertainties such as customer misuse, rate of labour availability, work share between partners, changing customer requirements, complexity of equipment, rate of rework and skill level of maintainers make up the uncertainty score for turnaround time. Furthermore, the averages of the relevant uncertainties make up the total uncertainty score for each cost driver. The value is divided by 7 (the highest possible score) to get a value between 0 and 1.

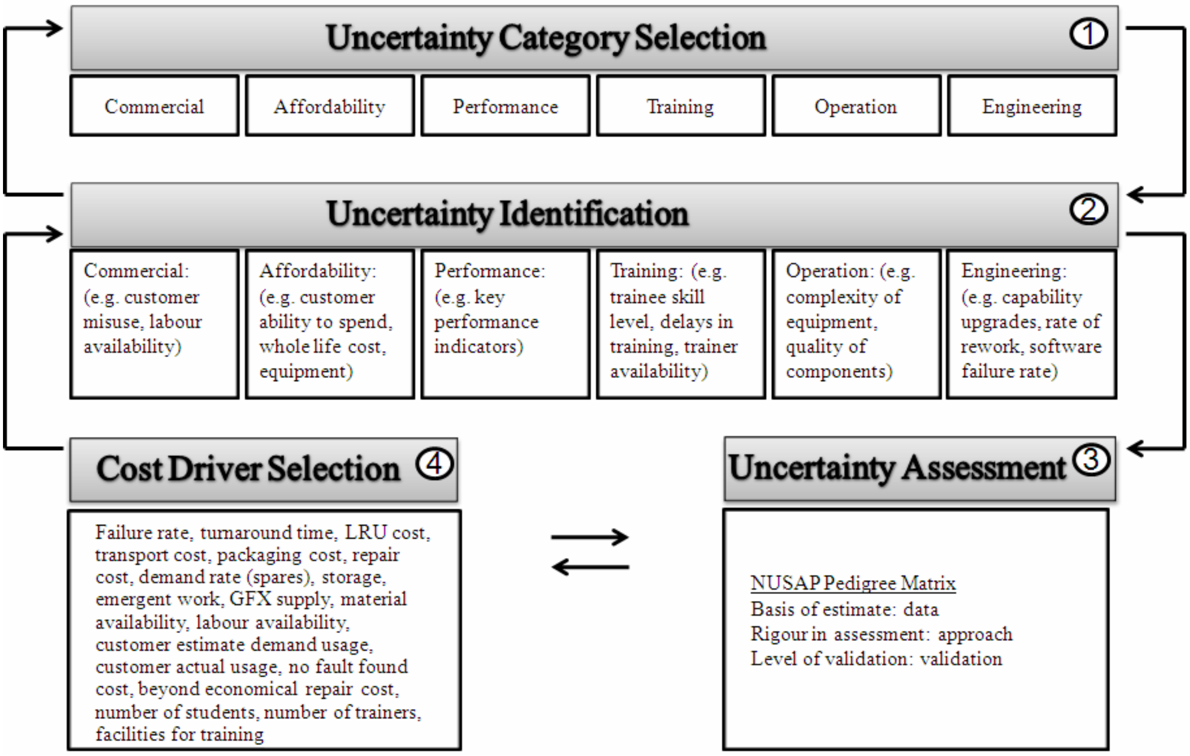

Figure 4. Uncertainty and cost driver assessment

4.2 Revise Cost Estimate

The simple but affective measure of uncertainty is the range of a cost estimate (Curran, 1989). Range estimating is an add on to the traditional cost estimate, by suggesting the potential level of variation between the estimated cost value and the actual. There are a number of ways for range estimating, including expert judgment, predetermined guidelines, simulation, analysis, parametric modelling (AACE, 2008). In this paper, the revision of an initial cost estimate is achieved through predetermined guidelines. This involves establishing a table of contingency values and ranges based on the Association of Advancement of Cost Engineers' (AACE) estimate or schedule classes with alternate values and ranges provided for five levels of project definition. For this purpose the uncertainty scores gathered in the first phase are used to allocate the cost driver in a suitable class. As represented in Table 1, a Class 5 refers to low level of project definition, where the cost estimate has stochastic features and requires expert judgment. On the other extreme, Class 1 fits into a deterministic methodology, where the range is expected to be the lowest. Based on the guideline the maximum and minimum range suggestions are also illustrated for each class in Table 1 (AACE, 2005). The main advantages of the approach are that it is simple, understandable, and consistent. A disadvantage is that the provided list of uncertainties suggest a typical list that can be expected in CfA, however uncertainties unique to a specific project will need to be added.

Table 1. Generic cost estimate classification matrix

Estimate class	Level of project definition	Methodology	Lower uncertainty value	Upper uncertainty value	Range-Minimum	Range-Maximum
Class 1	50% to 100%	Deterministic	0	0.3	-10	15
Class 2	30% to 70%	Primarily deterministic	0.3	0.5	-15	20
Class 3	10% to 40%	Mixed but primarily stochastic	0.5	0.7	-20	30
Class 4	1% to 15 %	Primarily stochastic	0.7	0.9	-30	50
Class 5	0% to 2%	Stochastic or judgment	0.9	1	-50	100

After using the uncertainty score to define the range for each cost driver through the predetermined ranges, revision of cost estimates takes place. This requires an input involving either a cost estimate for each of the cost drivers, or alternatively a total cost figure can be an input. In the latter case, through a prioritisation technique such as the Analytic Hierarchy Process (AHP) the contribution of each cost driver to the total cost can be assessed. The advantage of this approach particularly early on at the bidding stage is that the specific cost significance of each cost driver may not be known and it enables to utilise expert opinion to compare the importance of cost drivers. AHP applies a pair wise comparison of the alternatives as represented as A_1 and A_2 in Equation (1) (Saaty, 2006).

$$R(A_1 / A_2) = \prod_{j=1}^{N} (a_{1j} / a_{2j})^{w_j} \qquad (1)$$

where N is the number of criteria, a_{ij} is the actual value of the *i*th alternative in terms of the *j*th criterion and w_j is the weight of the *j*th criterion. As a result, within the framework the user is required to score the uncertainty level for a given set of cost drivers (e.g. spares, transport, repair) based on the list of uncertainties provided. Thus, by combining the cost estimate for each cost driver and the uncertainty range, the cost estimate is revised and a single point estimate is turned into a three point estimate to be used in the agent based model.

4.3 Agent based model

In literature, ABM has mostly been used to define the engagement across a supply chain, but the approach has wide application including domains such as economics and manufacturing (Nilsson and Darley, 2006). In the supply chain literature there tends to be a set of fixed relationships and the effects of different patterns of decision making on overall stock levels is explored (Allwood and Lee, 2005). The main theme has been to capture the interaction with the customer. In defining an agent four key properties have been referred to including autonomy (e.g. function without user intervention), proactive (e.g. independently working towards a goal), reactive (e.g. respond to environment) and social (e.g. interact with other agents) (Wooldridge and Jennings, 1995). The fact that agents can react to changes, adapt and re-plan if a better approach is realised, based on information sharing between agents, makes it a dynamic system, which is key to representing a continuously changing world.

In the presented agent based model, the incentive mechanism plays a critical role in determining the actual cost estimate for maintenance, which is considered to compose of resource costs, spares costs and other costs. The incentive mechanism is achieved through the arrangement of TPPI between the solution provider and the customer. This involves consideration of variable costs (e.g. spares inclusive repairs) subject to 50:50 gain and pain share while keeping aside a certain level of savings. The threshold for the gain and pain share levels is 10% and 3% profit for the solution provider. This is calculated based on the difference between actual cost and payment or price for variable costs which are adjusted annually based on changes to contract assumptions. Annul adjustment can also compare baseline cost/risk against actual cost/risk spend to calculate the pain or gain share.

Figure 5, represents the agents and the main aspects that trigger interactions between agents. Information is initially generated by the customer agent (equipment usage and price), which is shared with the solution provider. Subsequently, based on the failure rate, the solution provider sends messages to spares and resource suppliers to source the amount that is above its capacity. The information that the solution provider receives from the customer feeds into deciding the gain/pain level based on the difference between the actual cost and the price for the equipment usage level. Furthermore, many parameters and variables serve the purpose of defining characteristics for each agent and what-if scenarios can be performed by adjusting them.

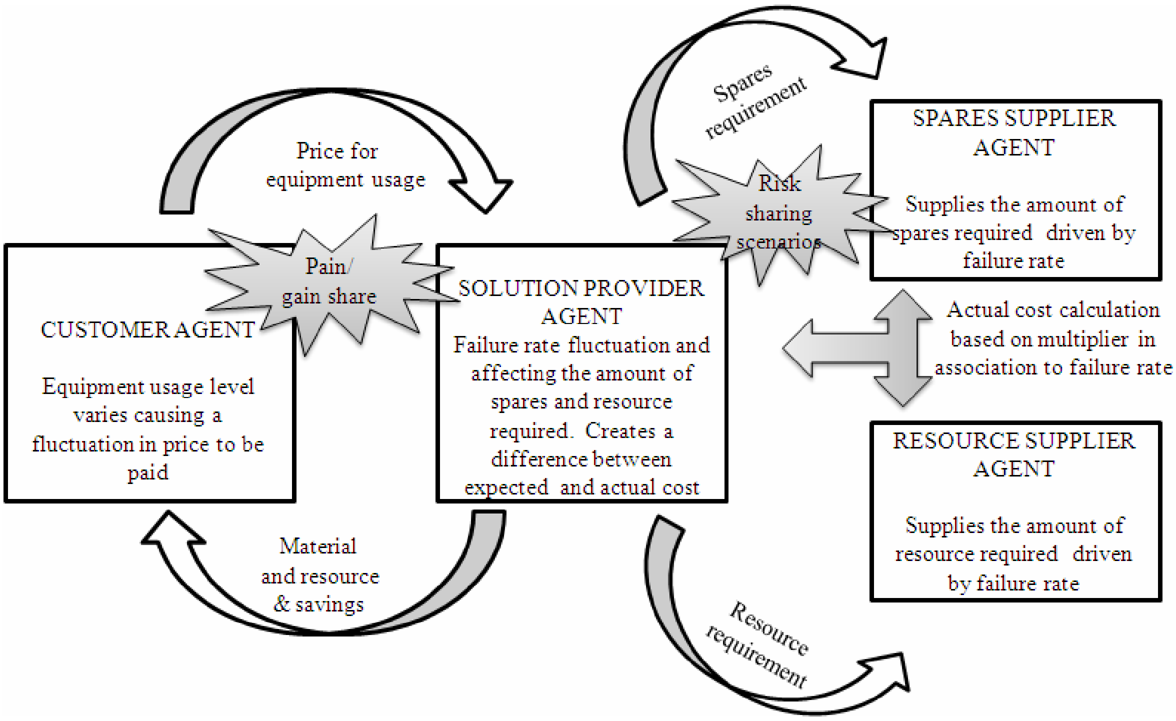

Figure 5. Relationships in the agent based model

Customer agent: The customer agent is interested in achieving the equipment usage level that it desires over the CfA. Accordingly, as an input a pre-defined level of price is used for the equipment usage level. The model assumes that the equipment usage level will comply within a given boundary. So the customer agent requires input regarding the price that it will pay for the various levels of equipment usage (e.g. for 30.000 hours of flying=£30.000, and 32.000 hours=£32.000). The variation in the usage level is achieved through a random number generator between the ranges. Variables such as ‘price’, ‘total usage required’, ‘total actual usage’ are used to represent these aspects. The only message that the customer agent sends to the solution provider is the price that it will pay for the level of equipment usage. In the model the customer agent can measure the performance of the supply chain through a variable called ‘value’, which takes into account the savings through the pain/gain mechanism (sent from the solution provider) and the escalation (e.g. 5%) of price.

Solution provider agent: The solution provider sets a cost level for a given level of spares and resource requirements for each member of the supply chain. This involves definition of a certain cost for the allocated fraction of spares and resources generated from the suppliers. This is a dynamic process, which requires recognition of actual requirements for spares or repairs against the contracted amount. The dynamism is managed through a triangular distribution to represent the failure rate, which triggers the change in demand for spares and resources. Furthermore, it is assumed that independent to the equipment usage level the uncertainty in failure rate affects the demand for spares and resources and the communication with the suppliers. The failure rate is represented as events, where for each year, 10 events occur for each cost driver, which are allocated into three categories spares, resources and other. In the model the shift in failure rate may cause to move away from the estimated or expected level of requirements. If actual requirements exceed expectations or capacity, solution provider obtains this from the suppliers, which defines the level of technical investment. This variable has an initial value of 10 and depending on the rate of change in the spares requirement level, the technical investment changes equally through a multiplier. So if the number of events raises from 10 to 15 the technical investment needs to increase with the same proportion in order to avoid any extra spending in procuring from the supply chain and facilitating in-house repairs like more stringent inspection to avoid events such as no fault found. Depending on the selected risk sharing scenario, either the supplier, solution provider or both are responsible for this investment. On the other hand, gain and pain share mechanism is used between the customer and the solution provider in order to allocate the profit when it exceeds 10% or if it is below the 3% level. This also sets the contribution of the customer towards the technical investment. To sum up there are two forms of variables in the solution provider agent:

Firstly, those those focus on calculating actual cost. These trigger communication between the solution provider and the suppliers. Actual cost is the key variable considered in this category. This is calculated as a sum of the cost generated from the spares and resource suppliers, other costs and the cost that arises from using in-house capacity. Other cost involves inputs from phases 1 and 2 in the ABM framework as the estimate value is based on cost drivers such as training, LRU cost and transport cost, where variation is based on the uncertainty score that is represented through a triangular distribution. Other cost also contributes to the total estimated cost, which represents the expected cost level and the uncertainty comes from considering triangular distributions to represent the variation in these cost drivers. It also requires the estimate values for spares and resources, which are again calculated based on input from Phases 1 and 2 in the ABM framework. The estimate value for spares is made up of cost drivers such as storage cost, material availability, turnaround time. The estimate value for resource involves cost drivers such as labour availability, repair time, and emergent work. As some of the cost drivers contribute to both spares and resource requirements (e.g. failure rate) the spares and resource contribution fraction as an input from the user is used to capture this. The total estimate cost value is used in assessing the incentive mechanism between the customer and solution provider, which feeds into the second category of variables in this agent. There is an assumption that the in-house capacity can accommodate between 15 to 20% of the actual spares and resources request and the rest is sourced from the suppliers.

Secondly, those are in relation to the incentive mechanism through the gain and pain mechanism. This considers the difference between the actual cost and price. This focuses on communication between the customer and the solution provider. The key variables considered in this category are price, profit and the pain/gain level based on the 3 and 10% profit levels.

Spares supplier agent: The spares supplier is in charge of fulfilling the demand that arises from the failure rate that the solution provider raises. At this point the difference between the technical investment and the spares failure rate triggers a change from the estimated cost level to be reflected as actual cost. If there is no difference between the technical investment and spares failure rate, then the actual cost stays the same as the estimated cost. Also, in the case of scenario 3, where spares supplier and solution provider share the risk, there is a variable, 'OEM Share' to represent the proportion of cost that the solution provider will take if the actual cost exceeds the estimated cost with the spares supplier. In this case, Actual cost for the spares supplier is revised by taking out the cost that the solution provider is responsible for. The responsibility of managing obsolescence is assumed to be with the spares supplier.

Resource supplier agent: The resource supplier agent is conceptually similar to the spares supplier agent. In this case resource failure rate is used as a multiplier to estimate the actual cost for the resource supplier based on the initial estimated value. Initially the actual cost and the estimated cost are assumed to be equal but with the varying failure rate, the actual cost also varies.

4.3.1 Assumptions

The model is developed with the assumption of peace state and war scenarios are not considered. Other assumptions include:

- The customer and solution provider have TPPI arrangement
- No cannibalisation
- The spare consumption rate is assumed to be stochastic and expressed by a probability distribution attaining values from 1 onwards
- Spare consumption rate is independent of equipment usage and may increase irrespective of equipment usage
- A certain amount of technical investment is necessary to reduce spare costs both in case of supplier and the solution provider

4.3.2 Scenario configuration

Three scenarios are considered where first, the risks are with the solution provider, e.g., any shift from estimated costs is borne by the solution provider, in the second scenario, the spares supplier takes all the risks and thirdly both share the risks. The selected scenarios focus on the solution provider and the supplier, due to the nature of CfA, which pass responsibility from the customer along the supply chain.

Scenario 1: Risk with solution provider: In this scenario the solution provider is responsible for the technical investment, where there is an incentive to sustain the delivery of requirements by adjusting the capacity. Within this scenario it is assumed that if the customer aims to get more from the gain/pain share mechanism then the solution provider may have an opportunistic behaviour towards investments by passing on most of the responsibilities to the suppliers.

Scenario 2: Risk with supplier: In this scenario the supplier is responsible for technical investment, where a gap between capacity and maintenance requirements creates an increase or decrease of investment. Depending on the level of requirements the capacity level also varies over time. The uncertainty arises from the time and the quantity of spares requirements. Furthermore, the supplier is paid per unit repair, and there is no incentive to invest unnecessarily to account for the anticipated large amount of repairs.

Scenario 3: Solution provider and supplier sharing risk: The technical investment is shared between the solution provider and supplier. As the solution provider shares the cost risk, in the case where requirements diminish the supplier is less concerned about reducing the investment level and the capacity level is less likely to diminish. The model similar to the pain/gain share mechanism requires definition of a risk sharing level in order to allocate the cost level above the estimated value that is generated at the spares supplier (‘OEM Share’ variable).

5. Validation

The framework was validated using expert opinion and a pilot case study in order to identify the limitations, weakness and benefits of the model.

5.1 Expert opinion

The first respondent who has over 20 years of experience in cost estimation, and has project management experience highlighted that for the early stages of the bidding the framework was able to represent the events in maintenance delivery realistically. It was mentioned that the framework would be too tedious to follow at the line replaceable unit (LRU) level and a systems view would be more adequate. It was highlighted that the approach would enable to learn across projects due to the uncertainty assessment scheme in Phase 1. It was also highlighted that the framework enables to understand the influence of specific uncertainties on cost drivers. In the agent based model it was suggested to have further consideration of obsolescence by considering the influence of different types of obsolescence on cost and also the way in which responsibility is allocated across the supply chain.

The second respondent has over 25 years of experience in modelling maintenance costs largely in the naval domain at a major company in the defence industry. It was highlighted that after the initial stages of bidding, when information regarding service requirements becomes clearer it would be necessary to take account of the complexities of the supply chain, including issues such as supplier reliability, and variation in costs arising from different suppliers. The models' TPPI considerations would have to be considered on a project by project basis and it would not be possible to apply generic values for this purpose. The presented models' focus on three scenarios was suggested to be reasonable; however, estimation of various other key performance indicators such as availability could also be considered as useful outputs. Furthermore, at the more mature phases of the bidding stage the model would need to account for different scenarios in relation to the equipment usage conditions (e.g. weather conditions, humidity). Also it was highlighted that the model would need to take account of different requirements for the air and naval domains. This refers to the fact that in an aircraft all parts of a system have to work, whilst for the naval context this does not apply. It was also suggested that rules for interaction between agents could be considered in more detail (e.g. delivery of items varies). Overall, the expert suggested that the model was sufficiently flexible to capture the cost uncertainties early on during bidding and it was emphasised that the approach was a useful way forward to model maintenance costs.

The third respondent whom has over 30 years of experience in cost estimation in various phases of the life cycle at a large organisation in the defence and aerospace industries. The respondent was interested in the benefits of visualising the variation in cost based on changing various parameters such as pain/gain share. Also comparison among the scenarios was suggested to be a good feature to organise the interaction across the supply chain. It was highlighted that the model shows a good representation of how costs change based on changes in equipment usage level and failure rate over time, however visualising the interplay between cost and availability would also be a good output.

The fourth respondent is an expert in risk and uncertainty modelling with over 5 years of experience at a major company in the defence industry. It was highlighted that one limitation of the framework is related to making sure that all the uncertainties and cost drivers have been captured. One key outcome of the expert opinion was the need for the ABM framework to be applied in an integrated manner. This enables a systematic approach which helps to understand the root cause of variation in cost estimates. Also, the affect of uncertainties on cost drivers can be assessed in an iterative manner through Phases 1 and 2. This in turn enhances confidence in the estimates.

5.2 Pilot Case Study

The case study is a very large military system-of-systems project in the naval domain involving over 60 sub-systems of which only a minority are manufactured in-house. The project is currently engaging with the customer to establish the maintenance requirements and the company is challenged to develop credible cost models. Three subject matter experts participated in running the current ABM in the case study. The goal of the case study was to assess the suitability of the ABM framework in terms of comparing different scenarios for the early phases of the bidding stage where there is a lack of information. For this purpose three experts initially went through the list of uncertainties and scored those uncertainties that were expected to affect their project (Phases 1 and 2). A small system was considered for costs, in pounds at the thousand pound level. A what-if analysis was performed to compare the how the actual cost would vary by changing the solution provider share of risk taking for the scenario of solution provider and spares supplier share the risk. Three alternatives are considered as shown in Table 2. This is done in order to assess the suitable level of risk to be taken by the solution provider. The other inputs are kept equal, such as pain/gain share (0.3), spare cost fraction (0.45), resource cost fraction (0.35), GFX labour (0.8), cannibalisation (0.1), initial total cost (10000), failure rate cost (430,48), turnaround time cost (207.32), LRU cost (131.53), transport cost (1458.08), packaging cost (184,05), repair cost (170.0), demand rate-spare cost (436.56), storage cost (430. 58), emergent work (430.58), GFX supply cost (410.95), material availability cost (826.34), labour availability cost (1643.21), customer demand usage (92.70), customer actual usage (207.32), NFF cost (430.58), BER cost (933.14), number of students (863.87), number of trainers (282.24), facilities for training (430.58). 100 runs were conducted in the simulation.

The what-if analysis represented in Table 2 shows that as the solution provider takes on more of the share of uncertainty in funding the excess cost arising from the increased failure rate the actual cost increases. The mean values indicate a smooth increase from scenario 1 (11170.30), 2 (11268.48) and 3 (11293.78). However, driven by the failure rate by taking on more of the responsibility the uncertainty, assessed through standard deviation, diminishes. Thus meaning there is a trade-off between additional costs and attaining lower uncertainties. As indicated by the high standard deviations, there is high uncertainty in the outputs, which reflects the conditions of the bidding stage. The lack of information is represented through large triangular distributions for each cost driver, which in turn causes large variation in actual cost estimate. As can be seen across the scenarios there is a trend which indicates that as the solution provider takes a higher proportion of the uncertainty, then the overall level of uncertainty in actual cost estimate reduces. The results also indicate that the initial total cost estimate was under estimated and would potentially cause profitability issues for the solution provider and it may also reflect optimism bias. Furthermore, at the 95% confidence level the range between the lower cost limit and the upper cost limit is narrowing, from the first scenario to the third suggesting that the level of uncertainty is reduced. The decision making regarding which scenario to select would need to be based on the standard deviation, and scenario 3, with the lowest level, would be the suitable option to arrange the interaction between the spares supplier and the solution provider.

Table 2. Comparison of risk sharing between solution provider and spares supplier

	Scenario 1	**Scenario 2**	**Scenario 3**
OEM Share in sharing uncertainty with spares supplier	0.1	0.5	0.7
Mean	11170.30	11268.43	11293.78
Standard deviation	720.374	685.101	594.207
Lower cost limit at 95% confidence	9729.59	9898.23	10105.37
Upper cost limit at 95% confidence	12611.12	12638.63	12482.24

The case study showed that the required data for the ABM framework can be provided and the requirements were realistic. Some of the key outcomes of the pilot case study regarding the presented simulation framework include:

1. Costs can be predicted for specified periods as well as for the long term. Though, the model specifically suits the early stages of bidding where there is very limited information
2. Intelligent management of the influence of uncertainty over cost early on in order to negotiate across the supply network
3. Driven by uncertainty in failure rate the cost responsibilities in a TPPI type arrangement across the supply network can be visualised. The solution provider and the customer have a better understanding between the interplay between performance requirement and cost.
4. Sensitivity to costs deriving from variation in failure rate can be examined
5. Exploration and evaluation of different uncertainty sharing approaches can be compared to reach a desirable solution between the spares supplier and the solution provider

6. Discussion

The presented ABM framework offers a number of benefits to understand the way in which cost varies across a supply chain in CfA specifically for the very early phases of bidding as discussed in Section 5. One of the aims of this paper has been to apply ABM in cost engineering, in order to set out a map for the use of this simulation approach. For this purpose some of the main challenges that have been observed through literature review and industrial interaction in uncertainty based cost estimation in CfA include:

1. The need for improving the prediction of uncertainties such as equipment reliability or failure rates (mean time between failure), repair time (mean time to repair), demand rate for spares, obsolescence, and technology refresh over cost estimates
2. Difficulties that derive from the lack of useful data and poor timeliness of its availability. This particularly enhances the importance of expert opinion
3. Limited time that is available to build uncertainty based cost estimates

4. Service delivery particularly depends on the service supply chain, where challenges arise from the sustainability of the supplier, aggregate influence over work breakdown structure, cost effectiveness, timely and quality provision of service. Also, as a source of complexity, suppliers do not show homogeneous characteristics.
5. Difficulties in systematic representation of uncertainty driven by the be-spoke nature of offerings.

Along with these considerations application of ABM will need to address challenges associated to too much reliance on expert opinions, better consideration of the uncertainties that originate from the customers in contributing to availability performance, difficulty of using bottom up cost estimates throughout the bidding stage, communication problems with the customers regarding performance delivered, prediction of maintenance activities in the future (10-15 years), inability to understand cost impact of customer focused risks (Roy and Cheruvu, 2009). Based on these challenges it is evident that there is need for improved estimating techniques and processes across the bidding stage especially early on in order to take account of the increased range and scale of uncertainties typical in CfA.

Driven by this challenge, this paper has focused on ABM to address a strategic level problem that arises early on in determining the form of interaction across the supply chain through incentive mechanisms involving various risk sharing approaches between the solution provider and the spares supplier. A major strength of ABM is related to capturing emergent behaviour of a system or a supply chain over a life cycle. It is particularly beneficial in modelling more dynamic conditions where interaction requires adaptation over time due to independent decision making architectures, as is the case in the service oriented approach of CfA. However, it is hard to define boundaries around the way in which ABM should be constructed as in literature a universally accepted design methodology is missing.

7. Conclusions

The simulation framework covered in this paper considers the early bidding stage where there is limited information available for a Target Price Performance Incentive (TPPI) type arrangement in CfA. In the agent based model failure rate is considered to trigger variation in cost drivers that are typically the most important uncertainty variable in a CfA. Furthermore, the uncertainty in the cost drivers are considered by defining a range to each cost driver based on the uncertainty assessment. This proved to be an effective way to address the financial risk questions associated with providing maintenance services. The complex, interactive and dynamic effects of the supply chain in terms of varying customer equipment usage requirements, satisfying the demand for spares and resource requirements made the simulation approach effective for the early stages. This paper has sought to justify precisely why ABM is appropriate for considering complex and distributed networks in CfA early on in the bidding stage. The main advantage of the approach is driven by the fact that static models lack the ability to replicate the real world by relying on average long term performance, while ABM offers a dynamic approach. Through the presented model a systematic framework is suggested, in order to conduct what-if analysis to better understand the influence of uncertainty in cost estimates early on. It is anticipated that the presented simulation framework makes a contribution towards growing the use of ABM in cost engineering.

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