

Optimized Mismatch Resolution for COTS Selection



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Research Section

The use of Commercial Off-The-Shelf (COTS) products in the software development process requires the evaluation of existing COTS products, and then selecting the one that best fits system requirements. In this process, it is inevitable to encounter mismatches between COTS features and system requirements. Mismatches occur as a result of an excess or shortage of COTS capabilities. Many of these mismatches are resolved after selecting a COTS product. Existing COTS-selection approaches fail to properly consider these mismatches. This article presents MiHOS (Mismatch Handling for COTS Selection), an approach that aims at addressing mismatches while considering limited resources. MiHOS can be integrated with existing COTS-selection methods at two points: (i) When evaluating COTS candidates in order to estimate the anticipated fitness of the candidates if their mismatches are resolved. This helps to base our COTS-selection decisions on the fitness that the COTS candidates will eventually have if selected. (ii) After selecting a COTS product in order to plan the resolution of the most appropriate mismatches using suitable actions, such that the most important risk, technical, and resource constraints are met. A case study from the e-services domain is used to illustrate the method and to discuss its added value. Copyright © 2008 John Wiley & Sons, Ltd.

KEY WORDS: COTS *versus* requirements mismatches; MiHOS; COTS-based development

1. INTRODUCTION AND MOTIVATION

Employing commercial off-the-shelf (COTS) products to develop software systems has the potential to reduce development time and effort. The term COTS refers to both commercially available and open-source products (Torchiano and Morisio 2004) that are reused to build software systems (Vigder *et al.* 1996, Firesmith 2005). A crucial factor in the

success of the final system is to perform a good COTS selection (Maiden and Ncube 1998), a process that aims at evaluating existing products and selecting the one that best fits the requirements.

In the so-called buy-and-adapt approach (Vigder *et al.* 1996), the selected COTS product, although best-fitted, would still have many mismatches with the requirements. These mismatches occur as a result of an excess or shortage of COTS features¹.

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¹ The term 'mismatch' as used in this article should not be confused with other types of mismatches such as architectural mismatches, which are encountered between different parts integrated together in a software system (Gacek *et al.* 1995, Garlan



Such mismatches are inevitable as COTS products are made for broad use while system requirements are specific to their context (Carney *et al.* 2000, Alves 2003). Many of these mismatches are resolved after the selection.

We argue that in the COTS-selection process, the selection decision should be based on the anticipated fitness of COTS candidates if their mismatches are resolved. However, due to the fact that there are usually limited resources (i.e. effort and budget) for resolving these mismatches, we typically can only resolve a subset of all COTS mismatches. Resolving different subsets of mismatches will have different impacts on the COTS product fitness. The question is, what is the 'right' subset of mismatches that should be addressed under the given resource constraints? This subset has to be identified when comparing the COTS candidates so as to estimate their anticipated-fitness values, and thus make appropriate COTS-selection decisions.

In addition, it is not enough to only identify the right mismatches but also to apply the right resolution actions. Alternative resolution actions can be used with each mismatch. Different resolution actions require different amounts of resources, and impose different risks on the system. The question is, what is the right set of resolution actions that should be chosen such that the right mismatches are resolved, with the least risk, and within the given resource constraints?

This problem gets more and more complex as the number of mismatches and their alternative resolution actions increase. For some projects, inefficient decisions might not only affect the functionality and quality of the final system but might also result in serious consequences such as losing market share. Therefore, we suggest the use of decision-support techniques (Ruhe 2003) to address this problem.

Decision support is a proven means to assist humans to make decisions in case of semi-structured or unstructured problems encountering incomplete or uncertain information. The paradigm of decision support suggests the pro-active evaluation of decision alternatives and aims at providing the best knowledge available to the decision maker to make more informed, transparent and effective decisions.

This article tries to address the COTS mismatch problem by providing support to decision makers when selecting COTS products. The selection is done based on pro-active analysis of the impact of *mismatch handling*. Mismatch handling is the process in which mismatches and their resolution actions are analyzed; and a selected set of mismatches is resolved using certain resolution actions. For that, the article presents **Mismatch Handling for COTS Selection (MiHOS)**, an approach that can be integrated into existing COTS-selection methods to support handling mismatches. MiHOS has two objectives that may be realized during and after the selection process:

Objective 1 (During COTS selection): MiHOS is used to estimate the anticipated fitness of candidates if the right mismatches for each candidate are resolved.

Objective 2 (After COTS selection): MiHOS is used to help plan the resolution of the right mismatches for the selected COTS using the right set of resolution actions.

MiHOS follows an iterative and evolutionary decision-support framework called EVOLVE (Ruhe and Ngo-The 2004). Instead of providing only one solution to decision makers, MiHOS suggests a portfolio of qualified and structurally diverse solutions (Ngo-The and Ruhe 2008). The decision makers are then invited to explore and analyze these solutions, and then they can either accept one solution, or refine the problem model and regenerate further refined solutions. This kind of interactive decision support allows decision makers to have more participation in and control over the decision-making process.

This article consists of six sections. In Section 2, a short overview of COTS selection and mismatch handling is given. Section 3 illustrates MiHOS, while Section 4 describes a case study in the e-services domain. Section 5 gives the limitations of applicability. Finally, Section 6 provides conclusions and suggestions for future research.

2. COTS SELECTION AND MISMATCH DETECTION

2.1. COTS-Based Development Process

Although the scope of this article does not cover the full life cycle of the COTS-Based Development (CBD) process, it is necessary to understand the

et al. 1995, Shaw 1995, Shaw and Clements 1997, Yakimovich *et al.* 1999)



process of CBD in order to position the presented work. Overall, CBD includes five phases (Abts *et al.* 2000, Boehm *et al.* 2003):

1. *Requirements Engineering*, which defines the desired capabilities and constraints, and helps in establishing the COTS evaluation criteria.
2. *COTS Selection*, which ensures selecting COTS products that best fit the system requirements. This activity is described in the next section (Section 2.2).
3. *COTS Tailoring*, which involves customizing the COTS product to address unsatisfied (or partially satisfied) requirements. This activity is described in the next section.
4. *COTS Integration*, which is the process of assembling a set of selected COTS products and components together to produce a system.
5. *System Evolution*, which includes maintenance issues such as updating the system with new COTS releases, adding new functionality to the system, and fixing errors.

How does MiHOS, the proposed approach, fit into the above CBD model? MiHOS is a method that supports the process of single '*COTS Selection*', and at the same time investigates the impact of '*COTS Tailoring*' on the selection process. MiHOS also helps human experts plan for '*COTS Tailoring*' after the selection process. On the other hand, MiHOS relies on existing methods such as PORE (Maiden and Ncube 1998) for performing the '*Requirements Engineering*' activity. Lastly, MiHOS does not address '*COTS Integration*' or '*System Evolution*'.

2.2. The General COTS Selection Model

Several approaches have been proposed to model the COTS-selection process; e.g. OTSO (Kontio 1995), CAP (Ochs *et al.* 2000), and IQMC (Franch and Carvallo 2003). Although there is no generally accepted method for COTS selection (Ruhe 2003), all methods share some key steps that might be iterative and overlapping. These steps formulate what we refer to by the general COTS-selection model:

Step 1: Define evaluation criteria based on system requirements.

Step 2: Search for COTS products.

Step 3: Filter search results based on a set of must-have criteria and define a shortlist of products.

Step 4: Evaluate COTS candidates in the shortlist.

Step 5: Analyze evaluation data and select the best-fit COTS product.

As described in the CBD model (Section 2.1), the selected COTS product is tailored in order to resolve as much as possible of its mismatches with the requirements. However, it is not clear in existing COTS-selection methods how the mismatches of COTS candidates influence the COTS-selection decision at step 5, especially when limited resources prevent the resolution of all mismatches. Resolving COTS mismatches, as stated by Vigder *et al.* (1996), can be realized by:

- *Add-ons:* to acquire additional add-ons that add functionality to the COTS product.
- *Scripting:* to write custom code using a scripting language supported by the COTS product. Examples of such scripting languages include JavaScript, VisualBasic, and Perl.
- *API:* to develop a controlling program that calls COTS functions using its API interface.
- *Modifying source:* to modify the COTS source code if available. This is a risky action because of several maintenance issues (Brownsword *et al.* 1998, Morisio *et al.* 2000, CeBASE).

To decide which mismatches are to be resolved using which actions, several factors should be considered: (a) the impact of different mismatches on the COTS product fitness, and (b) the effort, cost and risk of alternative resolution actions for each mismatch. In addition, the application of the selected set of resolution actions should not exceed available project resources.

2.3. Detecting Mismatches in MiHOS

MiHOS suggests to hierarchically define the COTS-selection criteria using goals (Kontio 1996). MiHOS defines two types of goals: strategic goals and technical goals. Strategic goals refer to high-level requirements that cannot be directly measured in the COTS product, i.e. by measuring the performance of one functional attribute of the COTS product. Each strategic goal is decomposed into more refined goals (see Figure 1). The decomposition process continues until defining goals that are at the same level of granularity of COTS features. We refer to goals at this level as '*technical goals*', which represent measurable criteria. The result is a

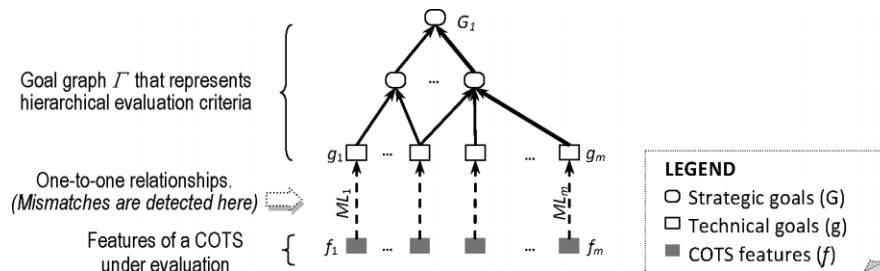


Figure 1. Hierarchical - criteria definition

goal graph Γ that addresses stakeholders' strategic needs at the strategic levels, and maps to COTS features at the technical level.

A COTS product evaluation is done by comparing the COTS features with the technical goals in 1-to-1 relationships. The evaluation score is represented by a matching level (ML) (Mohamed 2007) which indicates different levels of satisfaction of technical goals by corresponding COTS features. ML might be estimated on different scales, but eventually ML value is normalized to the range from 0 to 1; 1 indicates full satisfaction of the technical goal by the COTS feature, and 0 no satisfaction.

It is worth mentioning that COTS selection as performed in MiHOS is performed using a simple weighing-and-aggregation-method. The relative weights of the technical goals are computed (as described in the next section). Then, the ML values are multiplied by the weights, and the weighted scores are summed.

A mismatch m_i occurs between a COTS feature f_i and a technical goal g_i when $f_i \neq g_i$. A mismatch m_i can be classified into one of five types (Mohamed 2007):

1. *ZeroMatch*: a COTS product fails to satisfy a technical goal.
2. *PartialMatch*: a COTS feature partially satisfies a technical goal.

3. *Surplus*: a COTS product has an extra feature that is not required.
4. *OverMatch*: a COTS feature exhibits more capability than required.
5. *Equivalence*: a COTS feature contributes to achieving the strategic goal behind a required technical goal, but does not match the technical goal itself.

3. MIHOS: A PROPOSED APPROACH TO HANDLE COTS MISMATCHES

MiHOS is a three-phase approach that allows decision makers to interactively participate in and have more control over the decision-making process. The kernel of MiHOS is a formal model of the mismatch-handling problem. This formal model is described in Section 3.1; and then MiHOS is described in detail in Section 3.2.2.

3.1. Mismatch Handling: A Formal Model

Suppose a COTS product has a set of mismatches $\{m_i : i = 1 \text{ to } \mu\}$ with the technical goals $\{g_1, g_2, \dots, g_\mu\}$. The key aspects of the formal model are described in the next two subsections (see Table 1).

Table 1. Input parameters of MiHOS

Technical goals		COTS1										COTS2		...				
ID	Relative weight	Mismatches		Resolution actions										Mismatches	Resolution Actions	...		
		ID	Amount	$a_{i,1}$...	$a_{i,J}$									
				ID	Decision Variables	effort	cost	risk	...	ID	Decision Variables	effort	cost	Risk				
g_1	Ω_1	m_1	$Amount_1$	$a_{1,1}$	$x_{1,1}$	$effort_{1,1}$	$cost_{1,1}$	$r_{1,1}$...	$a_{1,J}$	$x_{1,J}$	$effort_{1,J}$	$cost_{1,J}$	$r_{1,J}$
g_2	Ω_2	m_2	$Amount_2$	$a_{2,1}$	$x_{2,1}$	$effort_{2,1}$	$cost_{2,1}$	$r_{2,1}$...	$a_{2,J}$	$x_{2,J}$	$effort_{2,J}$	$cost_{2,J}$	$r_{2,J}$
...
g_μ	Ω_μ	m_μ	$Amount_\mu$	$a_{\mu,1}$	$x_{\mu,1}$	$effort_{\mu,1}$	$cost_{\mu,1}$	$r_{\mu,1}$...	$a_{\mu,J}$	$x_{\mu,J}$	$effort_{\mu,J}$	$cost_{\mu,J}$	$r_{\mu,J}$

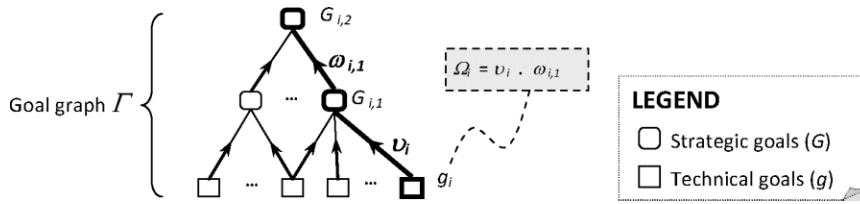


Figure 2. Relative importance of technical - goals

3.1.1. Problem Characteristics

3.1.1.1. Relative Importance of Technical Goals Consider a mismatch m_i that exists between a COTS feature and a technical goal g_i . This technical goal is at the leaf level of a hierarchical graph which consists of Y levels of strategic goals $G_{i,y} : y = 1$ to Y . Now, assume g_i is assigned a weight of importance v_i ; and $G_{i,y}$ is assigned a weight of importance equal to ω_{iy} . Then, for a uniquely defined path $\rho[g_i, G_{i,Y}]$ between the nodes g_i and $G_{i,Y}$, the relative importance Ω_i of the node g_i with respect to $G_{i,Y}$ is obtained by multiplying all weights of the arcs along ρ (see Figure 2):

$$\Omega_i = v_i \cdot \prod_{y=1 \dots (Y-1)} \omega_{i,y}$$

In case there is more than one path from a technical goal to the highest-level strategic goal, then the path resulting in the maximum relative importance is considered.

3.1.1.2. Mismatch Amount For a mismatch m_i between a COTS feature f_i and a technical goal g_i , the amount of mismatch, $Amount_i$, can be estimated by measuring how much f_i fails to satisfy g_i ; $Amount_i = 1 - ML_i$, where ML_i is the matching level between f_i and g_i .

3.1.1.3. Decision Variables Assume that for each mismatch m_i we identified a set A_i of J possible resolution actions,

$$A_i = \{a_{i,1}, a_{i,2}, \dots, a_{i,J}\}$$

For instance, if the mismatch m_i indicates that a required functionality is not supported by a COTS product, then A_i will include possible ways to tailor this COTS product so as to support this functionality; e.g. $A_i = \{‘tailor by custom-code’, ‘tailor by add-ons’, \dots\}$. In MiHOS, the goal is to select one resolution action $a_{i,j}$ for each mismatch

m_i . This is described by the set of decision variables

$$X_i = \{x_{i,1}, x_{i,2}, \dots, x_{i,J}\}$$

where $x_{i,j} = 1$ if the resolution action $a_{i,j}$ is chosen to resolve the mismatch m_i , and $x_{i,j} = 0$ otherwise. This means if a mismatch m_i is to be resolved using action $a_{i,1}$, then $X_i = \{1, 0, 0, \dots, 0\}$; and if $a_{i,2}$ is to be used, then $X_i = \{0, 1, 0, 0, \dots, 0\}$, and so on.

Note that for the set A_i , we define each resolution action $a_{ij} \in A_i$ to be sufficient to completely resolve m_i . Therefore, we are constrained by choosing only one resolution action to resolve each m_i . This constraint is represented by $\sum_j x_{ij} \leq 1$. In case a mismatch m_i is tolerated, no resolution action is chosen, and thus $X_i = \{0, 0, \dots, 0\}$.

3.1.1.4. Constraints There are two types of constraints considered by MiHOS: resource constraints and preassignments:

Resource Constraints: Applying resolution actions requires different resources. Each resource has a maximum capacity that should not be exceeded. Assume we have T resource types, and a capacity Cap_t for each resource type t . Every action a_{ij} uses an amount $Usage_{ijt}$ of resource t . Thus, the total amount of resources consumed by the selected set of resolution actions (represented by decision variables x_{ij}) must be less than the total capacity of these resources,

$$(\forall t) : \sum_{i,j} x_{ij} \cdot Usage_{ijt} \leq Cap_t$$

For this article, we consider two types of resources: *available_budget* and *available_effort*. The method remains applicable also if more constraints are defined. That is, we assume each resolution action $a_{i,j}$ requires an effort equal to $effort_{i,j}$ and costs an amount of $cost_{i,j}$. The total effort and budget consumed by the selected resolution actions must be less than the available resources. Thus, the above



equation can be broken into the following two equations:

$$\sum_{i,j} x_{i,j} \cdot \text{effort}_{i,j} \leq \text{available_effort}$$

$$\sum_{i,j} x_{i,j} \cdot \text{cost}_{i,j} \leq \text{available_budget}$$

Preassignments: The user has the option to preassign a certain mismatch to be either ‘resolved’ or ‘tolerated’ before running the model. If m_i is preassigned to be resolved, then the model must select exactly one resolution action to apply. In this case, the sum of decision variables related to all resolution actions A_i applicable to m_i must equal to 1 (i.e. $\sum_j x_{ij} = 1$). On the other hand, if a mismatch m_i is to be tolerated, then no resolution actions should be suggested for it (i.e. $\sum_j x_{ij} = 0$).

3.1.1.5. Technical Risk We assume applying each resolution action a_{ij} imposes a technical risk equal to r_{ij} . The technical risk is estimated based on: (i) *Failure risk*: the risk that the developers might fail to apply the action $a_{i,j}$, and (ii) *Instability risk*: the risk that an action $a_{i,j}$ would cause instability of the target system. Both (i) and (ii) may be estimated on a 9-point ordinal scale {1, 3, 5, 7, 9}; this indicates very low, low, average, high, and very high risk. Even numbers can be interpreted as intermediate values. Assuming equal distance between the 9-point scale, the technical risk can be estimated from the formula, $r_{ij} = \alpha \cdot \text{FailureRisk}_{ij} + \beta \cdot \text{InstabilityRisk}_{ij}$, where: $\alpha + \beta = 1$; α and β indicate the relative importance of the two types of risks, and are defined by experts. In our work, both types are of equal importance, and thus, we use $\alpha = \beta = 0.5$.

3.1.1.6. Stakeholders In many cases, several stakeholders are involved in the estimation process of ‘the goals’ relative importance’ and ‘the technical risk of resolution actions’. Assume we have a set S of K stakeholders abbreviated by $S = \{s_k : k = 1 \text{ to } K\}$. The degree of importance of each stakeholder s_k is determined by the relative importance $\lambda_k \in \{1, 3, 5, 7, 9\}$; this indicates very low, low, medium, high and very high importance respectively. Even numbers (e.g. $\lambda_k = 2, 4, 6,$ and 8) indicate a refinement of values above and below. We use a 9-point ordinal scale to allow sufficient differentiation between stakeholders’ degrees of importance.

For aggregating different stakeholders’ estimations, we use a weighted average function: (i) If

each stakeholder s_k estimated a relative importance Ω_{ik} for a goal g_i , then the overall relative importance is $\Omega_i = \sum_k \lambda_k \cdot \Omega_{i,k}$. (ii) If s_k estimated a technical risk r_{ijk} for a resolution action a_{ij} , then the resultant technical risk is determined by $r_{i,j} = \sum_k \lambda_k \cdot r_{i,j,k}$.

3.1.2. Objective Function

The objective function brings together the problem facets described so far in Section 3. Typically, planning for mismatch handling aims at: (i) Maximizing COTS product fitness, (ii) Minimizing risk for resolution of mismatches, and (iii) Fulfillment of resource constraints.

Point (i) is influenced by the goals’ relative importance Ω_i and the mismatch amounts $Amount_i$, point (ii) is influenced by the technical risk r_{ij} of selected resolution actions, and point (iii) is relevant to the resource consumptions and constraints. The proposed objective function brings these aspects together in a balanced way. The objective is to maximize function $F(x)$ subject to the satisfaction of the above constraints. $F(x)$ is given as:

$$F(x) = \sum_k (Amount_i \cdot \Omega_i \cdot \sum_j (x_{i,j} \cdot \Delta r_{i,j}))$$

Where $\Delta r_{i,j} = 10 - r_{i,j}$ indicates how safe an action a_{ij} is. We use Δr_{ij} instead of r_{ij} because maximizing $F(x)$ should yield the minimum risk (i.e. the maximum safety) of selected actions.

3.2. MiHOS in Action

3.2.1. Generating Alternative Solutions

Qualified Solutions: The above formal model constitutes an optimization problem that could be solved by optimization packages. We used a package called LINGO (LINDO_Systems). As most optimization packages, LINGO is designed to provide one optimal solution at a time for each instance of the problem. However, for decision making under uncertainty, having a set of near-optimal (or ‘qualified’) solutions is more relevant than having just one (Ngo-The and Ruhe 2008). As discussed below, MiHOS provides a portfolio of five qualified solutions. Each solution represents a plan that suggests a strategy for resolving a subset of COTS mismatches. The motive of offering five plans to the decision maker instead of only one is that it allows addressing implicit and additional concerns not formally described in the original



problem statement. In fact, the quality of the five solutions is very similar, but they may differ in terms of their ability to accommodate additional concerns.

MiHOS generates the qualified solutions as follows: Assume that LINGO² identifies an optimum solution X_0 with the maximum possible objective function value equal to $F(X_0)$. We define a qualified solution as any near-optimum solution X^* that possesses two characteristics: (i) X^* lies in the feasible space delimited by the problem constraints, and (ii) $F(X^*) \geq \alpha \cdot F(X_0)$, where α is a predefined quality level, and $\alpha \in (0,1)$. In MiHOS, we choose the quality level $\alpha = 0.95$ in order to address the uncertainty involved when defining the values of problem parameters. Requiring higher accuracy would make little sense with such uncertainty.

Diversified Solutions: The generated alternative solutions should also be significantly different; otherwise they are not really alternatives. A strategy that tries to achieve diversification was introduced in Ngo-The and Ruhe (2008). This strategy tries to simplify the problem by searching only a subset of the feasible space for the most diversified solutions. However, this strategy does not guarantee the identification of the solutions with the maximum diversification among the whole feasible space.

In our approach, we developed another diversification algorithm that tries to increase the level of diversification incrementally:

1. Apply LINGO to the original problem formulation to obtain an optimal solution X_0 .
2. Set $\eta = 1$. η represents the number of structural differences that any two plans in the final solution should have.
3. The algorithm then tries to find four qualified solutions having η structural differences by adding more and more constraints to the problem formulation to ensure diversification:
 - (a) LINGO is asked to search for a solution X_1 that is qualified (i.e. $\alpha = 0.95$) and satisfies the constraint: ' X_1 must have exactly a number of η structural differences with X_0 '.
 - (b) Then LINGO is asked to search for another qualified solution X_2 such that it satisfies

two constraints: ' X_2 must have η differences with X_0 ,' and ' X_2 must have η differences with X_1 '.

- (c) Similarly, the algorithm repeats (i) and (ii) to get X_3 and X_4 .
4. In steps (i) through (iii), if LINGO could find all four solutions, then these solutions as well as X_0 are stored in the final solution set $SOL = \{X_0, X_1, X_2, X_3, X_4\}$.
5. η is incremented, and step 3 is repeated with the new value of η . The algorithm keeps incrementing η until LINGO fails to solve the problem. When this happens, then the last successfully saved set SOL becomes the required portfolio of solutions.

Our algorithm has the advantage of searching the whole set of qualified solutions for maximally diversified solutions. However, our strategy assumes equal distances between the diversified solutions, which still does not guarantee maximum diversification because in reality the distance between the diversified solutions might vary. Yet the diversification obtained from our strategy is very close to the maximum because LINGO searches the whole set of qualified solutions, and keeps trying to find solutions with larger diversification until failing to do so.

In addition, our strategy takes more time than the strategy proposed in Ruhe and Ngo-The (2004) – about three to six times longer. Nevertheless, in the case of generating only one set of five alternative solutions, the increase in time would only be in terms of seconds or a few minutes, depending on the speed of the computer used in solving the problem and the size of the problem.

Note that our diversification strategy might fail in very rare (unrealistic) cases. For example: if the resource constraints are very low and can only resolve one mismatch, and in the qualified solution space there are no five mismatches that the strategy can pick under the given resource constraints. This is obviously an unrealistic case because MiHOS should only be used when we have many mismatches and the resource constraints, although limited, are sufficient to resolve more than one mismatch.

3.2.2. A Hybrid Approach for Mismatch-Handling during COTS Selection

The above process of solutions generation is applied in MiHOS in a 3-phase process. Before describing

² Although in this section we describe our diversification algorithm as applied in MiHOS using LINGO, the algorithm could be implemented using any other optimization package.

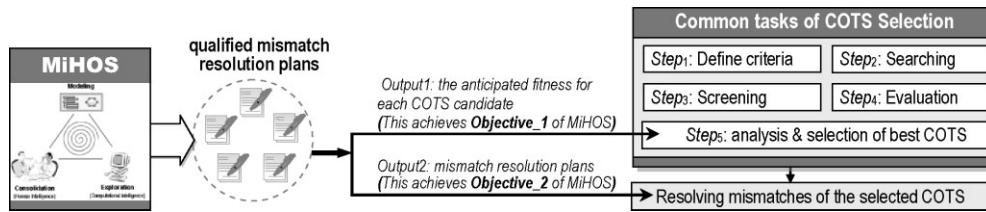


Figure 3. Integrating MiHOS to the general COTS selection process

the details of this process, we will give the big picture of how MiHOS is integrated into the general COTS-selection (GCS) process described in Section 2.2. MiHOS generates a set of plans, which are used to generate two outputs (Figure 3):

Output1, the anticipated fitness of COTS candidates if these plans are used to resolve the COTS mismatches. This output is fed to step 5 of the GCS model to help selecting the best-fit COTS-based product. This output is used to realizing objective 1 of MiHOS, as discussed earlier.

Output2, a portfolio of mismatch-resolution plans. This output is fed to the COTS tailoring step of the GCS model to help in resolving the mismatches of the selected COTS. This output is used to achieve objective 2 of MiHOS.

In order to generate the above two outputs, MiHOS follows a framework called EVOLVE (Ruhe and Ngo-The 2004) that provides decision support using hybrid intelligence that brings computational and human intelligence together. The computational part of MiHOS is used to solve the formal model of the problem and to generate a set of

qualified solutions with maximum diversification as described earlier. The decision makers are then invited to analyze these solutions and either accept one of them, or refine the formal model based on their knowledge, which evolves through successive iterations. Such iterative and evolutionary approach allows addressing the wicked and uncertain character of the problem. This process is realized in three phases: Modeling, exploration, and consolidation (see Figure 4).

3.2.2.1. Modeling

The modeling phase aims at describing the settings of the mismatch problem to be suitable for the format given in Section 3. This includes three main tasks:

1. *Identify mismatches and resolution actions*: For each COTS candidate, identify the set of mismatches m_i and the applicable resolution actions A_i , the technical risk r_{ij} associated with each resolution action a_{ij} , and the resources (i.e. *effort_{ij}* and *cost_{ij}*) required for each resolution action a_{ij} . Estimating the effort and cost using a combination of expert judgment with formal models (e.g. Li *et al.* 2006) has proven promising (Briand and Wiczorek 2001).
2. *Identify relative goal importance*: This task includes estimating the relative importance Ω_i of each technical goal g_i that has a mismatch m_i with a COTS feature.
3. *Estimate constraints*: This task includes estimating both available resource constraints as well as performing any preassignments for mismatches resolution.

3.2.2.2. Exploration

In this phase, the solution space is explored, and a set of alternative qualified solutions (plans) with maximal diversification is generated as discussed earlier (Section 3.2.1). To explain the structure of

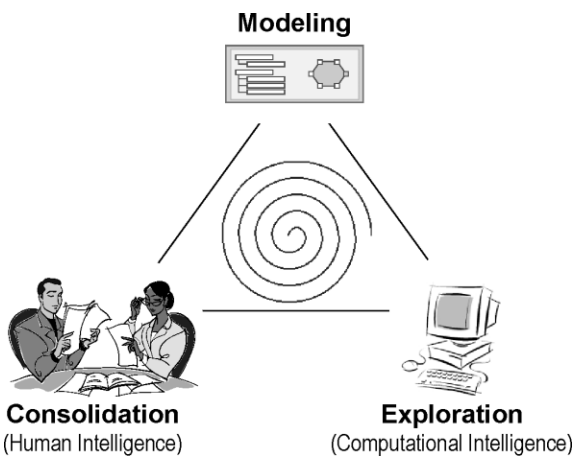


Figure 4. Hybrid intelligence to support the mismatch handling process



the resolution plans, consider a COTS product having a set of mismatches $\{m_1, m_2, \dots, m_\mu\}$. A mismatch-resolution plan Y is represented by the set $\{y_1, y_2, \dots, y_\mu\}$, where, for each mismatch m_i , a suggestion y_i may take one of the following values:

- $y_i = \text{'Do not resolve } m_i\text{'}$. All decision variables $x_{i,j}$ are set to zero; no resolution action is used.
- $y_i = \text{'Resolve } m_i \text{ using action } a_{i,1}\text{'}$. Only $x_{i,1} = 1$ while $x_{i,j} = 0$ otherwise; i.e. $X_i = \{1, 0, 0, \dots, 0\}$.
- $y_i = \text{'Resolve } m_i \text{ using action } a_{i,2}\text{'}$. Only $x_{i,2} = 1$ while $x_{i,j} = 0$ otherwise; i.e. $X_i = \{0, 1, 0, \dots, 0\}$.
- ...
- $y_i = \text{'Resolve } m_i \text{ using action } a_{i,j}\text{'}$. Only $x_{i,j} = 1$ while $x_{i,j} = 0$ otherwise; i.e. $X_i = \{0, 0, 0, \dots, 1\}$.

Based on the five generated plans, the two outputs of MiHOS are generated as follows:

For Output1: The anticipated fitness of a COTS candidate is estimated in three steps:

1. MiHOS assumes that the first mismatch-resolution plan is applied, and the mismatches are resolved as it suggests.
2. Having the assumption in (1), MiHOS recalculates the fitness of COTS candidates using the weighing-and-aggregation method described in Section 2.3.
3. MiHOS repeats (1) and (2) for the remaining four mismatch-resolution plans. The overall anticipated fitness is the average of the five fitness values obtained in these three steps:

Anticipated_Fitness

$$= \frac{\sum_{n=1..5} \text{Anticipated fitness assuming plan } Y_n \text{ is applied}}{5}$$

Where Y_n is a mismatch-resolution plan generated by MiHOS, $Y_n = \{y_1, y_2, \dots, y_\mu\}$

For Output2: The second output of MiHOS is the same five mismatch-resolution plans originally generated with the aid of LINGO (LINDO.Systems). These plans are given to decision makers so that they can select the one that best suits their interests.

3.2.2.3. Consolidation

In this phase, decision makers review the output of the exploration phase. They might then refine the problem settings as necessary and go to the next iteration.

For Output1: after evaluating COTS products, MiHOS' consolidation phase enables decision makers to perform *what-if* analysis to examine the impact of 'changing the problem settings' on the 'anticipated fitness' of different COTS candidates. For example, decision makers might want to compare COTS candidates if all mismatches related to security are resolved. This is done using the 'pre-assignment' feature of our model. Decision makers can then analyze COTS candidates based on their 'anticipated security scores' as well as their 'anticipated overall scores'.

For Output2: when trying to resolve mismatches of the selected COTS product, MiHOS' consolidation phase enables decision makers to extensively review and analyze the alternative plans suggested in the exploration phase. The decision makers then have the choice either to accept one of the plans, or refine the problem settings and go to the next iteration. During each iteration, decision makers' knowledge evolves and more refinement of the underlying model occurs. The iterations continue until a desirable alternative solution is found.

4. CASE STUDY

To illustrate the proposed method, we use a real-world case study from the e-services domain. The aim of the case study was to acquire a content management system (CMS) for creating an e-business solution. CMSs are used to facilitate the creation of news portals using managed contents (i.e. text, images, videos, etc). Due to the page limitation, we briefly describe the main results from the case study in this article, while full details are given in Mohamed *et al.* (2006) Mohamed (2007).

Initially, a set of 275 goals were defined to represent system needs at different levels of abstraction. From these, 153 goals were defined at the technical-goals level. The COTS market was searched, and a subset of 30 must-have technical goals was used to define a shortlist of five COTS candidates using progressive filtering (Maiden and Ncube 1998). All candidates had mismatches with different mismatch amounts. On the other hand, the system resources for resolving selected COTS mismatches were estimated as: available effort = 60 person-hours, available budget = \$2000.



The cells containing 'x' suggest tolerating relevant mismatches, while other cells suggest solving relevant mismatches m_i using actions a_{ij} . The last four columns show the evaluation of the suggested plans. As can be seen, these five suggested plans have a consensus on the majority of resolution actions. Therefore, we felt more confident to use those actions. On the other hand, we focused our analysis on the differences between the suggested plans. All alternative plans were reasonable, and eventually *Alt1* was adopted as it required the least amount of resources.

5. LIMITATIONS

As in the case with any approach, the quality of MiHOS' results relies on the quality of the input data. In order to reduce the uncertainty in the input data, we use an evolutionary and iterative approach so as to refine the input values based on experts' feedback after analyzing the output. MiHOS generates a set of near-optimal solutions being structurally diversified instead of only one 'best' solution. Having such tolerance when accepting qualified solutions minimizes the effect of inaccuracies in input values. A similar approach that uses comparable techniques has proven promising in the area of software release planning (Ruhe and Ngo-The 2004, Ngo-The and Ruhe 2008).

Also, MiHOS requires extra effort to apply. The total effort required in the case study was 256 person-hours: 96 person-hours for running MiHOS activities (37.7%), and 160 person-hours (62.3%) for running other activities in the general COTS-selection model (i.e. criteria definition, searching for COTS, etc). However, we argue that the extra effort needed for applying MiHOS during and after the selection process is more helpful and less risky than acting reactively if problems occur. We suggest using MiHOS in big projects in which inefficient decisions would have critical consequences, e.g. related to finances or human safety. We also recommend applying MiHOS during the selection process only after having a small set of the most promising COTS candidates so as to reduce the effort required for defining the problem settings. However, once the problem settings are defined, it is very easy and almost effortless to rerun MiHOS several times so as to explore different scenarios of the problem. For example, in our case study, the

scenario 'evaluate COTS candidates if their security score is maximized' was done in no time, and yet yielded important information that significantly affected our decision.

In addition, MiHOS is currently dedicated for single COTS selection. Also, MiHOS is not designed to handle mismatches related to non-functional requirements (NFR). This problem arises from the difficulty of estimating the effort/cost for achieving a specific target level by solving such mismatches. Although in our case study MiHOS was able to deal with several NFRs (e.g. security), applying it to some other NFRs (e.g. reliability) would be difficult.

6. SUMMARY AND OUTLOOK

We proposed MiHOS, a decision-support approach that can be integrated with most existing COTS-selection methods at two points: (1) when evaluating the most promising COTS products in order to estimate the anticipated fitness if the right mismatches are resolved for each COTS; and (2) after selecting a COTS product in order to help plan the resolution of the right mismatches using appropriate resolution actions. MiHOS takes into consideration factors such as the impact of a mismatch on COTS product fitness, and the cost, effort and risk of resolution actions. The case study showed the significance of using MiHOS in qualifying the COTS-selection decisions.

Despite the limitations in Section 5, the structure of MiHOS is of high *extensibility* to address more complex problems. For example, instead of considering the overall effort for applying resolution actions, the formal model can be easily modified to address more refined types of effort; e.g. development, testing and documentation efforts. This differentiation between effort types is necessary when having different teams in the project with different effort constraints.

Also, instead of assuming that each mismatch is resolved by only one resolution action, the formal model can be modified to consider several resolution actions that together can solve one or more mismatches. This can be done by adding some technological constraints that define the dependencies between resolution actions.

We are also working on exploring the use of 'linear combination' for formulating the objective function, and comparing the results to the current



objective function. Linear combination might be useful to conduct more complex 'what-if' analysis. This increases the customizability of the objective function towards experts' preferences.

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