RE-PREF: Support for REassessment of PREFerences of Non-functional Requirements for Better Decision-making in Self-adaptive Systems

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***Abstract*—Modelling and reasoning with prioritization of non-functional requirements (NFRs) is a research field that needs more attention. We demonstrate RE-PREF, an approach that supports the modelling of NFRs and their preferences, and discovery of possible scenarios where badly chosen preferences can either make the runtime system miss or suggest unnecessary adaptations that may degrade the behavior of a self-adaptive system (SAS). Specifically, we showcase how RE-PREF is used in a remote data mirroring (RDM) system. The model of NFRs and the analysis of their preferences are enabled by using dynamic decision network (DDNs) and Bayesian Surprise.**

***Index Terms*—Self-adaptation; decision making; non-functional requirements trade-off, uncertainty.**

I. Introduction

Due to the nature of the conflicting requirements involved, decision making process implied multi-objective decision making [1], [2]. Multi-objective decision making techniques often depend on constructing a utility function, defined as the weighted sum of the different objectives associated with the NFRs. Different techniques have been used to specify utility preferences for NFRs and decision-making strategies of self-adaptive systems (SAS). These preferences are defined during design-time and it is well known that correctly identifying the weight of the quality attributes is a major difficulty [1]. In this poster we present RE-PREF, our ongoing work on a model based on dynamic decision networks (DDNs) [3] and a set of criteria to reassess NFRs given new evidence found at runtime. RE-PREF uses both, conditional probabilities provided by DDNs and the concept of Bayesian surprises [4]. By using RE-PREF we will showcase (i) how high NFRs preferences can trigger unneeded adaptations and (ii) how low NFRs preferences can prevent needed adaptations. RE-PREF highlights the benefits of run-time analysis of preferences and contributes to explain the potential of the use of utility functions based on models of DDNs combined with Bayesian surprises [4] to allow the reassessment of NFRs preferences at runtime.

II. Background

DDNs have been used as a mechanism which allows SASs to keep track of the current state and trade-off of NFRs [3], [5]. They are abstractions for reasoning over time about the world [6]. DDNs provide a set of random variables that represent the NFRs. Fig. 1 shows a DDN during several time slices where X_t denote a set of state variables (i.e. NFRs) at time t, which are unobservable, and E_t to denote the observable evidence variables. A DDN links decision maker preferences U_t (i.e. utility nodes), state and evidence variables to make informed decisions D_t (i.e. decision nodes).

A Bayesian surprise measures how observed data affects

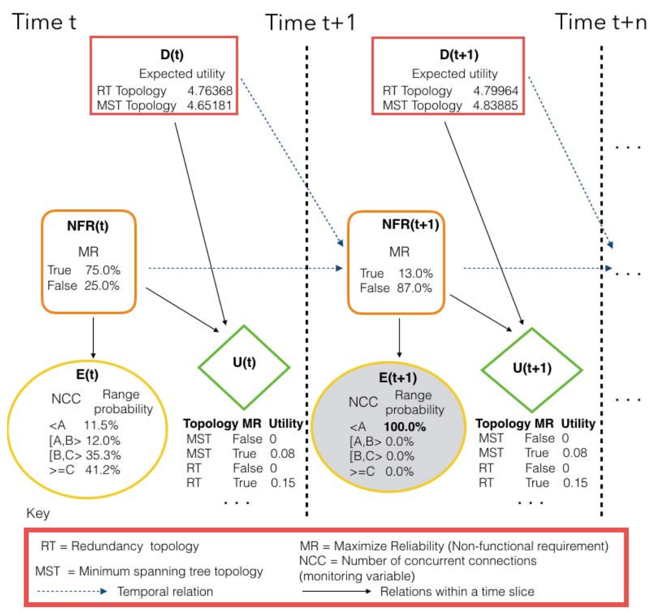

Fig. 1. Example of DDN structure.

the models or assumptions of the world during runtime [4]. The surprise represents the divergence between the prior and posterior distributions of a NFR and is calculated by using the Kullback-Leibler divergence (KL) [7]. Lets us have a non-functional requirement NFR_i, and E representing the evidence provided by the properties monitored as variables in the execution environment. P(NFR_i) is the prior probability of the non-functional requirement NFR_i being partially satisficed and P($NFR_i|E$) is the posterior probability of the NFR_i being partially satisficed given the evidence E.

$$S(NFR_i, E) = KL(P(NFR_i|E), P(NFR_i)) =$$

$$\sum_i P(NFR_i|E) \log \frac{P(NFR_i|E)}{P(NFR_i)} \qquad (1)$$

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III. Toward reassessing utility preferences

RE-PREF allows the access to runtime evidence about possible adverse effects of utility preferences during execution by (i) Allowing the identification of a range of scenarios during the execution of the system and the corresponding effects they have on the satisfaction of relevant NFRs (ii) Highlighting the environmental properties in the execution environment which have highest effects on the satisfaction of the NFRs (and possible unknown at design time). By using surprises and conditional probabilities provided by the DDN, the approach supports better understanding of the execution environment while assessing the responses of the running system.

A. RE-PREF case study

A real case study based on a Remote Data Mirroring (RDM) [8] was used to apply RE-PREF. RDM is a technique with the goal of protecting data against inaccessibility and to provide further resistance to data loss [8]. An RDM application can be configured in different ways, for example in terms of the network's topology, minimum spanning tree (MST) vs. redundant topology (RT). A RT topology offers a higher level of reliability than a MST topology. However, the costs of maintaining a RT topology may be prohibitive. These context has been modelled by using a DDN which included as NFRs Minimize Operational Cost (MO) and Maximize Reliability (MR). Preferences were defined at design time, and the model was analysed at runtime. RE-PREF has the following steps (see Fig. 2):

- Compute Bayesian surprises between probability distributions of NFRs for each two consecutive time slices.
- If a surprise is detected, using conditional probabilities provided at runtime by the model, the current level of satisfaction of the NFRs is analysed.
- If the self-adaptation strategy chosen at runtime by the model (i.e, the decision performed) is producing a negative impact on the current satisfaction levels of the NFRs, this scenario is highlighted by RE-PREF as a possible opportunity to improve the decision making process by reassessing the NFRs preferences. Surprises and conditional probabilities are not influenced by the NFRs preferences of the stakeholders. However, the decision making process of the model is based on the utility preferences defined initially by the stakeholders.

By using RE-PREF, we will demostrate details of the experiments performed.

B. Analysis of results

Two scenarios have been identified to flag up the need for revisiting the quality attribute preferences defined by the stakeholders previously, (i) **Scenario 01 - surprises and needed adaptation**. There are surprises, there is no adaptation, and the conditional probabilities suggest to make an adaptation and (ii) **Scenario 02 - surprises and unneeded adaptation**. There are surprises, there is adaptation, and the conditional probabilities suggest to not to make an adaptation. The approach provides an opportunity to improve the decision making and behaviour of the system.

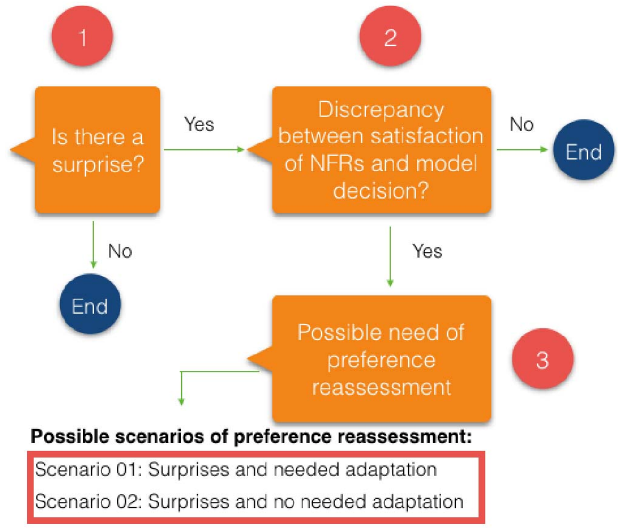

Fig. 2. Approach for preference reassessment at runtime

IV. Conclusions and future work

The next step for RE-PREF will be to explore mechanisms for autonomic NFRs preferences updating. Some MCDA approaches such as Analytic Hierarchical Process (AHP) are being used for specifying NFRs preferences [10]. We believe that RE-PREF is novel and has potentially significant implications for RE research in other areas such, autonomous and self-aware systems. It is important to solicit feedback from the RE community and create awareness of the importance of the research topic for future editions of the RE Conference, RE 2016 is an ideal venue for this. We hope that by promoting RE-PREF at RE 2016, we may be able to identify collaborators for our future work in this area.

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APPENDIX

This appendix describes how the showcase will be organized.

A. POSTER

We will show how RE-PREF allows to discover possible scenarios where chosen preferences may not agree with contexts found at runtime that can either make the system miss adaptations or suggest unnecessary adaptations that may degrade the behaviour of the running system. We will show (i) how high NFRs preferences can trigger unneeded adaptations and (ii) how low NFRs preferences can prevent needed adaptations.

RE-PREF highlights the benefits of run-time analysis of preferences supported by the approach. The approach is applied to a real case study, a remote data mirroring (RDM) application, which is used to explain our goals, we will show how requirement engineers and domain experts will be supported to reason about discovering possible needs of NFRs preference reassessment. An overview of RE-PREF will be shown using Figures 1,2, 3, 4, 5 and 6. Specifically Fig. 1 shows part of a DDN representation with decision and utility nodes, highlighting the NFRs preferences defined by the stakeholders at design-time. Solving a decision network (DN) refers to finding the decision that maximizes the expected utility (EU). The EU is computed using these preferences as follows:

$$\mathbf{EU}(\mathbf{d_j}|\mathbf{e}) = \sum_{\mathbf{x_i} \in \mathbf{X}} \mathbf{U}(\mathbf{x_i}, \mathbf{d_j}) \times \mathbf{P}(\mathbf{x_i} \mid \mathbf{e}, \mathbf{d_j}) \tag{2}$$

In equation 2 above, $P(x_i \mid e, d_j)$ is the conditional probability of $X = x_i$ given the evidence e and the decision d_j. The random variables X_i correspond to the levels of satisficement of the NFRs.

Fig. 3 shows how the surprises are calculated using the prior and posterior distributions of NFRs and the KL divergence. Surprises together with conditional probabilities provided by the DDN model, allows us to discover possible scenarios to provide a better informed decision making process at runtime. Fig.6 shows the context of the experiments and computed surprises during 13 time slices. Using RE-PREF, we will show:

1) how NFRs preferences, alternative decisions, NFR satisfaction levels and their relations can be represent at runtime using a probabilistic approach: DDNs. (Fig. 1)
2) how using Bayesian Surprise, and conditional probabilities,which can be detected at runtime (per each time slice), can be identified possible needs of NFR preferences reassessment. (Fig. 3)
3) possible scenarios, at runtime detected, as opportunities to enhance the decision making of the system. These scenarios will allow us to identify the need for revisiting the quality attribute preferences defined by the stakeholders previously and provide an opportunity to improve the decision making and behaviour of the system. (Fig. 2)

B. Applying RE-PREF: RDM Case Study

RDM, the case to be used is a technique with the goal of protecting data against inaccessibility and to provide further resistance to data loss.

DDN context: A DDN for the application RDM has been designed according to two alternatives network topologies: MST and RT as described above. Each configuration provides different levels of data protection and costs which are the quality attributes Minimize Operational Cost (MO) and Maximize Reliability (MR). The experiments scenario is as follows: the states of two monitored variables NCC=*"Number of Concurrent Connection"* and C=*"Active network links reduce operational costs"* are monitored dynamically. The value of C can be either true or false and the values for NCC are different possible ranges represented by the expressions: $NCC < A$, NCC in $[A, B >$, NCC in $[B, C >$, and NCC$>= C$. At design time, C have been considered valid (true) and NCC $>= C$.

Surprises context: For the experiments, the prior models for surprise computation are P(MR) and P(MO), and the posterior models when an evidence has been observed over the time are P($MR|NCC$) and P($MO|C$). Fig. 4 and Fig. 5 show prior and posterior distributions for MR and MO, and several time slices (e.g., time slice 9) show divergences between its distributions (Fig. 6). It has been computed surprises based on the KL-divergence. Surprises take place in several time slices where different scenarios have been identified. Fig. 6 shows the observed values for NCC and C variables and the surprises S1 and S2 which are the divergence between the prior and posterior distributions for the quality attribute MR and MO respectively. Both, S1 and S2, are computed for each time slice.

Experiments: Four specific scenarios were identified. The poster will highlight in special two of them: *Scenario 01 - surprises and needed adaptation*. and *Scenario 02 - surprises and unneeded adaptation*. Both scenarios are described below.

1) Scenario 01 - Surprises and needed adaptation: We can observe that in time slice 9 (Fig. 6) there are surprises, however, the DDN has not suggested any adaptation. Studying the conditional probabilities provided by the DDN under the current conditions: i.e. P($MR = true|NCCin[B, C >, C = true$) = 0.795 (see Fig. 4, time slice 9) and P($MO = true|NCCin[B, C >, C = true$)=0.953 (see Fig. 5, time slice 9), we can see that *the probability for MR is lower than the probability for MO*. The selected choice, i.e. *not to adapt*, may not be the best choice given the current situation: *lower probability for MR than the probability for MO*. Continuing using RT as the configuration would create unnecessary costs as the complementary information provided by the conditional probabilities suggest the use of the less costly topology MST. The surprises and the conditional probabilities that are not influenced by the

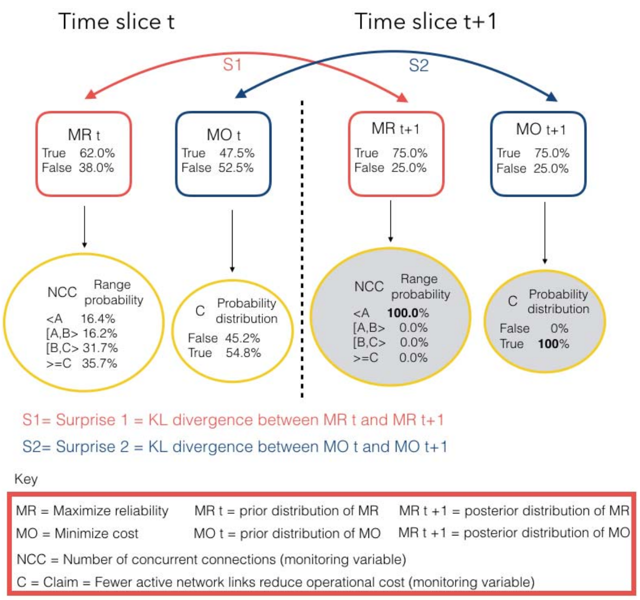

Fig. 3. Structure for Computing Surprises - Experiment

stakeholders' preferences, help us to flag up this situation. **This scenario is an example of how surprises and the conditional probabilities provided by the DDN can flag up the possible need of adaptation**. The above imply the need to revisit the quality attribute preferences defined by the stakeholders previously.

2) *Scenario 02 - Surprises and unneeded adaptation:* We can see that in time slice 3 (Fig. 6) there are surprises and an adaptation is suggested by the DDN. Studying the conditional probabilities provided by the DDN under the current conditions: P($MR = true|NCCin[A, B >, C = true$) = 0.133 (see Fig. 4, time slice 3) and P($MO = true|NCCin[A, B >, C = true$)=0.964 (see Fig. 5, time slice 3), we can see that *the probability for MR is low*. On the other hand, *the probability for MO is high*. The selected choice, *i.e. to adapt*, certainly may not be a good selection for the current situation: *low probability for MR and high probability for MO*. Using RT would create unnecessary costs as the complementary information provided by the conditional probabilities suggest to use the less costly topology MST. The surprises and the conditional probabilities supported flagging up the situation. **The scenario is an example of how surprises and conditional probabilities can highlight the need of avoiding unnecessary adaptations**. The previous findings imply the need to reasses the quality preferences defined by the stakeholders during design-time.

These scenarios have been detected by using RE-PREF and it is corroborated that RE-PREF may be applicable in real-world domains. Improved versions of this approach will explore new real-world contexts with simulation purposes, and could become the seed of a more sophisticated tools that could eventually be integrated in SASs.

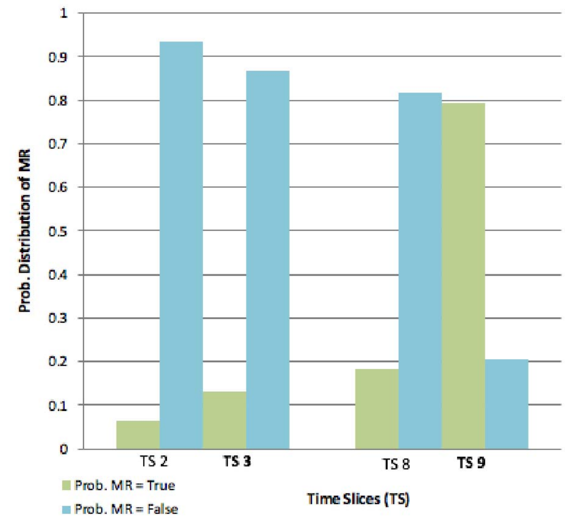

Fig. 4. Prob. distribution of NFR Maximize Reliability - Experiment

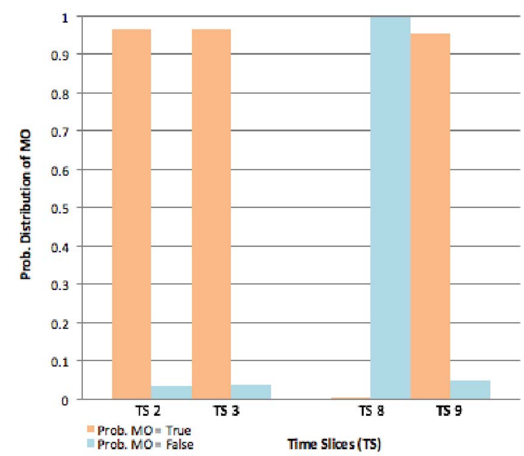

Fig. 5. Prob. distribution of NFR Minimize Costs - Experiment

Time slice (TS)	Adaptation	S1	S2	NCC Monitored values	C Monitored values	Current Topology
1	-	0	0	NCC >= C	True	RT
2	Yes	1.003584235223648	0.7150925003192315	NCC <A	True	MS
3		0.04381918744008068	1.6949044399769875E-4	NCC in [A,B>	True	RT
4		0.0	0.0	NCC in [A,B>	True	RT
5		0.0	0.0	NCC in [A,B>	True	RT
6		0.01424282209204613	4.76049740064592	NCC in [A,B>	False	RT
7		0.0	0.0	NCC in [A,B>	False	RT
8		0.0	0.0	NCC in [A,B>	False	RT
9		1.2757774188794533	8.762523955312945	NCC in [B,C>	True	RT
10		0.0	0.0	NCC in [B,C>	True	RT
11		0.0	0.0	NCC in [B,C>	True	RT
12		0.0	0.0	NCC in [B,C>	True	RT
13		0.0	0.0	NCC in [B,C>	True	RT

Fig. 6. Experiment - Summary of surprises and monitored values