WiRKSam: An Approach to Maximize the Functionality of Multi-Factor Systems

Sama Khosravifar
Computer Science, University of Tehran, Tehran, Iran
Email: sama.khosravifar@gmail.com

KEYWORDS

Service Coverage, Satisfaction, Performance Analysis.

ABSTRACT

We introduce in this paper a hospital system as a multi-factor model and concentrate on system's performance. We give a formalization of profit considering service fees and costs and use it to explain the reasoning process of such system that investigates the most efficient setting to to keep a maximal state of profit. The proposed system is domain-specific and considers some relative parameters. However, the approach is general and could be applied to other similar models. The architecture is illustrated in the paper and a discussion on the functionality of this approach in the design is presented.

1 INTRODUCTION

Multi-factor systems are models inspired by decision theory and used to create technological extensions to routine human-designed systems (4). These systems are designed to increase the model's performance in decision makings that yield best profit (3). Obviously, these systems are able to cope with the uncertainty on the environment and increase their individual utility (5). They are important due to bounded nature of human decision making's abilities in complex societies. Consider the following scenario. A big national hospital is known based on its reputation (7). The reputation reflects society's public opinion that is categorized to different factors about the performance of the hospital in serving patients. In general, people prefer highly reputed hospitals, however, some factors like their expenses might prevent vising one and some other factors like their surgery and diagnosis success might encourage one to visit. Preferences are the proactive attitude of individuals, the motor that make the individual patient act, while satisfying his given set of conditions.

In literature, there have been many attempts to address intelligent system designs (6). In the work done by Bhanu and Balasubramanie (2), authors extend the applicability of association rules. They propose a model to investigate the difference between two sets of rules from data-sets in diverse cases. Their result could be applied to generate the rules for a new situation based on available data obtained from the environment. Bastanfard and katebi in (1) consider a multi-agent system that hosts distributed agents with local perceptions that try to achieve a unique goal. Authors provide effective social intelligence and improved performance of individual agents in a cooperative multi-factor system. They obtain their results by decisions made by the agents using reinforcement learning methods. In (8), Rosenfeld applies the principle of Maximum Entropy (ME). Each information source gives rise to a set of constraints, to be imposed on the combined estimate. The intersection of these constraints is the set of probability functions which are consistent with all the information sources. The method is applied in SPHINX-II, Carnegie Mellons speech recognizer and results shows 10 to 14 percent reduction in error rates.

In this paper, we introduce a hospital reputation mechanism that considers some relative parameters to reputation evaluation and study the case where such reputation brings the best profit when serving customers. For simplicity reasons and to achieve a high focus, we discard some non-relevant (or not highly relevant) factors and restrict the reputation model to five crucial parameters: (1) hospital service coverage; (2) hospital satisfaction rate; (3) hospital mean expense value; (4) hospital surgery success rate; and (5) hospital diagnosis success rate. Considering these parameters, we evaluate hospitals reputation value and use it as a means to estimate expected revenue of the hospital. In general, we estimate the hospital's expected profit and investigate cases where optimal profit is achievable. In this mechanism, we use the normal distribution that models the random rates provided for the typical hospital. We aim to theoretically analyze the impacts that parameters have on one another and deduce cases where the hospital vividly expects maximum profit and can accordingly set the controllable parameters. For example, the hospital might invest on adding some service coverage and thus increase the associated factor. This act would bring more patients and thus more revenue that would compensate the investment. Adversely, the hospital might not obtain acceptable results from investing on the surgery success factor. Therefore, some learning and analysis is required to investigate the case where optimal profit is achievable.

The remainder of this paper is as follows. In Section 2, we develop the proposed model and introduce the important factors. In Section 3, we start the discussion about hospitals performance considering the optimal reputation. We base the discussions on the dependency of the optimal case to the involved factors. We elaborate on inter-relation of involved parameters and extract the op-

Proceedings 26th European Conference on Modelling and Simulation ©ECMS Klaus G. Troitzsch, Michael Möhring, Ulf Lotzmann (Editors)
ISBN: 978-0-9564944-4-3 / ISBN: 978-0-9564944-5-0 (CD)

timization problem as a linear program. In Section 4, we discuss some results obtained from theoretical analysis of the reputation parameters. We represent the simulation and outline the properties of our model in the experimental environment, and finally, Section 5 concludes the paper.

2 THE MODEL

2.1 Parameters

Considering the hospital (referred as u) reputation model as a multi-factor system, we extend more details about each one of the considered parameters and their co-relation with optimal profitable case. These factors are listed in the following.

Hospital Service Coverage ($u.cg$): This value represents the extend to which a hospital is able to provide service to customers ($u.cg \in [0, 1]$). For example, a well-equipped hospital assigns a better coverage parameters than a small hospital that lacks some equipments and fails to provide some certain services. This value is discretely evaluated for all hospitals and is clear to the community. However, an investment in coverage system would increase this value. Obviously, high coverage factor results in more demand regarding patients. Adversely, high coverage brings more maintenance fee for the hospital and therefore, a rational system would consider reasonable rate before design. The reasonability is inspired by the environment where the system is designed.

Hospital Satisfaction Rate ($u.sf$): This value represents the extent to which a hospital provides satisfactory services ($u.sf \in [0, 1]$). This value is computed by accumulating the satisfaction feedback posted by the visiting patients (p). These feedback only extends patients impression about the service. Therefore, could be different considering two different patients. For instance, a patient might post negative feedback only because she felt the service was expensive, whereas the other one posts positive feedback because she is happy with the diagnosis even though she paid a fortune. In satisfaction accumulation, we respect different opinions, but we relax the accumulation by applying the time discount factor to bring up more recent feedback that reflect recent service quality of the hospital. This idea helps up to prevent feedback affect regarding two years ago influence hospital's satisfaction rate in a wrong way.

Consider two types of feedback posted by patient p: $+1$ for positive impression and -1 for negative impression for any reason whatsoever. The posted feedback regarding hospital u by patient p is refereed by $p.f_u$ and the time discount factor associated to this feedback is denoted by $p.f^t$. To evaluate the satisfaction rate, we simply collect all the positive feedback and divide by the sum of all posted feedback. We consider the notion of time to act impartial with respect to time of posting feedback. Equation 1 computed $u.sf$ parameter.

$$u.sf = \frac{\sum_t \sum_{p \in P} (\frac{p.f_u + 1}{2}) \times p.f^t}{\sum_t \sum_{p \in P} |p.f_u| \times p.f^t} \tag{1}$$

Hospital Mean Expense Value ($u.ep$): This value represents the extent to which the hospital is expensive. This value is also ranges between 0 and 1. One can consider $u.ep$ as a factor to predict the cost of her specific service request ($expectedCost = f_1(u.ep, serviceType)$). This value is also assigned by the hospital and is under its control. The hospital would decide about the rate and considers its influence on the satisfaction rate and the customer absorbtion.

Hospital Surgery Success Rate ($u.sg$): This value represents the hospital's success rate in operation. The rate is ranged in $[0, 1]$ and inspired by public community's giving rates. This value is out of control of the hospital. However, by investment the hospital expects improvement in this rate. In general, the investment to improve successful surgery rate is quite expensive since it involves research, high salaries, and expensive equipments. Meanwhile, the improvement dramatically influences the satisfaction rate provided by the patients. Like other parameters, the hospital has to balance this parameter to obtain acceptable profit.

Hospital Diagnosis Success Rate ($u.dg$): This value is similar to hospital's surgery success rate in the sense that it also reflects hospital's accuracy in providing the service. However, it is more general compared to surgery in the sense that a big portion of hospital's covered service falls into diagnosis and only a group of patients undergo a surgery treatment. Due to sensitivity of the surgery treatment and its crucial impact on hospital's reputation, we separate surgery success rate from the diagnosis rate to obtain more realistic image about the general reputation of the hospital. But similar to $u.sg$, hospital's diagnosis rate could be expected to improve upon investment. Without an investment, the hospital can compute the relaxed value regarding this parameter over time and keep it unchanged with respect to associated cost of maintenance. In fact, we assume that over time elapse, the hospital obtains an idea how well the diagnosis rate would be and if reasonable, decides to keep it intact.

2.2 Reputation Evaluation

Considering the aforementioned involved parameters, we proceed forward to compute the hospital's general reputation upon which one can use as a means to categorize her choices. For evaluating this value, we associate five different coefficient (c_i, $i = 1, 2, .., 5$) to apply weights that impose importance of the involved factor. Coefficients are ranged in $[0, 1]$and sum to 1. The reputation $u.Rep$ is computed (see equation 2) as a dot product of

coefficients and parameters vectors. c_i by default could be considered as 0.2. But inspired by the community, the system could associate variety of values to these coefficients. Logically the hospital will find out about these coefficients upon received periodic (could be annual) reports and accordingly could apply best strategies to the controlled ($u.cg$ and $u.ep$) and expected ($u.sf$, $u.sg$, and $u.dg$) parameters that yield the optimal profit.

$$u.Rep = \overrightarrow{c}.\overrightarrow{u} \quad where \tag{2}$$
$$\overrightarrow{c} = [c_1 \quad c_2 \quad c_3 \quad c_4 \quad c_5]^T \quad and$$
$$\overrightarrow{u} = [u.cg \quad u.sf \quad u.ep \quad u.sg \quad u.dg]^T$$

3 OPTIMAL REPUTATION

In previous Section, we computed the public reputation assigned to the hospital u in equation 2. But this pushes the hospital to a challenge to optimize the reputation to yield the maximum profit. In fact, the hospital is not aware of the exact coefficient values together with some expected parameters. But still, it learns based on experience of serving a number of customers and reports received on coefficients. To clarify the objective of this part, we disregard any non-relevant issue with respect to dynamism of the environment and components distributions. We only concentrate on policy alteration that cause reputation alteration and ends up in a terms we highlight as reputation change R. We compute the reputation change as the percentage of reputation increase (in some cases even decrease) with respect to any sort of policy alteration. Equation 3 computes this value that ranges in $[-1, +1]$. In this equation $u.NRep$ denotes the new reputation computed as a result of any sort of policy alteration such as service coverage increase, surgery or diagnosis success rate improvements, etc.

$$R = \frac{u.NRep - u.Rep}{u.Rep} \tag{3}$$

Now consider the obtained payoff as a result of a policy change. This would be the main challenge for the hospital. We compute the payoff by subtracting the investment (referred as $u.cst$) from the obtained revenue as a result of the policy alteration. The obtained revenue is the product of the reputation change R, mean visiting customer λ_c, and mean customer fee $\beta \times u.ep$. Here β represents a supreme fee and hospital's expense rate would generalize it to its mean charging fee. Equation 4 computes the payoff depending on the reputation change.

$$Pf = R \times \lambda_c \times (\beta u.ep) - u.cst \tag{4}$$

Since the hospital changes the policy, the reputation change would be only expected. Therefore, the obtained payoff is also expected (see equation 5).

$$[Pf] = [R] \times \lambda_c \times (\beta u.ep) - u.cst \quad where, \tag{5}$$

$$[R] = \frac{[u.Rep] - u.Rep}{u.Rep} \quad and$$
$$[u.Rep] = \overrightarrow{c}.[\overrightarrow{u}]$$

We conclude that the policy alteration is emerged by investing on some issues that bring an improvement expectation on some parameters. For simplicity, let the controllable parameters ($u.cg$ and $u.ep$) stay the same. In equation 6, we re-write the parameter vector $\overrightarrow{u}$ with the expected uncontrollable parameters.

$$\overrightarrow{u} = [u.cg \quad [u.sf] \quad u.ep \quad [u.sg] \quad [u.dg]]^T \tag{6}$$

In order to step forward addressing the optimal payoff, we need to compute the expected parameters. Then we can follow computing the best reputation change yielding the maximum obtained payoff. To this end, consider the parameters deviate with respect the applied investment and change by a factor called α. For instance, the expected satisfaction rate would be multiplied by $(1+\alpha_{sf})$. The following Equations substitute the expected parameters.

$$[u.sf] = u.sf(1 + \alpha_{sf}) \tag{7}$$
$$[u.sg] = u.sg(1 + \alpha_{sg}) \tag{8}$$
$$[u.dg] = u.dg(1 + \alpha_{dg}) \tag{9}$$

Combining the previous equations, we can compute the reputation differentials ($d(u.Rep)$) in the following equation. We carry on the assumption that controllable parameters stay intact.

$$d(u.Rep) = c_2\alpha_{sf} + c_4\alpha_{sg} + c_5\alpha_{dg} \tag{10}$$

In order to capture the realistic role of the optimal reputation in optimal payoff, we propose a heuristic function that utilizes an exponential function rather than a normal linear function. The rational behind this idea is the fact that reputation improvement dramatically boosts the profit. This assumption supports the idea that reputation lasts long and brings customers to the hospital. To this end, we believe it is realistic to consider exponential growth rather than linear one. However, the exponent in the heuristic function would not exceed 1 and this way we prevent huge values in profits. Equation 11 introduces a new parameter hospital's obtained payoff ($u.Opf$) and computes the value considering costs regarding satisfaction, surgery, and diagnosis improvements. We assumed so far that the coverage and expense rates stay intact, but we can assume overall service improvements that increase satisfaction factor. This could be simply an alteration in method of payments, or applying some policies that use the same budget, etc. In this Equation, c_{sf}, c_{sg}, and c_{dg} respectively denote costs regarding satisfaction, surgery, and diagnosis improvements.

$$u.Opf = pf(e^{\frac{d(u.Rep)}{u.Rep}} - 1) - (c_{sf} + c_{sg} + c_{dg}) \tag{11}$$

The objective is to maximize the hospitals obtained payoff $u.Opf$. Addressing this approach, first consider the case where the only attempt is to improve the satisfaction, therefore the only cost is c_{sf}. In this case, improving the overall service, the only updated parameter is $u.sf$. Therefore, reputation differential (originally obtained from Equation 10) would be re-computed in Equation 12. In this Equation, ϵ relaxes the unavoidable influences regarding overall service improvement. Accordingly, Equation 13 computes the exponent of the exponential heuristic function that we pointed out earlier.

$$d(u.Rep) = c_2\alpha_{sf} + \epsilon \tag{12}$$

$$\frac{d(u.Rep)}{u.Rep} = \frac{c_2\alpha_{sf} + \epsilon}{c_2\alpha_{sf} + c_4\alpha_{sg} + c_5\alpha_{dg} + \epsilon} \tag{13}$$

We highlight the fact that to be profitable, the alteration strategy would be applied if at the first spot the following condition is held.

$$e^{\frac{d(u.Rep)}{u.Rep}} > \frac{c_{sf} + pf}{pf}$$

Simplifying the inequality, we obtain a new inequality that we use it as a constraint in maximizing the hospital's obtained profit as a linear program.

$$\Rightarrow d(u.Rep) > u.Rep.ln(\frac{c_{sf}}{pf} + 1)$$

Forcing the constraint imposes positive rate of change to the reputation change R (computed in 3) in case of solely satisfaction improvement. Likewise, we obtain other constraints forcing profitable surgery investment, diagnosis improvement, and the package improvement as a whole. Equation 14 represents the $argmax$ of the hospital's obtained payoff as a linear program with respect to the crucial constraints.

$$u.Opf = argmax\ \ pf(e^{\frac{d(u.Rep)}{u.Rep}} - 1) - (c_{sf} + c_{sg} + c_{dg}) \tag{14}$$

$$subject\ \ to$$

$$d(u.Rep) > u.Rep.ln(\frac{c_{sf}}{pf} + 1)$$

$$d(u.Rep) > u.Rep.ln(\frac{c_{sg}}{pf} + 1)$$

$$d(u.Rep) > u.Rep.ln(\frac{c_{dg}}{pf} + 1)$$

$$d(u.Rep) > u.Rep.ln(\frac{c_{sf} + c_{sg} + c_{dg}}{pf} + 1)$$

Considering the results obtained in Equation 14, the hospital that applies diverse (costly) enhancement strategies needs to consider the obtained linear program with respect to its constraints to achieve the best possible payoff. We believe that using this linear system dramatically increase such hospital's performance in terms of profit.

Table 1: Different objects with diverse parameters and reputation values. In this environment all reputation coefficients c_i are constant and 0.2.

Objects	$u.cg$	$u.sf$	$u.ep$	$u.sg$	$u.dg$	$u.Rep$
u_1	0.60	0.47	0.38	0.31	0.51	**0.45**
u_2	0.64	0.41	0.54	0.11	0.72	**0.48**
u_3	0.72	0.37	0.27	0.19	0.87	**0.48**
u_4	0.43	0.29	0.39	0.45	0.46	**0.40**
u_5	0.28	0.54	0.73	0.27	0.37	**0.44**
u_6	0.58	0.68	0.48	0.38	0.32	**0.49**

In the next Section, we explore more details about the implemented system which its outcome performance is relevant to a multi-factor system. We expand details about different implemented models and their success rate to achieve the objective results.

4 EXPERIMENTAL RESULTS

In this section, we implement a system called $WiRKSam$ to model a multi-factor hospital reputation system. The objective is to maximize one's obtained profit as a result of systematic quality enhancement. To achieve this goal, we discuss in the rest of this chapter the parameters related to different cases that are obtained from different scenarios. We capture the progress pattern and compare it with the results we obtained in the theoretical part.

In the implemented system, entities are implemented as $Java^{©TM}$ objects, i.e. they inherit from the basic class $Java - Simulator^{©TM}\ Entity$. The object of the main class represent a hospital that is capable of applying a range of changes on its associated parameters. This object's reasoning capabilities are implemented as *Java modules* using logic programming techniques. As Java classes, the objects have private data called *Belief Data*. The different enhancement changes are given by a data structure and implemented using tables and the different actions expected by the object in the context of a particular enhancement strategies are given by a table called $data\_representative\_manager$. The different objects' reputation values that an object obtains in the system are recorded in a data structure called $data\_reputation$. In different scenarios, each object has a knowledge base about its improvements in the past scenarios, called $table\_reputation$. Such a knowledge base has the following structure: $Object - name$, $Object - reputation$, $Total - interaction - number$ and $Recent - interaction - time$. We highlight the most important results that is consistent with the results we obtained in the theoretical part.

Table 1 categorizes different objects from the same hospital class that follow different strategies. The parameters associated to these objects are randomly generated and follow a normal distribution. In this Table, the reputation parameter weights are considered as con-

Table 2: Different objects with diverse parameters and reputation values. In this environment the reputation coefficients c_i are random and different where the objects are not aware of them.

Objects	$u.cg$	$u.sf$	$u.ep$	$u.sg$	$u.dg$	$u.Rep$
u_1	0.60	0.47	0.38	0.31	0.51	**0.47**
u_2	0.64	0.41	0.54	0.11	0.72	**0.47**
u_3	0.72	0.37	0.27	0.19	0.87	**0.50**
u_4	0.43	0.29	0.39	0.45	0.46	**0.40**
u_5	0.28	0.54	0.73	0.27	0.37	**0.44**
u_6	0.58	0.68	0.48	0.38	0.32	**0.53**

Table 3: Matrix of coefficients regarding 6 different objects. In this environment the reputation coefficients c_i are random and different where the objects are not aware of them.

Objects	c_1	c_2	c_3	c_4	c_5
u_1	0.30	0.20	0.20	0.15	0.15
u_2	0.20	0.40	0.25	0.10	0.05
u_3	0.25	0.35	0.10	0.15	0.15
u_4	0.20	0.15	0.35	0.20	0.10
u_5	0.35	0.40	0.10	0.05	0.10
u_6	0.20	0.30	0.30	0.10	0.10

sistent portions of 0.2. A more realistic values with randomly generated portions are shown in Table 2. However, in Table 2, the objects are not aware of the intermittent portions and to thus follow more risky strategies in their further enhancement changes. The unknown portion weights regarding 6 different objects are presented in Table 3. Henceforth, we use these coefficients as a reference to compute one's reputation.

We continue the discussions with more details about different strategies that 6 objects could adopt in order to advance their reputation values. To complete this analysis, we categorize objects to three different classes of (1) *random strategy*, which is followed by objects u_1 and u_2; (2) *expense strategy*, which is followed by objects u_3 and u_4; and (3) *efficient strategy*, which is followed by objects u_5 and u_6. In general, we consider that all objects have same amount of budget, but use it by different strategies. The objects following random strategy consume the budget on different sectors and thus enhance the parameter values with no reasoning. These users might increase the coverage, or invest on enhancing the diagnosis, or decreasing the expense fees. Consequently, objects belonging to this category obtain different results based over their random enhancement changes. The objects following the expense strategy mainly concentrate on enhancing the expense factor and obtain results that correlate to their payoffs. To this end, the objects belonging to this group might enhance their reputation to some extent, but mainly focus on the ways to obtain more payoffs. But the objects following the efficient strategy consider the obtained results in their analysis and try a range of enhancement strategies to increase their reputations.

Table 4: Enhanced parameters of different objects following different strategies. This is an independent enhancement of the state represented in Table 2.

Objects	$u.cg$	$u.sf$	$u.ep$	$u.sg$	$u.dg$	$u.Rep$
u_1	0.80	0.49	0.38	0.35	0.55	**0.55**
u_2	0.64	0.45	0.52	0.15	0.75	**0.49**
u_3	0.72	0.50	0.40	0.22	0.85	**0.56**
u_4	0.47	0.50	0.43	0.47	0.50	**0.46**
u_5	0.58	0.62	0.70	0.28	0.40	**0.57**
u_6	0.68	0.69	0.40	0.39	0.35	**0.54**

Table 5: Enhanced parameters of different objects following different strategies. This is another independent (of results shown in Table 4) enhancement of the state represented in Table 2.

Objects	$u.cg$	$u.sf$	$u.ep$	$u.sg$	$u.dg$	$u.Rep$
u_1	0.75	0.52	0.35	0.32	0.59	**0.54**
u_2	0.75	0.50	0.50	0.12	0.72	**0.52**
u_3	0.72	0.40	0.50	0.25	0.87	**0.54**
u_4	0.65	0.32	0.40	0.45	0.46	**0.45**
u_5	0.45	0.60	0.73	0.35	0.40	**0.53**
u_6	0.60	0.70	0.55	0.39	0.35	**0.57**

The objects belonging to this group follow the methodology we represented in this paper. Tables 4 and 5 represent the upgraded parameters obtained from the state corresponding to Table 2. We also show the enhancement percentage of the overall reputation value with respect to the previous case for both of these enhancements in Table6.

The enhancement strategies adopted in Table 4 reflect object u_1's concern about investing on service coverage (0.60 is upgraded to 0.80). In this improvement, the object accordingly obtains higher satisfaction factor (0.47 is upgraded to 0.49). The object u_2 concerns more about the surgery and diagnosis factors and invest on these rates. However, for high investment and their costly enhancements, the improvement is not dramatic (0.11 is upgraded to 0.15 and 0.72 is upgraded to 0.75). Objects u_3 and u_4 mainly concern about the correlated factors with expense issues. The expense factor is highly enhanced by user u_3 (0.27 is upgraded to 0.40) and the satisfaction factor is advanced by u_4 (0.29 is upgraded to 0.50). Objects u_5 and u_6 concern about overall reputation value and investigate the methods that yield the best outcomes. Therefore, these objects start with enhancing the parameters on random basis to comprehend the estimated coefficients with respect to the obtained results. Following this strategy, these objects would have an impression on the fact that how they can effectively use their budget to enhance their reputation values to their optimal cases.

Results shown in Table 5 are also obtained from another independent enhancement over the state corresponding to Table 2. In this Table, objects follow their built-in strategies and therefore, obtain different results. Table 6 compare these two enhancements but their inde-

Table 6: Different reputation improvement results with respect to independent enhancement over state shown in Table 2.

Objects	$Table4$	$Table4$
u_1	17%	15%
u_2	4%	10%
u_3	12%	8%
u_4	15%	12%
u_5	29%	20%
u_6	1%	7%

Table 7: Continuation of different reputation improvement results with respect to independent enhancement over state shown in Table 2.

Objects	Imp_1	Imp_2	Imp_3	Imp_4	Imp_5
u_1	17%	15%	13%	17%	19%
u_2	4%	10%	27%	12%	12%
u_3	12%	8%	10%	9%	3%
u_4	15%	12%	10%	3%	20%
u_5	29%	20%	22%	15%	25%
u_6	1%	7%	8%	15%	19%

pendent enhancement does not show how well these objects act while they follow different strategies. To achieve this result, we carry on independent enhancements over state one (shown in Table 2) in Table 7 and compare over objects' success in improving their reputation values.

Considering the impact of strategic enhancement on the reputation parameters, we continue the first state's results and achieve better results that are compatible with our discussions in the theoretical part of this paper. Table 8 represent the cases that are followed by the first state shown in Table 2. In these cases, the reports obtained from each enhancement could be used in the further enhancement changes. The objects following the random strategies generally ignore the received reports and therefore, the continuous upgrade does not influence their enhancement strategies. However, the received reports mainly influence the objects that seek a specific goal, particularly the ones that use efficient strategy. These objects (u_5 and u_6) obtain best results thanks to strategic enhancement changes that they apply to their reputation parameters.

Table 8: Continuous reputation enhancement of different objects initiated from state one shown in Table 2.

Objects	Imp_2	Imp_3	Imp_4	Imp_5	Imp_6	Imp_7
u_1	7%	4%	3%	4%	7%	9%
u_2	3%	2%	7%	10%	5%	1%
u_3	18%	10%	10%	20%	15%	5%
u_4	15%	15%	12%	21%	12%	21%
u_5	21%	25%	26%	29%	27%	22%
u_6	18%	20%	22%	23%	24%	25%

5 CONCLUSION

In this paper, we proposed a strategic performance analysis that is used for multi-factor systems. We specifically considered a hospital system with its relative reputation parameters and mainly concentrated on the facts and reasons where the reputation of such a system undergoes some changes. The strategic performance analysis mainly aggregates different relative parameters and analyzes their influence directly on the reputation. This process is ended up in a linear programming concept that could be taken into account with the intelligent system once some decisions are made under uncertainty. The proposed model is divided into two parts: (1) theoretical part where we aggregate the relative parameters and compute the reputation of a hospital as a multi-factor system; and (2) the experimental part where we develop such a system and expose to diverse settings with known (and unknown) parameters from the environment. We discuss in details about the progress of the strategic model in different settings. We verify the efficiency of the strategic model in parameter settings with respect to the theoretical results.

For our future work, we have a number of ideas that could be applied to the system. We consider the following as our main future objectives: (1) we would like to apply learning methodologies to enhance the quality and efficiency of the hospital's decision making mechanism. The learning technique enables the system to expand more information from the received reports and therefore, forms a more complete impression about the experiences obtained from the past enhancement changes; (2) we also want to expand the experimental environment and expose the system to vaster settings. Accordingly, we would like to investigate the reasons where a system undergoes some changes or adversely why the final reputation value is constrained the same; (3) we also want to enhance the quality of our theoretical analysis by considering different statistical techniques while using different random distribution functions.

REFERENCES

[1] M. Bastanfard and S. D. katebi. Optimization and mutual information through machine learning technique. ISAST Transactions on Intelligent Systems, No. 1, Vol. 1, 2008.

[2] D. Bhanu, P. Balasubramanie. A Predictive and forecasting model for increased sales a rule mining approach. ISAST Transactions on Intelligent Systems, No. 1, Vol. 1, 2008.

[3] S.Y. Chao, Z. Lee, and A. M. Agogino. Warranty and maintenance decision making for gas turbines. In the Proceedings of the AAAI Spring Symposium on AI in Equipment Service Maintenance and Support, 1999.

[4] S. Gasson. Human-centered vs. user-centered approaches. Journal of Information Technology Theory and Application (JITTA), 5(2):29-46, 2003.

[5] A. Kapoor and E. Horvitz. On discarding, caching, and recalling samples in active learning. Proceedings of the Conference on Uncertainty and Artificial Intelligence 2007, AUAI Press, July 2007.

[6] C. Hayes, A. Goel, I. Tumer, A. Agogino and W. Regli. Intelligent support for product design: looking backwards, looking forwards. To appear in ASME Journal of Computing and Information Science in Engineering, 2011.

[7] K. Regan, P. Poupart, R. Cohen. Bayesian reputation modeling in e-marketplaces sensitive to subjectivity, deception and change. Proceeding of the 20'th AAAI Conference on Artificial Intelligence (AAAI), 2006.

[8] R. Rosenfeld. A maximum entropy approach to adaptive statistical language modelling. In Computer, Speech and Language, 10:187-288, 1996.