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PROJECT PORTFOLIO DECISION POLICY ALIGNED WITH ORGANIZATIONAL OBJECTIVES

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Abstract

A Markov Decision Process based decision model is proposed in this paper for computation of optimal decision policy for the project portfolios. As projects are one time activity, often sufficient past data is not available for estimation of the input values required for the decision model. This model requires two matrices the state transition matrix and rewards matrix as input. In this paper, Analytic Hierarchy Process is used for estimation of these input matrices through the use of collective wisdom of decision makers. Markov Decision Process is used for computation of the optimal policy. The developed model is applied on a case study.

Keywords: project management, portfolio management, AHP, MDP.

1. Introduction

The tools in the practice literature on project portfolio management (Project Management Institute, 2017) focus on reporting and review. These tools aim to present the information to the decision maker in effective ways, so as to enable him or her to make informed decisions. However, these tools lack power of computing and suggesting optimal strategies to the portfolio managers. Portfolio managers have responsibility of deciding priority of projects and programs for allocation of resources such as people, funds etc. and ensuring that projects and programs are aligned to organizational objectives (Project Management Institute, 2017). Portfolio managers often face situations where they have to take strategic decisions for achieving organizational objectives. However, the research on portfolio management has mostly been oriented towards selection of projects and design and control of portfolios (Arasteh et al., 2014; Asadabadi & Zwikael, 2020; Belaid, 2011; Blomquist, 2008; de Rooij et al., 2019;

Ghasemzadeh & Archer, 2000; Korde, 2017; Vilutienė & Zavadskas, 2003). The research on taking strategically aligned decisions on the projects by the portfolio management is scarce. In this paper, a model for computation of optimal portfolio policies for decisions to be taken on projects is developed. The proposed model makes use of the collective wisdom of the managing team and helps the portfolio management team with computation of the optimal decision policy. The developed model is applied on a case study and the results are analyzed.

2. Methodology

There are two challenges in finding optimal project portfolio decision policy. The first challenge is that as the projects are one time activity by definition, often historical data is not available for estimation of inputs such as transition probabilities to the computation models. And the second challenge is to compute the optimal portfolio policy for future based on the present state of the portfolio. To address the first challenge, it is proposed in this paper to use collective wisdom of the management team for deciding inputs to the model for computation, as a single decision maker often faces difficulty in making scientific and accurate decisions (Kim & Byeong-Seok, 1997). Curseu et.al., (2013) also suggest that collaborative decisions superior to the average intelligence of groups due to synergic effects (Curşeu et al., 2013). Outcomes delivered by small groups in strategic tasks exceed the most optimistic expectations, or in other words outcomes delivered by small groups in strategic tasks are better than the outcomes from the best (most skilled) individual of the group (Cooper & Kagel, 2005). Many researchers consider the Analytic Hierarchy Process (AHP) to be well suited for making decisions by a group, as it acts like a synthesizing mechanism (Bard & Sousk, 1990; Dyer & Forman, 1992). The group members make use of their knowledge and experience to structure a problem into a hierarchical order and solve it by applying steps of AHP (Al-Harbi, 2001). The AHP is briefly discussed in the section 2.1.

The second challenge is to find optimal project portfolio decision policy Bellman introduced the discrete version of the problem known as Markovian decision processes (MDPs) (Bellman, 1957). In MDPs, the new state reached after taking an action depends only on the previous state and the action taken. It doesn't depend on the previous states (Puterman, 1994). Howard devised the policy iteration method for MDPs (Beranek, 1961). Value iteration, a special case of policy iteration, reduces the amount of computation. Both policy iteration and value iteration are widely used methods. With the help of modern computers, DP methods can be used to solve MDPs with very high number of (millions) of states. As the number of states associated with the problem was very small, either of the policy iteration or value iteration could be selected. The MDP is briefly discussed in the section 2.2.

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2.1 Analytic Hierarchy Process (AHP)

Analytic Hierarchic Process (AHP) developed by Saaty (T. L. Saaty, 1977) is suitable for estimating state transition probabilities and rewards in this research for several reasons. First, it can be used to get objectified inputs for the Bayesian formula when the statistical estimates of probability are not possible and the AHP can be considered as the Bayesian process in this sense. The AHP allows the concerned decision-makers to do pair-wise comparisons, which in turn objectifies the decisions and formalizes the decision process (Mimović et al., 2015). Second, the AHP method supports group decision by a team of experts by combining their individual preferences. The AHP can be used for group decision by taking geometric mean of preferences of individual experts (T. Saaty, 2008). Third, the AHP method can measure and synthesize the several factors in a hierarchical structure (Forman & Gass, 2001) and provide a structure to the otherwise unstructured problem. Fourth, it is capable of handling both tangible and non-tangible (i.e. objective and subjective) attributes (Rao, 2007). Saaty suggested transformation of qualitative data into quantitative on a numerical scale (0-9) (T. L. Saaty, 1977). This scale is used in AHP, where '1'indicates equal importance or preference, whereas '9' indicates extreme importance or preference. Aragonés-Beltrán et al. (Aragonés-Beltrán et al., 2014) discuss in detail the steps involved in AHP calculations. There are several software packages developing and analyzing AHP models e.g. Expert Choice, Super Decisions (Baby, 2013).

The Super Decisions software package was used for development of the model for assessment of transition probabilities and rewards, pair-wise comparisons and final calculations, in this study. The structure of the model was created using the drag and drop tools of this software package. Thereafter, pair-wise comparisons were done for each node and inconsistency was checked. The acceptable limit for inconsistency is 0.10, it was ensured that it is always less than this value.

2.2 Markov Decision Process (MDP)

MDP is formulated as - a set of discrete time epochs T = {1,.... , N}; a set of States S = {S1 ,..... , SN}; a set of Actions A = {a1 ,..... , aM}; a matrix of assigned Rewards R: S×A associated with action a in state s; and a Transition Model P: S×S×A → [0,1], the probability of transitioning from a state i to another state j, on taking action a.

The project portfolio decision problem can be framed as a finite MDP, which means each of the the S, A, and R (states, actions, and rewards) will have finite number of elements. The R_t and S_t, respectively Reward and State at time t depend only on the preceding state and action. For particular values of these variables, s' ϵ S and r ϵ

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R, there is a probability of those values occurring at time t, given particular values of the preceding state and action(Sutton, R.S. and Barto, 2018):

$p(s',r|s,a) \doteq \Pr\{S_t=s',R_t=r \mid S_{t-1}=s,A_{t-1}=a\}$

for all $s',s \in S$, $r \in R$, and $a \in A(s)$.

In a MDP, the probabilities ‘p’ completely characterise the environment’s dynamics. The probability of each possible value of S_t and R_t depends only on the S_{t-1} and A_{t-1} and the earlier states and actions do not matter. Hence, the state in a MDP must include all the information that makes a difference for the future. And when it does so, then the state is said to have the Markov property.

Following information is required to frame a problem as a MDP:

Number of States (S) = N
Number of action alternatives (A) = M
State transition matrix (p) for each Action (A) = S×S

$$\begin{bmatrix} p11 & p12 & p.. & p1N \\ p21 & p22 & p.. & p2N \\ p.. & p.. & p.. & p.. \\ pN1 & pN2 & p.. & pNN \end{bmatrix}$$

Reward Matrix (r) =

$$\begin{bmatrix} p11 & p12 & p.. & p1M \\ p21 & p22 & p.. & p2M \\ p.. & p.. & p.. & p.. \\ pN1 & pN2 & p.. & pNM \end{bmatrix}$$

Discount Factor (γ) = A value to be chosen with the advice of experts

The state of the portfolio should represent the achievement of objectives sought to be achieved through portfolios, whereas the reward should represent the benefits obtained by taking action ‘a’ in state ‘s’. The decisions taken by the portfolio management affect the performance of the projects, which in turn affect the state of project portfolio and achievement of the organizational objectives. The state transition matrix is a N×N matrix of probabilities of transition from one state to another, when a particular action is taken.

The programming languages used in mathematical calculations such as Matlab and Python have toolboxes to solve MDPs. This paper has used MDPTOOLBOX of Python. The parameters required for solving the MDP using this toolbox are explained in the Python documentation (Python, n.d.):

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The procedure used for optimum policy is: mdptoolbox.mdp.PolicyIteration (*transitions*, *reward*, *discount*, *policy0=None*, *max_iter=1000*, *eval_type=0*, *skip_check =False*).

The combination of MDP with AHP forms the method for computation of the optimal policy, in this paper. The MDPTOOLBOX of Python and Superdecisions software package are used for MDP and AHP respectively.

3. Model Deployment, Results and Discussion

3.1 Computation of Project Portfolio Policy

The model was deployed on a project portfolio of a defence production company in India. The project portfolio had two objectives (i) to earn profit, and (ii) to enhance customer satisfaction. The states of the portfolio can be represented in the terms of these two objectives. S1, S2, S3 and S4 are states of the project portfolio, as shown in table I.

Table I
States of the project portfolio

Is the profit above the threshold?	**Is the customer satisfaction above the threshold?**	**State**
profit> profit_threshold	customer_satisfaction> customer_satisfaction_threshold	
FALSE	FALSE	S1
FALSE	TRUE	S2
TRUE	FALSE	S3
TRUE	TRUE	S4

The scope of the projects in the portfolio included absorption of technology from the overseas Transfer of Technology (ToT) partners, engineering documentation and project management documentation, sourcing of parts and components, assembly and production, testing and commissioning of a passive electronic surveillance systems. The parts and components suggested by the ToT partners were from the suppliers based in Europe and USA.

Although it was not a typical decision that the portfolio management takes, the project portfolio management had to take decisions regarding the sourcing of the parts and components. This decision was being taken at portfolio level for two reasons. First reason was that the portfolio management wanted to develop parts/components of strategic importance. And the second reason, the few parts/components were used not only in one project but in multiple projects of the portfolio. Hence, these decisions will have wide impact. There were two options for action related to the parts/ components.

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The first option was to source it from the source suggested by the ToT partners, whereas, the second option was to develop local substitutes. So,

a1 = Buy from supplier suggested by the ToT partner

a2 = Develop a local substitute of the part/ component

Each choice of action had its own merits and demerits. The parts and components sourced from the suppliers suggested by ToT partners had higher probability of being of good quality and lower probability of being low cost, whereas, the local substitutes had lower probability of being of good quality and higher probability of being low cost. In addition, these actions have timeline related uncertainties also associated with them. The cost and the quality are related to the portfolio objectives of earning profit and enhancing customer satisfaction.

However, the perceptions of the members of the decision making team vis-a-vis effect of the actions on time, cost and quality parameters of the projects; and effect of these project performance parameters on the state of the portfolio differed a lot. The differing perceptions of members of decision making team were synthesized using the AHP model shown in Fig. 1, to generate state transition probabilities. Superdecisions software package was used for development of the AHP model. Pair-wise comparisons were done by each of the 4 key personnel and geometric mean was calculated and value rounded off to the nearest integer was entered in the AHP model. The node 'p under action a' is probability of transition from one state to another. FS1, FS2, FS3 and FS4 represent the 'from states' or the initial states; TS1, TS2, TS3 and TS4 represent the 'to states' or the states to which the transition is taking place. The states TS1, TS2, TS3 and TS4 are compared in pairs against each other for the likelihood of transition from each of the FS1, FS2, FS3 and FS4. The inconsistency was also checked for each comparison and found to be below 0.10. The model was synthesized and weighted super matrix was computed.

The state transition matrix is derived from the weighted super matrix by transposing it. It should be noted here that FS_i and TS_i represent the same state i, prefixes F and T connote 'From' and 'To' respectively (Table II). The action options are not explicitly mentioned in the AHP model for state transition, however, pair-wise comparisons are done keeping in mind the choice of action. State Transition Matrix (under action a1) is shown in table IIIa.

In the similar fashion pair-wise comparisons were done keeping in mind the action choice 'a2'; and subsequently State Transition Matrix (under action a2) was derived from the weighted super matrix (under action a2). State Transition Matrix (under action a2) is shown in table IIIb.

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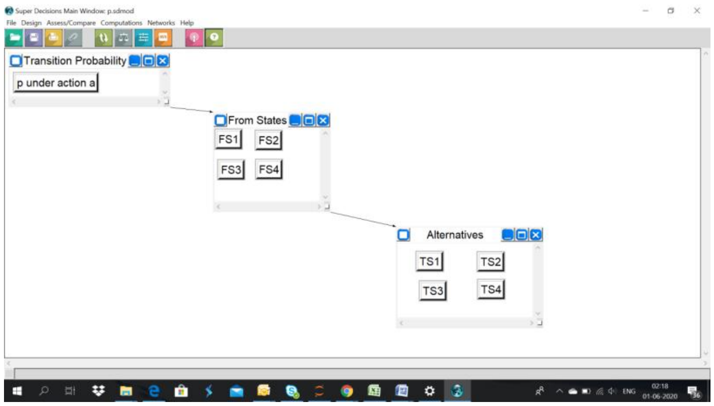

Fig 1. AHP model for state transition

Table II
Weighted Super Matrix for transitions (under action a1)

		Alternatives				**From States**				**Transition Probability**
		TS1	*TS2*	*TS3*	*TS4*	*FS1*	*FS2*	*FS3*	*FS4*	*p under action a*
Alternatives	*TS1*	0	0	0	0	0.27	0.36	0.48	0.36	0
	TS2	0	0	0	0	0.27	0.06	0.17	0.22	0
	TS3	0	0	0	0	0.16	0.31	0.14	0.06	0
	TS4	0	0	0	0	0.30	0.27	0.21	0.36	0
From States	*FS1*	0	0	0	0	0	0	0	0	0.25
	FS2	0	0	0	0	0	0	0	0	0.25
	FS3	0	0	0	0	0	0	0	0	0.25
	FS4	0	0	0	0	0	0	0	0	0.25
Transition Probability	*p under action a*	0	0	0	0	0	0	0	0	0

Table IIIa
State Transition Matrix (under action a1)

IIIa		**To States**			
		S1	*S2*	*S3*	*S4*
From States	*S1*	0.27	0.27	0.16	0.30
	S2	0.36	0.06	0.31	0.27
	S3	0.48	0.17	0.14	0.21
	S4	0.36	0.22	0.06	0.36

Table IIIb
State Transition Matrix (under action a2)

IIIb		**To States**			
		S1	*S2*	*S3*	*S4*
From States	*S1*	0.31	0.32	0.16	0.21
	S2	0.12	0.28	0.31	0.29
	S3	0.20	0.17	0.32	0.31
	S4	0.41	0.37	0.15	0.07

Similarly, reward matrix is computed from the weighted super matrix of rewards. The values in reward matrix were multiplied by 100. This multiplication doesn't affect the preference and hence does not alter the final optimization results.

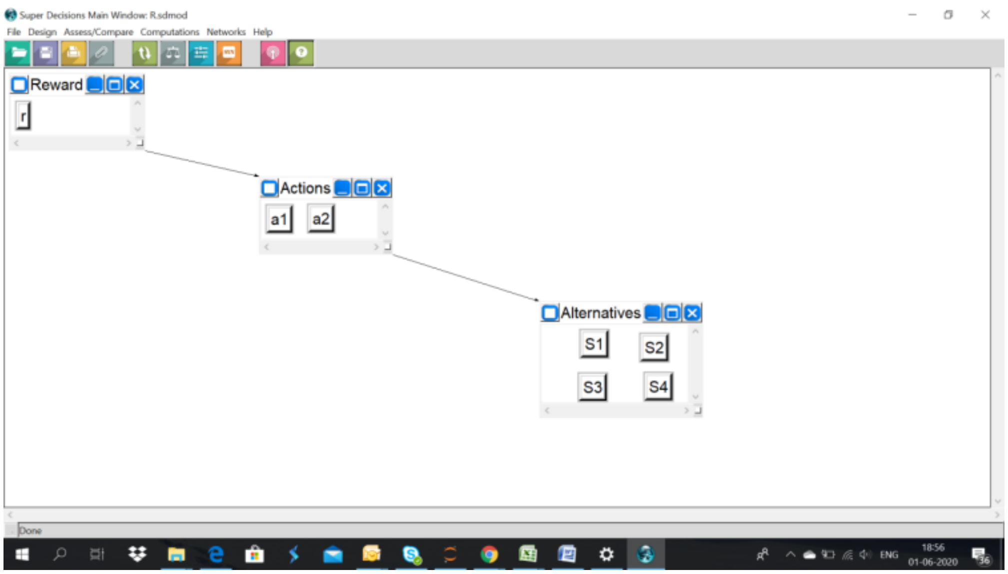

Fig 2. AHP model for reward

The Superdecisions AHP model for rewards, rewards weighted super matrix computed from the model and the final rewards matrix are shown in the Fig.3, table IV and table V respectively.

Table IV
Weighted Super Matrix for rewards

		Actions		**Alternatives**				**Reward**
		a1	*a2*	*S1*	*S2*	*S3*	*S4*	*r*
Actions	*a1*	0	0	0	0	0	0	0.5
	a2	0	0	0	0	0	0	0.5
Alternatives	*S1*	0.068877	0.454678	0	0	0	0	0
	S2	0.452242	0.151559	0	0	0	0	0
	S3	0.297675	0.262508	0	0	0	0	0
	S4	0.181206	0.131254	0	0	0	0	0
Reward	*r*	0	0	0	0	0	0	0

Table V
Rewards Matrix

		Actions	
		a1	*a2*
States	*S1*	7	45
	S2	45	15
	S3	30	26
	S4	18	13

The discount factor of 0.90 was taken with the concurrence of experts.

The MDP problem represented by the state transition and reward matrices was solved by running a small code in python. The code uses mdptoolbox of python. The solution of MDP suggests the policy to take action 'a2' in state 'S1' and 'S4' and action 'a1' in the states 'S2' and 'S3'. It can be seen here that the decisions suggested by the optimum policy are not based on the immediate rewards alone, but take into account the future awards also.

3.2 Analysis of actions taken

The default policy of the project portfolio management was to use the components suggested by the ToT partner, often due to delivery schedule constraints. In the entire duration of the project portfolio, only 12 times decisions were taken for development of local substitutes. Three sample states and actions relevant for this study are shown in table VI and these descriptive details are mapped into states and actions defined in this paper. On the similar lines table VII is generated, which presents a summary of all 12 instances when action 'a2' was opted. These are then compared with the computed policy.

It can be observed in the table VII, that in 7 cases action 'a2' is the recommended action of the computed policy. So these seven decisions were in line with the computed policy and can be called on-policy decisions. Out of these 7 cases, 6 times the results were favourable. In the other 5 cases, the decisions taken were not in line with the recommendations of the computed policy. Out of these 5 cases, the outcomes were favourable 2 times and not favourable 3 times.

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Table VI
Sample from portfolio decisions

S. No.	Date	Part/ Component Description (Used in multiple projects)	Description of State, Action Taken and Result	State	Action Taken	Action suggested by computed policy
1	Aug, 2016	Mech Parts	This decision was taken in the initial phase. As the customer perception and financial position of the project portfolio both were positive, it was assumed to have been in the state S4. This decision resulted in a cost effective high quality project leading to both profit and customer satisfaction.	S4	a2	a2
2	Dec, 2017	Electronic Modules - 5 types -B	The customer perception was good, but profits were down (S2). Decision to develop local substitute was taken with the aim of reduction of the material cost. The local substitute was low cost but had high failure rates.	S2	a2	a1
3	May, 2018	System testing automation software	The profits were getting adversely affected as the pace of work was slow and the customers were also not happy with the lagging schedules (S1). There were limited numbers of s/w licenses provided by ToT partner. A bug in the testing software was causing later stage failures. The substitute of s/w was developed in-house. It was low cost and far superior in quality than the original s/w provided.	S1	a2	a2

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Table VII
Summary of project portfolio decisions

S. No.	State	Action suggested by computed policy	Action Taken	Result of the action taken (OK/ NOT OK)
1	S2	a1	a2	OK
2	S1	a2	a2	OK
3	S1	a2	a2	OK
4	S4	a2	a2	OK
5	S3	A2	a2	OK
6	S4	a2	a2	OK
7	S1	a2	a2	NOT OK
8	S3	a1	a2	NOT OK
9	S2	a1	a2	NOT OK
10	S1	a2	a2	OK
11	S2	a1	a2	OK
12	S2	a1	a2	NOT OK

4. Conclusions

The model proposed in this paper can provide useful tool to the portfolio/ top management for computing the policies which are aligned with the organizational objectives. The values of the matrices used as input to the model namely – transition and rewards matrices represent the aggregated preferences of the decision making team. AHP is used as an aggregation tool to synthesize the collective wisdom of the decision making team for estimation of inputs of the model. The output of the MDP model is optimal project portfolio decision policy represented as state-action pairs.

References

Al-Harbi, K. M. A.-S. (2001). Application of the AHP in project management. *International Journal of Project Management*, *19*(1), 19–27. https://doi.org/https://doi.org/10.1016/S0263-7863(99)00038-1

Aragonés-Beltrán, P., Chaparro-González, F., Pastor-Ferrando, J.-P., & Pla-Rubio, A. (2014). An AHP (Analytic Hierarchy Process)/ANP (Analytic Network Process)-based multi-criteria decision approach for the selection of solar-thermal power plant investment projects. *Energy*, *66*. https://doi.org/10.1016/j.energy.2013.12.016

Arasteh, A., Aliahmadi, A., & Omran, M. M. (2014). A Multi-stage Multi Criteria Model for Portfolio Management. *Arabian Journal for Science and Engineering*, *39*(5), 4269–4283. https://doi.org/10.1007/s13369-014-0987-9

Asadabadi, M. R., & Zwikael, O. (2020). The ambiguous proposal evaluation problem. *Decision Support Systems*, *136*(July), 113359. https://doi.org/10.1016/j.dss.2020.113359

Baby, S. (2013). AHP Modeling for Multicriteria Decision-Making and to Optimise Strategies for Protecting Coastal Landscape Resources. *International Journal of Innovation, Management and Technology*, *4*(2). https://doi.org/10.7763/ijimt.2013.v4.395

Bard, J. F., & Sousk, S. F. (1990). A tradeoff analysis for rough terrain cargo handlers using the AHP: an example of group decision making. *IEEE Transactions on Engineering Management*, *37*(3), 222–228. https://doi.org/10.1109/17.104292

Belaid, F. (2011). Decision-making process for project portfolio management. *International Journal of Services Operations and Informatics*, *6*(1–2), 160–181. https://doi.org/10.1504/IJSOI.2011.038324

Bellman, R. E. (1957). A Markovian decision process. *Journal of Mathematics and Mechanics*, *6*(5), 679-684.

Beranek, W. (1961). RONALD A. HOWARD "Dynamic Programming and Markov Processes,." *Technometrics*, *3*(1), 120–121. https://doi.org/10.1080/00401706.1961.10489934

Blomquist, T. (2008). *Project Portfolio Control and Portfolio*. *September*. https://doi.org/10.1002/pmj

Cooper, D. J., & Kagel, J. H. (2005). Are two heads better than one? Team versus individual play in signaling games. *American Economic Review*, *95*(3), 477–509. https://doi.org/10.1257/0002828054201431

Curşeu, P. L., Jansen, R. J. G., & Chappin, M. M. H. (2013). Decision Rules and Group Rationality: Cognitive Gain or Standstill? *PLOS ONE*, *8*(2), 1–7. https://doi.org/10.1371/journal.pone.0056454

de Rooij, M. M. G., Janowicz-Panjaitan, M., & Mannak, R. S. (2019). A configurational explanation for performance management systems' design in project-based organizations. *International Journal of Project Management*, *37*(5), 616–630. https://doi.org/10.1016/j.ijproman.2019.03.002

Dyer, R. F., & Forman, E. H. (1992). Group decision support with the Analytic Hierarchy Process. *Decision Support Systems*, *8*(2), 99–124. https://doi.org/10.1016/0167-9236(92)90003-8

Forman, E. H., & Gass, S. I. (2001). The Analytic Hierarchy Process—An Exposition. *Operations Research*, *49*(4), 469–486. https://doi.org/10.1287/opre.49.4.469.11231

Ghasemzadeh, F., & Archer, N. P. (2000). *Project portfolio selection through decision support*. 73–88.

Kim, S., & Byeong-Seok, A. (1997). GROUP DECISION MAKING PROCEDURE CONSIDERING PREFERENCE STRENGTH UNDER INCOMPLETE INFORMATION. *Computers & Operations Research*, *24*(12), 1101–1112.

Korde, A. (2017). *Importance of Project Portfolio Management (PPM) – Approach and Benefits Realization for the Information Services and Products Industry*. *march*. https://www.cognizant.com/services-resources/ApplicationServices/importance-of-project-portfolio-management.pdf

Mimović, P., Stanković, J., & Milić, V. J. (2015). Decision-making under uncertainty - The integrated approach of the AHP and Bayesian analysis. *Economic Research-Ekonomska Istrazivanja*, *28*(1), 868–878. https://doi.org/10.1080/1331677X.2015.1092309

Project Management Institute. (2017). The Standard for Portfolio Management. In *Management* (Issue Exhibit 2).

Puterman, M. L. (1994). *Markov Decision Processes: Discrete Stochastic Dynamic Programming* (1st ed.). John Wiley & Sons, Inc.

Python. (n.d.). *Markov decision process MDP toolbox: mdp module*. Retrieved May 27, 2020, from https://pymdptoolbox.readthedocs.io/en/latest/api/mdp.html

Rao, R. (2007). *Decision Making in Manufacturing Environment using Graph Theory and Fuzzy Multi Attribute Decision Making Methods*. Springer.

Saaty, T. (2008). Decision making with the Analytic Hierarchy Process. *Int. J. Services Sciences Int. J. Services Sciences*, *1*, 83–98. https://doi.org/10.1504/IJSSCI.2008.017590

Saaty, T. L. (1977). A scaling method for priorities in hierarchical structures. *Journal of Mathematical Psychology*, *15*(3), 234–281. https://doi.org/https://doi.org/10.1016/0022-2496(77)90033-5

Sutton, R.S. and Barto, A. G. (2018). *Reinforcement Learning - An Introduction*.

Vilutienė, T., & Zavadskas, E. K. (2003). The application of multi-criteria analysis to decision support for the facility management of a residential district. *Journal of Civil Engineering and Management*, *9*(4), 241–252. https://doi.org/10.1080/13923730.2003.10531335