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Structuring and Solving Multi-Criteria Decision Making Problems using Artificial Neural Networks: a Smartphone Recommendation Case

Amaral de Sousa Victor[1], Simonofski Anthony[1], Snoeck Monique[1], Jureta Ivan[2]

1- KU Leuven - LIRIS Department
Oude Markt 13, 3000 Leuven- Belgium
2- UNamur - PReCISE
Rue de Bruxelles 61, 5000 Namur- Belgium

Abstract. Several techniques can be used to solve multi-criteria decision making (MCDM) problems and to provide a global ranking of the alternatives considered. However, in a context with a high number of alternatives and where decision criteria relate to soft goals, the decision problem is particularly hard to solve. This paper analyzes the use of artificial neural networks to improve the relevance of the ranking of alternatives delivered by MCDM problem-solving techniques. Afterwards, a model using a combination of artificial neural networks and of the weighted sum model, a particular MCDM problem-solving technique, is built to recommend smartphones.

1 Introduction

Decision making refers to a situation where a Decision Maker (DM) has to choose a course of action among multiple alternatives [1]. When the DM tries to achieve multiple objectives conflicting with each other, this situation is referred to as a Multi-Criteria Decision Making (MCDM) problem [2]. Solving an MCDM problem comes down to determining the optimal alternative A^* with the highest degree of desirability with respect to all relevant criteria C_j, each being assigned a weight of importance W_j [2].

As explained in [2], a wide variety of techniques to solve MCDM problems exists and generally follows a three-step process. The first step consists in determining what are the relevant goals (and criteria used to measure to which extent the goals are satisfied), as well as the alternatives among which a choice must be made. In the second step, numerical measures are attributed to the importance of the criteria and on the impact of the alternatives on these criteria. Finally, in the evaluation step, all of these numerical values are processed to produce a ranking of the alternatives.

Solving MCDM problems may seem quite straightforward with simple and intuitive underlying mathematics. However, applying this process to a concrete case can be quite difficult because of the evaluation step, particularly when decision goals are classified as soft goals. Indeed, soft goals are by definitions goals for which there is no clear-cut criterion determining the extent to which they are satisfied. Some techniques offer to guide the decision maker in the evaluation through continuous

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pairwise comparisons between alternatives [2]. This approach makes the evaluation easier but is not scalable when there is a high number of alternatives and/or criteria [3]. Therefore, finding a solution to help evaluating the alternatives is one way to improve the relevance of the rankings of alternatives provided by existing MCDM problem-solving techniques.

Evaluating an alternative regarding a given decision criterion can be considered as a function approximation problem. The inputs of this function are the tangible characteristics of the alternative along with the preferences of the decision maker. As of the output, it would be the impact of the alternative on the criterion. In this paper, we will use the Artificial Neural Networks (ANNs) to approximate such a function and help assessing the impact of the alternatives on the decision criteria [4, Sec. 13.4.7].

The goal of this paper is thus to answer the following research question: *"How can Artificial Neural Networks be used in order to improve the relevance of the ranking of alternatives delivered by existing MCDM techniques?*". In this paper, we will study the case of a Smartphone recommender system to illustrate both the theoretical and practical challenges arising in MCDM techniques as well as how ANNs can help to solve them. This use case is particularly relevant as, in the choice of a smartphone, many alternatives and soft goals arise. Furthermore, the evaluation would be significantly different from one person to another.

2 Background

The specific MCDM technique we will focus on in this paper is the Weighted Sum Model (WSM). With this technique, each alternative is assigned a score which is a weighted sum of the (numerical) impact of the alternative on the decision criteria. The solution to the MCDM problem is then the alternative which has the highest score. Other techniques offer relevant solutions to solve MCDM problems such as the Weighted Product Model (WPM), Analytic Hierarchy Process (AHP) or the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), and variants of these.

There are two main methods to produce a ranking of the alternatives using ANNs. The first one consists in computing a score for each alternative using ANNs, and then to rank the alternatives based on this score [1]. In this case, it is a prediction problem. Another way to do so is to take a classification approach, where an ANN will define which alternative has the highest probability of being the best one [5]. Using an ANN to produce the ranking (directly or indirectly) seem to be the most common approach. In different cases though, (parts of) traditional MCDM techniques are used in order to fulfill steps of the solving process that come before the ranking of the alternatives.

The main integrations of MCDM techniques and ANNs found in the literature consider techniques such as (fuzzy) AHP or TOPSIS. In the first case, AHP can be used for two different tasks: either the decomposition of the decision problem [6] or for the definition of the weights assigned to the decision criteria [1]. When used in combination with TOPSIS, the most common goal of ANNs seems to be the prediction of a performance score. In this context, TOPSIS is used as a technique to rank different units considered as alternatives (e.g. airline companies or banks) in

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terms of performance or efficiency. The ranking which is produced will then be used as output to train an ANN aiming at predicting the performance of a theoretical unit (alternative) based on different factors [7], [8].

In this paper, we will apply ANNs to the WSM technique to demonstrate how this integration can be applied to a practical case and which challenges emerge from it. In that regard, we will be able to further underline the relevance of this integration for future practical applications and research in that domain.

3 Research Model

In order to evaluate the relevance of using ANNs to predict the extent to which particular soft goals are satisfied by alternatives in an MCDM problem, we built a concrete model recommending smartphones to consumers. This model takes as inputs the particular use that the consumer has of a smartphone as well as the technical characteristics of a given smartphone. Then, the extent to which soft goals of the consumer would be satisfied by the smartphone at hand are predicted using ANNs. The resulting predictions are then processed using a particular MCDM technique (the Weighted Sum Model), which gives a score to the smartphone as result.

In order to build the smartphone recommendation model, we conduct a number of different steps following the methodology described in [9]. The first one was to understand what were the drivers of the satisfaction of consumers towards their smartphone, and what were their purchase criteria. This was done through an exploratory review of papers that discuss factors influencing the smartphone purchase decisions [10]–[12] and through semi-structured interviews with smartphone owners following literature’s best practices [13]. The main considered dimensions were the following: User Experience Satisfaction, Battery Life Satisfaction, Camera Satisfaction, Gaming Satisfaction, Browsing Experience Satisfaction, Storage Satisfaction and Design Satisfaction. The second step is the development and the dissemination of a questionnaire to gather data about opinions and behavior of the target population on the cited dimensions. After having collected the necessary data (N=255 respondents or “data points”), we proceed to the data analysis and building of ANNs to make the required predictions with the R software. After that, the predictions were processed using a Weighted Sum Model, which gives each smartphone a global score. Finally, the relevance of the results delivered by the integrated model (ANNs and WSM) has been analyzed and further validated with 3 respondents.

4 Results

For each dimensions of the satisfaction towards a smartphone, a separate ANN model was built. This choice results from an issue related to the number of degrees of freedom. The more variables are taken into account in the model, the more data points are required for the model to be trained correctly. In the case of a single data prediction, less variables are involved and a smaller dataset can therefore be used. Considering that the gathered data consisted of 255 data points and that we aim at

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predicting 7 variables, this approach is more appropriate, as we could use all the data points for each variable to predict.

4.1 Variable Selection

The considered variables to make the predictions about the dimensions can be grouped in two categories: variables that represent preferences of the decision maker and variables representing technical specifications of the smartphones. In order to build the ANNs, we selected a number of candidate variables for each dimension to predict. Then, we used backward stepwise regressions to define which ones to keep in the model.

4.2 ANN Models

When building ANNs, a number of elements needs to be defined. The elaboration of a smartphone recommendation model is here mainly a proof of concept. Considering this, only basic ANNs models were built. For each variable to predict, a 3-Layer Multi-Layer Perceptron (MLP) was trained using cross-validation (10-folds) and the error backpropagation algorithm with default parameters. The chosen activation function and error measurement were, respectively the logistic function and the Root-Mean Squared Error (RMSE). Regarding the topology of the ANNs, only one hidden layer was considered. The rationale behind this choice is that theoretically, a 3-layers MLP can approximate any continuous function to any degree of accuracy [4]. To guide the choice of the number of hidden neurons in this unique hidden layer, the ρ-ratio rule [14] has been used. This ratio is calculated based on the number of data points in the training set and on the number of connections of the ANN (based on the chosen topology). Ideally, this ratio should fall within a given range. As this was considered as a guide, a broader range of potential number of hidden neurons was evaluated, and the topology providing the best results (i.e. lowest cross-validated RMSE) was kept.

4.3 WSM Design

In order to use the Weighted Sum Model to evaluate the candidate smartphones, two elements need to be defined. The first one is the satisfaction score for each dimension of the smartphones, and the second is the weight associated to each dimension. The determination of the satisfaction score is handled by the ANNs. To determine the weights, a questionnaire needs to be filled in by the decision maker, where (s)he is asked to give a score of importance to each dimension. These scores were used as weights in the WSM. Figure 1 summarizes how smartphones are evaluated (i.e. given a global score) using this model.

To validate the approach suggested in this paper, the recommendation system was tested on different respondents. For the global ranking, two respondents filled-in the questionnaire used to define their preferences and a list of three smartphones (high-end, mid-end, low-end) were ranked for them. For one respondent, the ranking was accurate and for the other, two smartphones needed to be switched because of a particular preference that could have been easily added as a direct (optional) filter on the results.

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To evaluate the ability of the ANNs to predict scores regarding different dimensions of a smartphone, we evaluated the smartphones of 3 respondents to predict their respective scores, and we validated the results with the owner of the smartphone. Overall, the results were accurate, and when deviations were noticed, some leads for improving the model could be derived (e.g. under the form of other variables to take into account).

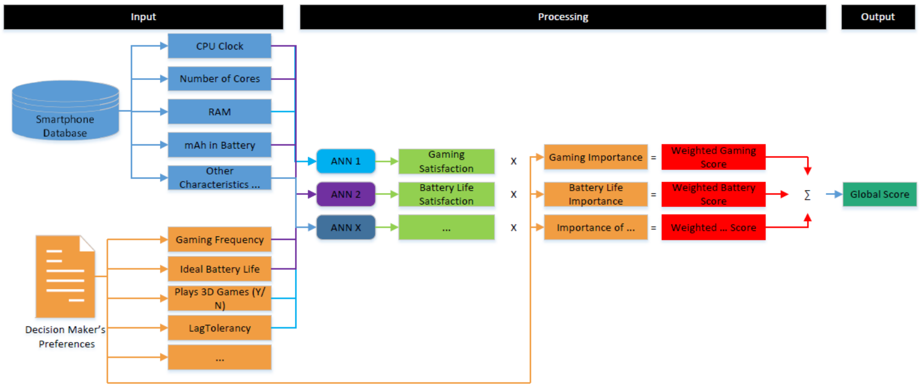

Figure 1 – Evaluating a Smartphone

5 Conclusion and Future Work

This paper contributes to the integration of ANNs within MCDMs techniques for evaluating alternatives both at theoretical and at practical level. As implication for theory, this paper described another possibility of integrations between ANNs and MCDMs problem by describing how ANNs improve the relevance of the rankings of alternatives delivered by MCDM problem-solving techniques. As implication for practice, this paper has suggested a proof-of-concept that could in further development lead to a fully-fledged recommendation system. The potential of this proof of concept has already been validated thanks to a close validation with practice.

On top of traditional limitations linked with ANNs (risk of overfitting, risk of being trapped in local optima, black box functioning and difficulty to find optimal parameters), this paper also has limitations that open the discussion for further work. One dimension for which the predictive model performed unsurprisingly less good was the design of the smartphone and this constitute an excellent lead for further research. Indeed, design is very subjective and an important part of the variables representing the preferences of the stakeholders regarding the design were not identified as relevant predictors. This is an aspect that should be further investigated to improve the smartphone recommendation model. In the model which was developed, the weights of the different decision criteria were given directly by the decision makers. This fact leads us to a last aspect that would require further investigation, which is the integration of ANNs with other MCDM techniques. For instance, when choosing a smartphone, trade-offs between dimensions are important and the AHP approach for the determination of the weights could provide interesting results in such a context.

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6 References

[1] D. Golmohammadi, "Neural network application for fuzzy multi-criteria decision making problems," *Int. J. Prod. Econ.*, vol. 131, no. 2, pp. 490–504, 2011.

[2] E. Triantaphyllou, B. Shu, S. Nieto Sanchez, and T. Ray, "Multi-criteria decision making: an operations research approach," *Encycl. Electr. Electron. Eng.*, vol. 15, pp. 175–186, 1998.

[3] J. Chen and S. Lin, "An interactive neural network-based approach for solving multiple criteria decision-making problems," *Decis. Support Syst.*, vol. 36, no. 2, pp. 137–146, 2003.

[4] A. Brabazon, M. O'Neill, and S. McGarraghy, *Natural Computing Algorithms*, 1st ed. Berlin, Heidelberg: Springer Berlin Heidelberg, 2015.

[5] P. Hanafizadeh, A. Z. Ravasan, and H. R. Khaki, "An expert system for perfume selection using artificial neural network," *Expert Syst. Appl.*, vol. 37, no. 12, pp. 8879–8887, 2010.

[6] R. J. Kuo, S. C. Chi, and S. S. Kao, "A decision support system for selecting convenience store location through integration of fuzzy AHP and artificial neural network," *Comput. Ind.*, vol. 47, no. 2, pp. 199–214, 2002.

[7] C. P. Barros and P. Wanke, "An analysis of African airlines efficiency with two-stage TOPSIS and neural networks," *J. Air Transp. Manag.*, vol. 44–45, pp. 90–102, 2015.

[8] P. Wanke, M. D. A. K. Azad, and C. P. Barros, "Predicting efficiency in Malaysian Islamic banks: A two-stage TOPSIS and neural networks approach," *Res. Int. Bus. Financ.*, vol. 36, pp. 485–498, 2016.

[9] J. Recker, "Scientific Research in Information Systems," in *Scientific Research in Information Systems*, 2013.

[10] K. Lim Lay-Yee, H. Kok-Siew, and B. Chan Yin-Fah, "Factors Affecting Smartphone Purchase Decision Among Malaysian Generation Y," *Int. J. Asian Soc. Sci. Int. J. Asian Soc. Sci. ISSN Int. J. Asian Soc. Sci.*, vol. 3, no. 312, pp. 2426–2440, 2013.

[11] S. Malviya, M. S. Saluja, and A. S. Thakur, "A Study on the Factors Influencing Consumer' s Purchase Decision towards Smartphones in Indore," *Int. J. Adv. Res. Comput. Sci. Manag. Stud.*, vol. 1, no. 6, pp. 14–21, 2013.

[12] M. Jaganathan, A. N. Mustapa, W. A. W. Hasan, N. K. N. Mat, and J. M. E. Alekam, "Does dependency make a difference? the role of convenience, social influence, facilitating condition and self-efficacy on student's purchase behaviour of smartphone," in *AIP Conference Proceedings*, 2014, vol. 1635, pp. 332–339.

[13] E. Drever, *Using Semi-Structured Interviews in Small-Scale Research. A Teacher's Guide.* Edinburgh: Scottish Council for Research in Education, 1995.

[14] D. J. Livingstone, D. T. Manallack, and I. V Tetko, "Data modelling with neural networks: advantages and limitations.," *J. Comput. Aided. Mol. Des.*, vol. 11, no. 2, pp. 135–142, 1997.