A robust FITradeoff multicriteria method and its applications

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Abstract: This paper extends the Flexible and Interactive Tradeoff (FITradeoff) method by eliciting unknown marginal value functions in a robust ordinal regression (ROR) framework. This method asks a Decision Maker (DM) to compare different values alongside a criterion, determining if their difference is larger or smaller than a threshold to find, at the end, the best alternative in a set. In each step, a representative value function is computed to identify which values to compare, their threshold, and to provide visual feedback on the marginal value functions. Compared to FITradeoff the proposed method does not require ex-ante knowledge of the marginal value functions, a strong assumption in the original model. A case study on battery-based energy storage systems and one on supplier selection are provided to verify the feasibility and effectiveness of the method.

Keywords: MCDA, Robust ordinal regression, Additive model, Representative value function

1.1. Introduction

Battery Energy Storage Systems (BESS) present solutions to numerous challenges associated with renewable technologies; these systems have evolved into indispensable components within modern power grids thanks to their flexibility efficiency. Their primary advantage lies in their rapid response to changes in demand, whether by storing excess electrical energy or supplying additional power as needed. This allows BESS to promptly address fluctuations in the power grid, contributing to the grid frequency stability and ensuring a continuous high-quality power supply. Overall, BESS facilitate the deployment of renewable energy, helping to reduce carbon emissions and lowering costs for businesses and households (Suberu et al. 2014; Luo et al. 2015). The landscape of energy storage batteries encompasses different technologies (Dunn et al. 2011; Poullikkas 2013; Alotto et al. 2014), such as lead-acid batteries, lithium-ion batteries, supercapacitors, nanobatteries, vanadium redox flow batteries, sodium-sulphur batteries, and so on. Different BESS exhibit different performances from an environmental, technological, safety-oriented, and cost-oriented point of view; hence it is necessary to develop an assessment method to select the appropriate BESS. Multicriteria decision-making (MCDM), also known as multi-objective decision-making with limited alternatives, chooses the optimal alternative from a set, or ranks alternatives, considering multiple criteria. The multiple additive utility theory (MAUT) refers to a subset of these MCDM methods, assessing the alternatives values by weighting and summing individual values on a set of criteria (Keeney and Raiffa, 1993; Shafiee and Abouee-Mehrizi, 2010). In the context of selecting BESS, MCDM in general and MAUT in particular emerge as suitable frameworks (Zhao et al. 2018; Zhao et al. 2019).

Criteria weights are crucial for evaluating inter-criteria relationships in any MCDM method based on an additive model (Weber and Borcherding 1993; Riabacke et al. 2012). The literature on these methods investigates how weights incorporate scale constants and trade-offs, and how they reflect the decision-maker (DM) preferences (Saaty, 1980; Edwards and Barron, 1994; Eisenführ et al., 2010; Rezaei, 2015). Among the MCDM methods relying on weights, the Analytic Hierarchy Process (AHP) is one of the most widely adopted. It determines the relative importance of each criterion by constructing a judgment matrix and performing pairwise comparisons (Saaty, 1980). The best-worst method (BWM) is a variant of AHP and addresses the large number of pairwise comparisons required to determine weights, which generate a computational burden and complicate the overall process (Rezaei, 2015). Edwards and Barron (1994) introduced in 1994 variations of the Simple Multi-Criteria Rating Technique (SMART), such as SMART Exploiting Ranks (SMARTER) and SMART Using Swings (SMARTS), to explore the relationship between criteria weights and their respective value functions. In the context of handling imprecision in MCDM, Mustajoki et al. (2005) proposed interval SMARTER and SMARTS to address questions related to weight ratios using intervals. Overall, eliciting weights is challenging and often requires a level of precision that the DM struggles to provide. The procedures to determine these weights themselves are often error-prone, especially in situations where the DM has uncertain preferences or lacks a complete understanding of the process. To address these challenges, de Almeida et al. (2016) proposed in 2016 the Flexible and Interactive Tradeoff (FITradeoff) method with a fixed marginal value function for each criterion. To remove this last assumption, it is possible to apply the concept of Robust Ordinal Regression (ROR) (Greco et al. 2008; Greco et al. 2010; Greco et al. 2011; Balugani et al.

2021; Lolli et al. 2024), which considers all feasible marginal value functions at the same time. This inclusion is aimed at enhancing the flexibility and robustness of the model. In this context, a novel method, combining FITradeoff and ROR, is presented for the flexible elicitation of marginal value functions that satisfy incomplete preference information within an additive model.

The paper's content is organized as follows: in Section 2, we provide an overview of some fundamental ROR concepts; in Section 3, we introduce a novel approach called robust FITradeoff multicriteria method; Section 4 demonstrates the application of the proposed method in the selection of battery-based energy storage systems and in the selection of suppliers; Section 5 concludes the paper with a summary of the findings and a discussion on future research directions.

2. Robust Ordinal Regression

Greco et al. (2008) introduced ROR in 2008. ROR examines the model parameters alignment with preference relations among alternatives. Given:

- $A = \{a_1, \dots, a_n\}$, a set of alternatives.
- $A^R = \{a_1^*, \dots, a_k^*\}$, a set of reference alternatives, with $A^R \subseteq A$.
- $C = \{c_1, \dots, c_m\}$, a set of criteria.
- For each alternative a_i and criterion c_j, $x_{ij} \in R$ is an objective assessment on that criterion on that alternative; the greater x_{ij} the more desirable is alternative a_i is on criterion c_j.
- For each criterion j v_j is a value function such that $v_j(x_{ij}) \in [0,1]$.

The DM provides a partial preorder on A^R. They can, for example, assert that a_k^* is at least as good as a_i^* (i.e., $a_k^* \succcurlyeq a_i^*$), or declare a strict preference for a_k^* over a_i^* (i.e., $a_k^* \succ a_i^*$). The additive value function, evaluating all the marginal value functions, is expressed, for each alternative, as:

$$V(a_i) = \sum_{j=1}^{m} v_j(x_{ij}) \tag{1}$$

normalized between 0 and 1:

$$\sum_{j=1}^{m} max_i \left(v_j(x_{ij})\right) = 1 \tag{2}$$

$$min_i \left(v_j(x_{ij})\right) = 0 \; \forall c_j \in C \tag{3}$$

ROR utilizes the DM's partial preorder as input data to generate sets of compatible marginal value functions. These value functions are subject to the following constraints:

$$V(a_k^*) \geq V(a_i^*) + \varepsilon \; if \; a_k^* \succ a_i^* \tag{4}$$

$$V(a_k^*) = V(a_i^*) \; if \; a_k^* \sim a_i^* \tag{5}$$

$$v_j(x_{kj}) \geq v_j(x_{ij}) \; if \; x_{kj} \geq x_{ij} \tag{6}$$

$$v_j(x_{kj}) = v_j(x_{ij}) \; if \; x_{kj} = x_{ij} \tag{7}$$

$$\sum_{j=1}^{m} max_i \left(v_j(x_{ij})\right) = 1 \tag{8}$$

$$min_i \left(v_j(x_{ij})\right) = 0 \; \forall c_j \in C \tag{9}$$

where ε is an arbitrarily small positive value. If no value function can satisfy such constraints the DM partial preorder is inconsistent.

In ROR it is possible to identify necessary and possible weak preference relations, $a_k \succcurlyeq^N a_i$ and $a_k \succcurlyeq^P a_i$ respectively, for $a_k \in A$ and $a_i \in A$. These preference relations are defined as:

- $a_k \succcurlyeq^N a_i$ if $V(a_k) \geq V(a_i)$ for every set of marginal value function compatible with the previous constraints.
- $a_k \succcurlyeq^P a_i$ if $V(a_k) \geq V(a_i)$ for at least one set of marginal value function compatible with the previous constraints.

3. The robust FITradeoff multicriteria method

In this section we propose a robust FITradeoff model. We start by build a separate linear programming model for each alternative $a_k \in A$:

$$max \sum_{j=1}^{m} v_j(x_{kj}) \tag{10}$$

s.t.

$$\sum_{j=1}^{m} v_j(x_{kj}) \geq \sum_{j=1}^{m} v_j(x_{ij}) \; \forall a_i \neq a_k \tag{11}$$

$$v_j(x_{ij}) \geq v_j(x_{lj}) \; if \; x_{ij} \geq x_{lj} \tag{12}$$

$$v_j(x_{ij}) = v_j(x_{lj}) \; if \; x_{ij} = x_{lj} \tag{13}$$

$$\sum_{j=1}^{m} max_i \left(v_j(x_{ij})\right) = 1 \tag{14}$$

$$min_i \left(v_j(x_{ij})\right) = 0 \; \forall c_j \in C \tag{15}$$

where the first constraint makes sure that alternative a_k is potentially optimal compared to all the others.

For each of these linear programming models, the existence of a solution is not guaranteed; if a solution exists, the corresponding alternative is potentially optimal; if not, the alternative cannot be optimal. We denote the set of potentially optimal alternatives as A^{opt} and the set of alternatives that cannot be optimal as A^{dom}. The sum of the value function differences between A^{opt} and A^{dom} alternatives is used in a different linear optimization problem:

$$max \sum_{\substack{a_k \in A^{opt} \\ a_i \in A^{dom}}} \left(\sum_{j=1}^{m} v_j(x_{kj}) - \sum_{j=1}^{m} v_j(x_{ij}) \right) \tag{16}$$

s.t.

$$v_j(x_{ij}) \geq v_j(x_{lj})\ if\ x_{ij} \geq x_{lj} \tag{17}$$

$$v_j(x_{ij}) = v_j(x_{lj})\ if\ x_{ij} = x_{lj} \tag{18}$$

$$\sum_{j=1}^{m} max_i\left(v_j(x_{ij})\right) = 1 \tag{19}$$

$$min_i\left(v_j(x_{ij})\right) = 0\ \forall c_j \in C \tag{20}$$

to obtain a representative value function (Greco et al. 2011) $v_j^r(x_{ij})$ for each alternative a_i and criterion c_j.

For each criterion c_j the objective assessments x_{ij} are sorted and the differences between their representative value functions is computed:

$$v_{kij}^r = v_j^r(x_{kj}) - v_j^r(x_{ij}) \tag{21}$$

$$if\ x_{kj} > x_{ij}\ and\ \nexists\ x_{lj}: x_{kj} > x_{lj}\ and\ x_{lj} > x_{ij}$$

The largest difference divided in half is the reference point for a new constraint. Given this v_{kij}^r, the DM is asked which one of the following inequalities holds:

$$v_j(x_{kj}) - v_j(x_{ij}) > \frac{v_{kij}^r}{2} \tag{22}$$

or:

$$v_j(x_{kj}) - v_j(x_{ij}) \leq \frac{v_{kij}^r}{2} \tag{23}$$

Consequently, the initial linear optimization problems become:

$$max \sum_{j=1}^{m} v_j(x_{kj}) \tag{24}$$

s.t.

$$\sum_{j=1}^{m} v_j(x_{kj}) \geq \sum_{j=1}^{m} v_j(x_{ij})\ \forall a_i \neq a_k \tag{25}$$

$$v_j(x_{ij}) \geq v_j(x_{lj})\ if\ x_{ij} \geq x_{lj} \tag{26}$$

$$v_j(x_{ij}) = v_j(x_{lj})\ if\ x_{ij} = x_{lj} \tag{27}$$

$$\sum_{j=1}^{m} max_i\left(v_i(x_{ij})\right) = 1 \tag{28}$$

$$min_i\left(v_j(x_{ij})\right) = 0\ \forall c_j \in C \tag{29}$$

and:

$$v_j(x_{kj}) - v_j(x_{ij}) \geq \frac{v_{kij}^r}{2} + \varepsilon \tag{30}$$

or:

$$v_j(x_{kj}) - v_j(x_{ij}) \leq \frac{v_{kij}^r}{2} \tag{31}$$

where ε is an arbitrarily small positive value.

A^{opt} and A^{dom} are updated according to the models' solutions. If there is still more than one alternative in A^{opt}, a new representative value function is computed using the linear optimization problem in Equations 16 to 21 with the new constraint (Equation 30 or Equation 31) included. New v_{kij}^r differences between representative value functions are recomputed as well, but any v_{kij}^r for which a constraint of type:

$$v_j(x_{kj}) - v_j(x_{ij}) > \frac{v_{kij}^{r_{old}}}{2} \tag{32}$$

already exists is computed as:

$$v_{kij}^r = v_j^r(x_{kj}) - v_j^r(x_{ij}) - \frac{v_{kij}^{r_{old}}}{2} \tag{33}$$

This way the differences with active constraints are penalised. Once the largest v_{kij}^r has been identified, if it is not one with an existing constraint, the DM is asked which inequality holds between Equations 22 and 23. If, instead, the largest v_{kij}^r already has an existing constraint of Equation 32 type, the question becomes:

$$v_j(x_{kj}) - v_j(x_{ij}) > \frac{v_{kij}^r}{2} + \frac{v_{kij}^{r_{old}}}{2} \tag{34}$$

or:

$$v_j(x_{kj}) - v_j(x_{kj}) \leq \frac{v_{kij}^r}{2} + \frac{v_{kij}^{r_{old}}}{2} \tag{35}$$

Then the correct constraint is added to the linear optimization problems and the algorithm repeats until only one alternative in A^{opt} remains. With this algorithm, the marginal value functions space is gradually reduced with the addition of a constraint in each iteration. The convergence speed varies depending on the size of such a space.

Summarizing, the proposed method follows these steps:

- Step 1, identify the alternatives and criteria in the MCDM problem.
- Step 2, construct and solve the linear optimization problems in Equations 10 to 15. This leads to a set of potentially optimal alternative and to a set of dominated alternatives.
- Step 3, compute the representative value functions by solving the linear optimization problem in Equations 16 to 20.
- Step 4, use the representative value functions to identify a question for the DM.
- Step 5, assess the DM preference.
- Step 6, construct and solve the new linear optimization problems in Equations 24 to 31. This leads to a set of potentially optimal alternative and to a set of dominated alternatives.
- Step 7, if there is more than one potentially optimal alternative go back to Step 3.

4. The robust FITradeoff multicriteria method

In this section two case studies are analysed, one on BESS and one on supplier selection, a problem traditionally tackled with MCDM methods.

Give, for each case study, an objective assessment for each alternative and criterion, a theoretical DM is using either:

- Linear marginal value functions.
- Quadratic marginal value functions.
- Square root marginal value functions.

to evaluate the alternatives over the criteria. The linear marginal value functions are:

$$v_j(x_{kj}) = \frac{x_{kj} - min_i(x_{ij})}{max_i(x_{ij}) - min_i(x_{ij})} \tag{36}$$

The quadratic marginal value functions are:

$$v_j(x_{kj}) = \left(\frac{x_{kj} - min_i(x_{ij})}{max_i(x_{ij}) - min_i(x_{ij})}\right)^2 \tag{37}$$

The square root marginal value functions are:

$$v_j(x_{kj}) = \sqrt{\frac{x_{kj} - min_i(x_{ij})}{max_i(x_{ij}) - min_i(x_{ij})}} \tag{38}$$

and the proposed method is compared to a naïve one, where the largest v^r_{kij} difference is not the one used to select which question to ask the DM.

At the beginning of the naïve method two constraints are added to the Equations 10 to 15 for every couple of adjacent x_{ij}:

$$v_j(x_{kj}) - v_j(x_{ij}) > 0 = lb_{kij} \tag{39}$$
$$if\ x_{kj} > x_{ij}\ and\ \nexists\ x_{lj}: x_{kj} > x_{lj}\ and\ x_{lj} > x_{ij}$$

$$v_j(x_{kj}) - v_j(x_{ij}) \leq 1 = ub_{kij} \tag{40}$$
$$if\ x_{kj} > x_{ij}\ and\ \nexists\ x_{lj}: x_{kj} > x_{lj}\ and\ x_{lj} > x_{ij}$$

Where lb_{kij} and ub_{kij} are the lower and upper bound for the couple x_{kj}, x_{ij}. These constraints have virtually no effect in the initial linear optimization problem.

In the naïve method the representative value functions are not computed, instead for every couple of adjacent x_{kj} and x_{ij}:

$$v^r_{kij} = ub_{kij} - lb_{kij} \tag{41}$$
$$if\ x_{kj} > x_{ij}\ and\ \nexists\ x_{lj}: x_{kj} > x_{lj}\ and\ x_{lj} > x_{ij}$$

The ub_{kij} and ub_{kij} associated to the largest v^r_{kij} are reference points for a new constraint; the DM is asked which one of the following inequalities holds:

$$v_j(x_{kj}) - v_j(x_{ij}) \geq \frac{ub_{kij} + lb_{kij}}{2} + \varepsilon \tag{42}$$

or:

$$v_j(x_{kj}) - v_j(x_{ij}) \leq \frac{ub_{kij} + lb_{kij}}{2} \tag{43}$$

where ε is an arbitrarily small positive value.

The correct constraint is then incorporated in the linear programming model and, if there is more than one alternative in A^{opt}, Equation 41 is computed again as a new step starts.

4.1. Case study 1, Battery Energy Storage Systems

In this case study, we apply the proposed method to the field of BESS to validate its effectiveness. These systems play a crucial role in managing and optimizing electricity supply and demand across various applications, they store excess energy generated during periods of low demand releasing it during peak demand periods. BESS are utilized in diverse settings, including residential, commercial, industrial, and in electric vehicles. This paper considers five alternatives (battery technologies) (Guo et al. 2015; Min et al. 2015; Mexis and Todeschini 2020):

- a_1 Lithium-ion.
- a_2 Valve regulated lead-acid.
- a_3 Sodium-sulphur.
- a_4 Sodium nickel chloride.
- a_5 Vanadium redox flow.

and eight criteria (performance measures) (Guo et al. 2015; Min et al. 2015; Mexis and Todeschini 2020):

- c_1 Damage on eco-system.
- c_2 Damage on human health.
- c_3 Damage on resource availability.
- c_4 Investment cost.
- c_5 Life cycle cost.
- c_6 Power capital cost.
- c_7 Technological performance.
- c_8 Maturity.

The objective assessments for the five alternatives on the eight criteria are obtained from Bulut and ÖZCAN (2021) and outlined in Table 1.

Table 1: Battery energy storage systems objective assessments.

	a_1	a_2	a_3	a_4	a_5
c_1	5.75	1.15	2.08	1.18	4.54
c_2	9.25	5.23	5.30	7.74	29.44
c_3	8.25	9.71	6.39	7.13	15.11
c_4	1300	300	340	350	790
c_5	30	72	41	33	31
c_6	2900	450	1850	350	1050
c_7	0.3676	0.2260	0.3250	0.2830	0.2910

c_8	7.80	9.40	7.90	7.70	7.17

In this case study, criteria c_1, c_2, c_3, c_4, c_5, and c_6 are cost criteria, while criteria c_7 and c_8 are benefit criteria. Cost criteria objective assessment signs are flipped before applying either the proposed or the naïve method. Table 2 outlines the number of steps that each method needs to identify the best solution.

Table 2: Number of steps required, in the BESS case study, by the proposed method and the naïve one.

	Linear function	Quadratic function	Square root function
Proposed	165	159	194
Naïve	212	249	271

The proposed method is more efficient in every instance.

4.2. Case study 2, supplier selection

In this case study we tackle a traditional MCDM problem, the selection of suppliers based on different criteria. Here ten suppliers are evaluated on seven criteria:

- c_1 Quality organization, which evaluates the supplier overall quality, its certifications, and the effectiveness of their quality control system.
- c_2 Service, which evaluates the supplier ability to keep due dates promises and supply the right amounts.
- c_3 Capability, which evaluates the supplier technology level and production capacity.
- c_4 Financial condition, which evaluates the supplier financial stability.
- c_5 Geographical condition, which measures the supplier geographic proximity.
- c_6 Reliability, which evaluates the supplier business experience, its references, and number of years of work together.
- c_7 Price, which evaluates the supplier sales prices.

The objective assessments are obtained from (Birgün Barla 2023) and reported in Table 3.

Table 3: Suppliers objective assessments.

	c_1	c_2	c_3	c_4	c_5	c_6	c_7
a_1	59.6	64.0	55.0	80	100	61.0	40
a_2	60.3	10.0	70.0	100	100	83.3	40
a_3	51.3	44.0	55.0	80	100	66.6	40
a_4	57.6	53.5	45.0	60	100	39.3	40
a_5	59.6	22.5	80.0	100	100	58.3	40
a_6	49.6	41.0	70.0	80	100	19.3	40
a_7	58.3	45.5	51.5	60	100	35.6	40
a_8	56.6	71.0	51.5	60	100	52.6	40
a_9	59.0	71.0	83.0	60	100	36.6	40
a_{10}	61.3	57.0	43.5	80	100	42.6	40

In this case study, criteria c_1, c_2, c_3, c_4, c_5, and c_6 are benefit criteria, while criteria c_7 is a cost criterion. Cost criteria objective assessment signs are flipped before applying either the proposed or the naïve methodology. Table 4 outlines the number of steps that each method needs to identify the best solution.

Table 3: Number of steps required, in the supplier selection case study, by the proposed method and the naïve one.

	Linear function	Quadratic function	Square root function
Proposed	265	131	123
Naïve	363	223	226

The proposed method is more efficient in every instance.

5. Conclusions

This paper introduces a robust FITradeoff multicriteria method, where the original FITradeoff multicriteria method (de Almeida et al. 2016) is integrated with an ROR (Greco et al. 2016) framework and applied to the selection of BESS (Bulut and ÖZCAN 2021) and to a traditional supplier selection problem (Birgün Barla 2023). In each step of the algorithm, we select a pair of alternatives, a criterion, a threshold, and ask the DM their preference. Compared to the original FITradeoff multicriteria method, this approach does not require ex-ante knowledge of the marginal value functions and, thus, reduces the number of assumptions. The method is compared to a naïve one in both case study, and it is proven more effective in every instance. One of the limitations of the proposed method is that, if the number of alternatives and criteria is too large, its convergence speed, measured by the number of steps required to reach a single solution, may degrade. To overcome this limitation, future research should consider different strategies to select questions for the DM.

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