A Decision Support Model for Prioritization of Regulated Safety Inspections Using Integrated Delphi, AHP and Double-Hierarchical TOPSIS Approach

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ABSTRACT Planning regulated occupational safety and health (OSH) inspections is dependent on the prioritization scheme followed by inspection agencies. It is probable that the methods used by OSH inspectorates for decision making on inspection priorities is not efficient enough to cover all the hazardous firms which is evidenced by less than expected reduction in injury rates in many countries. The objective of the current research is to present a prioritization model based on four criteria comprising thirteen subcriteria using an integrated Delphi, AHP and Double-Hierarchical TOPSIS (DH-TOPSIS) approach. The decision main and subcriteria as well as their pairwise comparisons were decided by a group of experts through a Delphi methodology. In addition, the weights of the main and subcriteria were determined using AHP method. Unlike the commonly applied TOPSIS method which uses subcriteria global weights in a single calculation process, the DH-TOPSIS method uses the local weights of the subcriteria to calculate the priority index of the alternatives (firms) with respect to the main criteria in a first TOPSIS calculation cycle. The resulting priority index is used as the evaluation scores of the firms in a second TOPSIS calculation cycle to prioritize firms for subsequent inspections. The DH-TOPSIS performed better than the global weight, single TOPSIS (GWS-TOPSIS) method with respect to the probability that the best alternative has the shortest distance to the ideal solution. Furthermore, the proposed model has a stable prioritization performance without rank reversal. As such, it is dynamic in handling large number of alternatives making it appropriate for prioritization of firms for OSH inspections. This approach can be further integrated with an appropriate scheduling methodology to improve the effectiveness of OSH inspections.

INDEX TERMS AHP-TOPSIS, Delphi, double hierarchical TOPSIS, multicriteria decision making, regulated OSH inspections, safety inspections prioritization.

I. INTRODUCTION Occupational safety and health (OSH) regulations are established and endorsed for the protection of workers’ health and wellbeing from workplace hazards. Tompa et al. [1] mentioned some OSH policy levers that improve regulatory compliance such as administrative monetary penalties, prosecutions, orders to comply, injunctions, inspections and audits, and consultations. Among these levers, workplace inspections have been found effective in reducing injuries especially when associated with penalties [1]–[3]. However, there is widespread concern that labor inspection services in many countries are not able to carry out their roles and functions due to inadequate resources in the form of budget and staff [4]–[7], and improper and/or inadequate criteria for prioritization of OSH inspections.

Priority of workplace inspection varies among inspectorates and countries. The most common prioritization criteria are industry size (e.g., large industries), industries with known hazardous conditions or high injury rates, low-wage
industries, industries with high complaint rates, industries with high-skilled workers and industries with unionized workers [4], [8]. Although there is a rationale behind using these criteria for inspection prioritization, relying only on one or few of them may affect the efficiency of the OSH regulation enforcement system. For instance, large industries have the highest probability of being inspected despite their higher level of compliance [4], [9]. Another example is that industries with low-skilled workers are less inspected although this is where violations usually exist [8]. Furthermore, many inspectorates rely on complaint-based inspections [5] despite previous studies revealed that complaints do not necessarily represent the actual work conditions. For instance, fear of job loss prevents vulnerable workers and those in unstable jobs from raising complaints about OSH violations and, on the other side, some complaints do not represent serious problems. Furthermore, complaint-based inspections are reactive in nature making it less efficient than the proactive programmed inspection strategy.

As a result of relying only on complaints or on one of the afore-mentioned priorities for OSH inspections, high percentages of workplaces have never been inspected or at best have low probability of being inspected in many countries [6]–[8]. In agreement with this, Ko et al. [10] found that high percentages (30–54%) among OSHA inspected firms during a 29-year period (from 1978 to 2006) were inspected only once, whereas Viscusi et al. [11] found high percentage of firms that have never been inspected.

Based on these, the OSH inspectorates are in urgent need to use more effective prioritization approaches that guarantee all firms be considered for inspection with reasonable probabilities or at appropriate periodicity based on their underlying OSH conditions. A good approach to prioritization is the use of risk-based inspections [12], [13]. An effective OSH regulation enforcement strategy using the risk-based inspections should consider many risk factors for prioritization. For example, prioritization should be based not only on criteria such as injury rate or complaints, but also on other criteria such as compliance rate, vulnerable workers, type (or hazard level) of industrial operations, etc. In other words, leading indicators should be used in addition to or rather than lagging indicators.

Since the research about the effectiveness of labor (including OSH) inspections is in its early stages, most of the research was forwarded to explore the important factors pertinent to the effectiveness of labor inspections such as inspection strategies or models [4]–[6], [8], [14]–[16], inspector practices [2], compliance standards [17] and inspection sequence [10]. Further studies are discussed in review papers such as Tompa et al. [1] and Maceachen et al. [18]. However, research on using supportive tools that improve decision making related to regulated inspection procedures (e.g., prioritization procedure) is scarce.

From previous research on labor and OSH inspections, it can be concluded that prioritization of firms for programmed inspections is one of the most crucial elements that have significant impact on the effectiveness of the OSH enforcement programs. The most important aspects of this element are the criteria considered for prioritization, the importance of each criterion, the techniques used for prioritization, and inspection planning and schedule based on the result of the prioritization stage.

According to Weil [4], prioritization is embodied in formal inspection procedures; however, codified procedures for ranking workplaces by inspectorates are often misaligned with underlying workplace problems. Prioritization for inspection might be thought of as a multicriteria decision making (MCDM) problem. As such, using proper MCDM approach can assist in improving prioritization procedure to be in agreement with the underlying OSH conditions in industries.

Using MCDM techniques for prioritization is not a new approach. MCDM problems are widespread in real life decision situations. Several methods have been proposed for solving MCDM problems, such as Analytic Hierarchy Process (AHP), Analytic Network Process (ANP), Technique for Order Preference by Similarity to the Ideal Solution (TOPSIS), VIKOR (stands for VlseKriterijuska Optimizacija I Komoromisno Resenje or Multi-criteria Optimization and Compromise Solution), Preference Ranking Organization Method (PROMETHEE), Electre (stands for ELimination Et Choix Traduisant la REalité or elimination and choice expressing reality) and many others. MCDM is often used to solve various decision making, ranking and selection problems such as supplier selection, system selection, personnel selection, location selection, technology selection, material selection [19] and to evaluate competitiveness or to rank the enterprises performance [20]–[22].

Several applications of MCDM methods and their fuzzy versions for solving OSH problems are found in the literature. For instance, Gul [23] reviewed 80 articles from 2003 to 2018 that applied classical and fuzzy MCDM techniques for OSH risk assessment in many sectors. In most of these papers (i.e., 65%), AHP, TOPSIS or their fuzzy versions were applied indicating that they are the most commonly used MCDM techniques in solving OSH decision problems. The author also concluded that the application of MCDM techniques in OSH risk assessment was found in a number of sectors and missing in others.

The wide application of MCDM in OSH risk assessment should encourage their application in regulated OSH inspections despite many differences exist. For instance, OSH risk assessment in a company and regulated OSH inspections nationwide have different perspectives. Risk assessment identifies sources of hazards in a company or specific sector and determines control measures [24] whereas regulated inspections cover all sectors with the objective of identifying incompliance to OSH regulations and determining legal actions to enforce the regulations. Therefore, the criteria for prioritization are different in both applications.
Criteria for OSH risk assessment cover factors such as probability and consequences of hazards [25]–[28], operational parameters, such as flow, pressure and temperature [29], risk source and environmental factors [30]–[32], organizational factors [33], and economic and managerial factors [34]. On the other hand, prioritization for regulated OSH inspections is based on criteria that measure the overall OSH performance of the individual company or the industrial sector, workers’ characteristics and unionization, and complaints [4], [8].

In spite of the wide application of MCDM techniques in OSH risk assessments and other real life problems, the author believes that there is a gap in research on using such techniques for prioritization and planning regulated OSH inspections for the following reasons:

1. Research on using MCDM techniques for prioritization of regulated OSH inspections is missing in the literature. Extrapolation of risk assessment MCDM models to regulated OSH inspections is unrealistic as they have different scope and objectives.
2. All published research on regulated OSH inspections reveals that inspectorates usually rely on one or two criteria for prioritization.
3. There is no MCDM model in the literature that OSH inspectorates can use or modify according to their needs and underlying conditions.

In agreement with this, Weil [4] noticed that despite the concept of prioritization is embodied in regulated inspection activities, codified procedures for ranking workplaces are often misaligned with underlying workplace problems.

Based on these, there is an urgent need to fill the gap in research on using MCDM techniques for regulated OSH inspections by presenting decision support models that enables OSH inspectorates to effectively prioritize and target industries for such inspections. Therefore, the objective of the current paper is to present a decision support model that can be used by OSH inspectorates to decide priorities of OSH inspections using a hybrid Delphi-AHP-TOPSIS approach. The Delphi method is used for deciding on prioritization criteria and their preferences as well as their assessment scale. The AHP method is used for determining the weights of the criteria and subcriteria. Finally, the TOPSIS method is used for the prioritization of firms for inspection through a double-hierarchical TOPSIS (DH-TOPSIS) calculation process.

The remainder of the paper consists of the following sections. Section 2 describes the proposed decision support model in detail, including the rationale behind selecting Delphi-AHP-TOPSIS hybrid approach, description of the DH-TOPSIS method, description of the decision criteria and their assessment method using Delphi method, and AHP-TOPSIS methods. Section 3 presents a numerical example to illustrate the application of the model. Section 4 presents discussion of the results and limitations of the proposed decision support model. Section 5 is a conclusion of the results and contribution of the study.

II. THE PROPOSED DECISION SUPPORT MODEL
A. STRUCTURE OF THE MODEL

The structure of the model is illustrated in Fig. 1. The model consists of four components that will be described in details in the following subsections: (1) developing the OSH decision criteria and subcriteria, and their pairwise comparisons using Delphi method; (2) calculation of the subcriteria and criteria weights using AHP technique; (3) calculation of the relative closeness ($C_{ij}^*$) of firms with respect to the main criteria using the subcriteria local weights by applying the first cycle of the DH-TOPSIS; and (4) calculation of the overall priority index ($C_i^*$) of firms using the main criteria weights and $C_{ij}^*$ by applying the second cycle of DH-TOPSIS.

The third component of the model is dependent on subcriteria weights from the second component and firm subcriteria scores from a relevant database and workplace inspections. On the other hand, the fourth component is dependent on data from both the second component (main criteria weights) and the third component (main criteria scores represented by their closeness indexes) of the model. The final overall firm closeness index is used as the priority index to plan subsequent OSH inspections. The results of inspections are always the inputs to the third component of the model. As such, the model is a dynamic one that receives scores of firms with
respect to the predetermined subcriteria and produces firm overall priority index by the DH-TOPSIS methodology. The overall priority index can be used for planning the subsequent inspections. Both Delphi and AHP methods are used once at the start of the application of the model and later on when the model needs to be revised or if the inspectorate decides to modify the main or subcriteria, their weights, or the scoring method of the subcriteria.

B. SELECTION OF THE MCDM METHODS FOR THE MODEL

As aforementioned, there are many MCDM methods for solving decision making problems. Each method has its own limitations, particularities and perspectives, and none of them are perfect nor can they be applied to all problems [35].

In AHP method, which was developed by Saaty [36], the complex problems are turned hierarchically into criteria, subcriteria, and alternatives from which the decision is made and, then the decision makers represent their preferences in the form of a matrix of pairwise comparisons for a set of criteria or alternatives with respect to a single criterion [37]. This enables one to obtain values that weight criteria, and define a ranking of the alternatives while the evaluation is bottom-up, i.e., beginning comparison of the alternatives with respect to the criteria or subcriteria of the last level [23]. AHP is the most widely used MCDM techniques for many reasons, such as its abilities to (a) combine the subjective aspects associated with the analysis of complex problems, (b) integrate subjective and objective opinions, and (c) integrate individual and group priorities and/or preferences [38]. However, it has the disadvantage of not being suitable for large number of alternatives because of the large number of pairwise comparisons needed [39]. For \( n \) criteria or alternatives, the number of pairwise comparisons is \( n(n-1)/2 \).

In AHP and other MCDM methods, it is assumed that the criteria are independent. In case of dependency or interaction, ANP is the most relevant MCDM method. The ANP method is a generalization of AHP and priorities are established in the same way they are in the AHP using pairwise comparisons and judgments [40]. However, ANP allows dependencies among criteria (or feedbacks) to be modeled and, in this case, the hierarch is replaced by networks. Because they are closer to reality, this yields more accurate results [35]. However, because feedback involves cycles, and cycling is an infinite process, the operations needed to derive the priorities become more demanding than is familiar with hierarchies [40]. In other words, there are more pairwise comparison matrices in ANP than AHP and, hence, it is difficult to solve [39].

The TOPSIS technique was developed by Hwang and Yoon [41] for solving MCDM problems on the basis that the best alternative is the one with the shortest distance from the Positive Ideal Solution (PIS) and the farthest from the Negative Ideal Solution (NIS). This is done by calculating the relative closeness coefficient \( (C_i^+) \) which has a minimum value of 0 (the alternative with the least priority) and a maximum value of 1.0 (the alternative with the highest priority). The TOPSIS method has a number of advantages that make it a major MCDM technique over other related techniques, such as [42]–[44]:

- Its flexibility to handle an unlimited range of criteria and alternatives with avoidance of pairwise comparisons.
- It allows explicit trade-offs and interactions among attributes, i.e., changes in one attribute is compensated for in a direct or opposite manner by other attributes.
- Compared to outranking methods (such as ELECTRE and PROMETHEE), TOPSIS method provides preferential ranking of alternatives with a numerical value that provides a better understanding of differences and similarities between alternatives.
- It is a relatively simple computation process with a systematic procedure.
- TOPSIS has the fewest rank reversals when an alternative is added or removed among the MCDM methods. Rank reversal can be further eliminated in TOPSIS by modifying the normalization step.

These advantages make TOPSIS requiring only a minimal number of inputs from the user and make its output easy to understand [35]. For these, the TOPSIS method is the second most popular method among MCDM approaches in the literature [19], [45].

The VIKOR method focuses on ranking and selecting from a set of alternatives in the presence of non-commensurable and conflicting criteria [46], [47] such as mixed subjective and objective criteria. The method determines a compromise solution which is the closest to the ideal one.

Despite both VIKOR and TOPSIS methods are based on an aggregating function representing ‘closeness to the ideal’, they differ in the way of determination of the compromise solution [46]. The VIKOR method of compromise ranking determines a compromise solution, providing a maximum group utility for the majority and a minimum of an individual regret for the opponent. As compared to TOPSIS, VIKOR method determines a compromise solution using three rankings based on three indexes, whereas TOPSIS method uses only one ranking based on one index that determines the relative distance to the ideal and the negative-ideal solutions.

ELECTRE methods are based on pairwise comparisons of the alternatives where every option is compared to all other options and final recommendations can be drawn without the need for compensation between criteria and any normalization process [35]. ELECTRE methods are suitable for handling decision problems with more than two criteria and if at least one the following conditions is satisfied [48]:

- The criteria are expressed in different units.
- The problem does not tolerate a compensation effect.
- There is a need to use indifference and preference thresholds, such that small differences may be insignificant although their sum of small differences is decisive.
- The options are evaluated on a scale presenting an order or on a ‘weak’ interval scale, where it is difficult to compare differences.
In the case of PROMETHEE, the final ranking is based on the positive and negative preference flows of each alternative. The positive preference flow indicates how an alternative is outranking all the other alternatives; the negative preference flow indicates how an alternative is outranked by all the other alternatives; and an alternative with a higher net flow is considered better than one with a lower net flow [49], [50].

Both ELECTRE and PROMETHEE are outranking methods where the preference order amongst the alternatives is the output without assigning a score to them [35].

MCDM techniques are classified into two categories: classical MCDM and fuzzy MCDM techniques. In real world, problems in regard to decision making are generally uncertain in many ways. For instance, lack of information, incomplete and imprecise data can lead to an unclear future state of the system. Furthermore, natural language is often employed in order to articulate thinking and subjective perceptions for evaluation, judgment, and decision [51]. Since in many MCDM problems this cannot be avoided, Bellman and Zadeh [52] introduced the fuzzy MCDM approaches to help linguistic variables be expressed appropriately. As a result, fuzzy MCDM approaches improve the quality of decisions by creating the development more efficient, rational and explicit [51].

In order to select a proper MCDM method for solving the decision problem of regulated OSH programmed inspections, the following requirements should be considered:

- The number of main or subcriteria for prioritization of firms for inspection is usually less than 7 (a maximum of 4 in the current model).
- The criteria/subcriteria are assumed to be independent.
- The weights of the criteria and subcriteria need to be decided.
- The number of firms (alternatives) is large and, therefore, a method that is capable of handling a large number of alternatives is required.
- A MCDM method that is easy to understand and to apply is preferred for determination of the weights of the criteria and subcriteria. In addition, the method should not involve excessive pairwise comparisons.
- For prioritization of firms for inspection, ranking of firms is not sufficient for decision making. In addition to ranking, a prioritization index is needed for planning future inspection by developing a mathematical relationship between the priority index and the time of the next inspection of a firm.
- The alternatives (i.e., firms) can be quantitatively assessed with respect to the subcriteria. A scoring method can be developed based on available quantitative data representing the performance of firms regarding each subcriterion. Hence, individual subjective assessments of subcriteria do not exist.
- The method used for prioritization should be simple, straightforward, and requiring minimum resources.

A comparison of the aforementioned MCDM methods regarding the decision problem features is presented in Table 1. Based on Table 1 and the other characteristics of the MCDM methods, it is decided that using AHP for the determination of criteria and subcriteria weights and TOPSIS method for prioritizing firms for inspection is more relevant than many other methods. Both AHP and TOPSIS methods are easy to use and can be even implemented in spreadsheets [53]. For these, numerous applications that integrate AHP and TOPSIS methods for solving various decision problems are found in the literature such as safety risk assessments [26], [54]–[56] and many other applications [57]–[65].

For the OSH inspection problem, TOPSIS method prioritizes firm for inspection based on the relative closeness index which represents the proximity to the ideal solution (the firm with the highest priority). The relative closeness index quantitatively reflects the OSH condition of an industry as it takes into account the numerical evaluation of the industry with respect to the OSH criteria determined by the inspectorate. Therefore, it can be further used for planning inspections throughout a predetermined period of time if an appropriate relationship with time of inspection is developed.

### Table 1. Comparison of common MCDM methods regarding important features of the decision problem.

| Comparison element                        | AHP  | ANP  | VIKOR | TOPSIS | ELECTRE | PROMETHEE | Fuzzy MCDM |
|-------------------------------------------|------|------|-------|--------|---------|-----------|------------|
| Determination of criteria weights         | ++   | ++   |   -   |        |         |           |            |
| Less subjective pairwise comparisons      | +    | -    |   NA  |   NA   |   NA    |           |            |
| Handling large number of criteria or      |      |      | ++    | ++     | ++      | ++        |            |
| alternatives                              |      |      |       |        |         |           |            |
| Absence of rank reversal                  | +    | +    |   +   | ++     | +       | +         |            |
| Provides consistency check                | +    | +    |   +   | ++     | -       | -         |            |
| Global ranking based on quantitative      | ++   | ++   |   ++  | ++     | -       | -         |            |
| score                                    |      |      |       |        |         |           |            |
| Easiness of interpreting the quantitative |      |      | ++    |        | NA      | NA        |            |
| score                                    |      |      |       |        |         |           |            |
| Inputs and simplicity of calculation      | +    | -    |   +   | ++     | +       | +         |            |

High preference: ++, Moderate preference: +, low preference: -, Not applicable: NA
In decision making, criteria selection and assessment is a key issue that needs to be carefully implemented, especially when subjective judgment is inevitable. For instance, it is less feasible to consider all the aspects of complex decision making problems by one decision maker [66]. Delphi method is widely used in decision making for collecting the most dependable judgment among decision makers (or experts) and determining the convergence of their opinions with the objective of narrowing of the range of assessment without producing errors that result from face-to-face interactions [38]. The Delphi technique is an expert opinion survey method with three basic characteristics: anonymous response, iteration and controlled feedback, and statistical group response [67]. Once a consensus is reached, a decision can be made or further technique is used if more analysis is needed.

Integrating Delphi technique with AHP and TOPSIS methods is widely used for solving many decision making problems, such as [59]–[62], [68]–[71]. Based on these, Delphi technique was selected in developing the current model for determining of the criteria, their relative importance and their assessment methods.

C. THE DOUBLE-HIERARCHICAL TOPSIS APPROACH

Before the application of TOPSIS method for evaluating the alternatives based on a number of criteria, the weights of the criteria should be determined. If the hierarchy of the decision problem consists of one level of criteria, the weights of the criteria are directly used for the calculation of the weighted normalized decision matrix as detailed in a subsequent section. However, many real-life decision problems involve multi-level hierarchy of criteria. In other words, each criterion is evaluated via a number of subcriteria. In this case, most of the previous TOPSIS-based models evaluated the alternatives against the subcriteria by considering their global weights and by using a single TOPSIS cycle of calculation. A subcriterion global weight is the product of its local weight (i.e., relative to other subcriteria under the same main criterion) and the weight of the main criterion it belongs to. Examples of this are found in [61], [71]–[73].

Using the global weights of subcriteria is a justifiable and straightforward approach. Additionally, it allows applying TOPSIS only once to evaluate the alternatives. However, when the determination of the weights of criteria and subcriteria involves subjective judgment, such as in the case of AHP pairwise comparisons, there will be some degree of uncertainty [74]–[76]. Multiplying two values that are associated with uncertainty is expected to produce a product with higher uncertainty ratio (i.e., the ratio of the uncertainty to the estimate of the variable in concern). This situation may affect the accuracy of the results obtained from the TOPSIS step for prioritization.

In addition to the global weight, there is another source of uncertainty which is the alternative assessment method. In many of the real life decision problems, the alternatives are evaluated via subjective judgment, qualitative data or ordinal scales. Using these methods in the decision-making process often leads to uncertainty due to the lack of information [23]. Therefore, using these assessments in a single calculation process of a MCDM method, such as TOPSIS, will result in inaccurate decision.

For this reason, a method that is more accurate than the global-weight single TOPSIS (GWS-TOPSIS) process is needed to overcome this problem. In this regard, fuzzy AHP and fuzzy TOPSIS approaches are widely proposed to successfully reduce the uncertainty and improve the process of decision making. However, this should not prevent finding other methods to improve the classical version of the methods.

The model presented in the current study proposes a method to minimize uncertainty due to global weight method and using ordinal scale for evaluating the alternatives by applying TOPSIS twice through a DH-TOPSIS process for evaluating the alternatives as follows:

1) First TOPSIS cycle: this cycle is applied on the subcriteria hierarchical level of the decision problem. The alternatives are assessed with respect to each main criterion separately via the relevant subcriteria considering the local weights of the subcriteria. The outcome of this cycle is new evaluation scores of the alternatives regarding each main criterion based on the concept of relative distance to ideal solution (the relative closeness index). By definition, the resulting evaluation score varies between 0 and 1.

2) Second TOPSIS cycle: this cycle is applied on the main criteria hierarchical level. The alternatives are evaluated based on the main criteria scores generated from the first cycle and considering the weights of the main criteria themselves. The outcome is the overall evaluation index of the alternatives which can be used for ranking and prioritization.

It is obvious that the global weights of the subcriteria are not needed in either of the two cycles. Furthermore, the raw evaluation scores of the alternatives with respect to the subcriteria, which are mostly in the form of ordinal Likert scale (e.g., from 1 to 5), are transformed into a more comprehensive evaluation scale from 0 to 1 by the first TOPSIS cycle. The use of such comprehensive, yet informative scale for evaluation of the alternatives in the second TOPSIS cycle is expected to improve the decision making process.

Worth mentioning that for the relative closeness index generated in the first TOPSIS cycle to be used as assessment scores for the alternatives with respect to the main criteria, the rank reversal problem should be eliminated. Although TOPSIS is the least MCDM method suffering this problem, it can be even eliminated by using appropriate normalization formula other than the one proposed by the original version of the TOPSIS [77]. Eliminating the rank reversal problem guarantees that the value of the relative closeness index of any alternative will be constant whatever the number of alternatives added or removed is. As such, the relative closeness
index can be used as a performance score with respect to the main criteria (in first TOPSIS cycle) or as an overall performance score (in second TOPSIS cycle).

The double TOPSIS methodology was proposed in several applications to improve decision making [66], [78]–[81]. However, dissimilar to the current model, in all of those applications, the first TOPSIS was used to determine the weights of decision makers and the second TOPSIS was used for ranking the alternatives.

TOPSIS method determines the best alternative as the one that has the shortest distance from the ideal solution and the farthest from the negative ideal solution, but it does not consider the relative importance of these distances. Therefore, it is criticized for that the highest ranked alternative is not always the nearest to the ideal solution although being as close as possible to the ideal is the rationale of human choice [46]. Based on this, the TOPSIS performance can be improved if the probability that the best alternative be the nearest to the ideal solution is increased. Definitely, this probability is expected to increase when the process of decision making is improved. Since the proposed double-hierarchical TOPSIS method is expected to improve the decision making quality by elimination of the uncertainty exaggeration effect of the global weight method, the improvement is expected to extend to the probability that the best alternative is the nearest to the ideal solution.

D. THE DECISION CRITERIA
In this study, the proposed criteria were decided using a Delphi technique that relies on experts’ judgments through a managed brainstorming process [68] in which 6 experts were involved (two OSH inspectors, two OSH professionals and two academicians specialized in OSH). Before the brainstorming sessions, the author proposed OSH inspection criteria and subcriteria based on literature review, a scoring method of subcriteria, and a form for pairwise comparisons of criteria and subcriteria. The author’s proposal was discussed in several meetings where additions and eliminations were made as necessary until a consensus was reached. In-series Delphi-AHP was used. That is a Delphi procedure was used only in the first phase of the AHP, when structuring the hierarchy, and then the rest of the AHP method was applied [38].

A 5-point Likert score system was decided for evaluating the subcriteria based on quantitative data from the findings of inspections and the information of firms that are assumed to be available to the inspectorate in charge. The scoring system was designed so that the firm that is compliant with a given subcriterion is given the lowest score (i.e., a score of 1). On the other hand, the worst condition of the subcriteria is scored 5.

The basis on which the subcriteria are evaluated is decided by the inspectorate in charge as appropriate to its policy. For instance, a subcriterion like firm injury rate may be scored 5 if its injury rate is higher than the 75th percentile of all firms, 4 if its injury rate is between the 50th and the 75th percentiles, 3 if its injury rate is between the 25th and the 50th percentiles, 2 if its injury rate is between the 5th and the 25th percentiles, and 1 if its injury rate is less than the 5th percentile. On the other hand, the subcriterion related to industry size may be scored 5, 4, 3, 2 and 1 if the firm size is very large (≥1000 employees), large (250–999 employees), medium (50–249 employees), small (10–49 employees) and micro (<10 employees), respectively. All other subcriteria may be evaluated and scored in similar ways, depending on the description of the subcriterias.

The decision main criteria proposed in the current prioritization model are as follows, whereas the detailed subcriteria are summarized in Table 2.

1) COMPLIANCE HISTORY
The most important objective of regulated OSH inspections is to assure firm compliance to the OSH regulations. Therefore, compliance history should be a main criterion for prioritizing inspections since it represents the underlying workplace conditions [4].

2) COMPLAINT HISTORY
In spite of the aforementioned drawbacks of prioritizing inspections based only on complaints, it is important to consider complaint rate as one criterion into prioritization for inspection [4] since significant portion of complaints are driven by factors related to underlying OSH problems [6].

3) INJURY RECORDS
It is common that inspection programs in most of the countries target the industries with the highest injury rates [9], [10], [14] since they are a direct indicator of the underlying safety and health conditions of firms. In the proposed model, the focus is on the individual firm injury records rather than on the sector level.

4) INDUSTRY CHARACTERISTICS
It is a common practice in many countries that OSH inspection priority is affected by industry characteristics. Some of these characteristics have positive impact on OSH performance and, hence, lower the priority for inspection, such as voluntary efforts to OSH [82]–[84]. Other characteristics, such as hazard level [12], [85] and workers’ characteristics [5], [8] increase the priority for inspection.

E. USING AHP FOR CRITERIA AND SUBCITERIA WEIGHTING
In the current model, AHP is used to calculate the weights of the criteria and subcriterias that are needed for TOPSIS to rank the alternatives. The AHP method comprises the following steps [36].
| Main criteria                      | Subcriteria                                                                                                                                 |
|----------------------------------|---------------------------------------------------------------------------------------------------------------------------------------------|
| **Compliance history (C1):**     |                                                                                                                                              |
| Number of previous violations (C11) | The number of violations cited during the last three years or other appropriate period can be considered as a measure of non-compliance [10,86]. |
| Seriousness of previous violations (C12) | The seriousness of violation is used as a criteria for inspection prioritization by OSHA and it can be classified as serious and other-than-serious [86]. |
| Employer response to non-compliance (C13) | Employer response to violation is an important criterion as it is a measure of deterrence and sustainability of compliance [4]. OSHA classifies response to willful, repeated and failure-to-abate violations [86]. |
| **Complaint history (C2):**      |                                                                                                                                              |
| Number of complaints (C21)       | The number of complaints is a common criteria for prioritization of OSH inspections in almost all inspection systems as it is assumed that it represents the actual underlying conditions [4,6] although it is not always true. It is the number of significant complaints related to OSH standards violations per worker (or per 100,000 workers for example) during the last 3 years (or other appropriate period). |
| Seriousness of complaints (C22)  | Since significant complaints are driven by violations, the same seriousness measures of violations can be used here [86].                                                                 |
| Employer response to complaints (C23) | This is similar to employer response to violations [6,86].                                                                                   |
| **Injury records (C3):**         |                                                                                                                                              |
| Injury rate (C31)                | This is the total number of lost-workday injuries (include both injuries with days away from work and injuries with restricted work activity) in three years (or appropriate period) per 100 fulltime workers [2]. It is a common criteria for inspection in most of the countries [9,10,14]. |
| Severity rate (C32)              | The severity rate is one of the most important lagging indicators of safety performance. It is calculated as the number of days away from work per 100 fulltime workers. The criterion of severity is included to prioritize industries with extremely serious injuries over those with less serious ones, even if they have higher injury rates. Other systems use injury or claim cost as a measure of severity [85], however, only severity rate is considered adequate in this model. |
| Major accidents (C33)            | These are accidents that result in death/total permanent disability, multiple injuries or catastrophe (i.e., substantial physical damage) within the last 3 years (or more appropriate period). Although they are already included in the severity rate calculation, it is necessary to be looked at separately. All inspection authorities give catastrophes and fatal accidents a high priority in inspection, such as OSHA [86]. |
| **Industry characteristics (C4):**|                                                                                                                                              |
| Number of workers (C41)          | It is common that inspectors give high priority to large industries with large number of workers [4,8]. Although some authors assumed that large industries have higher level of compliance [4,9], others reported that large portion of workers in large industries are exposed to occupational hazards [87]. |
| Vulnerable workers (C42)         | Vulnerable workers, such as child, young, aging, women, immigrant, seasonal (temporary), low-wage, low-skilled and disabled workers are subjected to worst work conditions and, therefore, used as a criteria for prioritization [6,8,88,89]. |
| Hazard level of industry (C43)   | Specific high-hazard industries are prioritized for inspection in many countries. These industries are determined based on the injury rates on an industry level rather than on a firm level [12,85]. |
| Voluntary efforts to OSH (C44)   | It has been shown in previous studies that the OSH performance and, hence, regulatory compliance of an organization may be improved by voluntary (nonregulatory) efforts such as OSH, environment and quality management systems [82-84]. |
TOPSIS calculations.

In this case, the goal is to calculate the weights of the main and subcriteria that are needed for TOPSIS calculations. The hierarchy structure consists of the main and subcriteria presented in Table 1.

2) CONSTRUCTION OF THE PAIRWISE COMPARISON MATRICES FOR EACH SET OF SUBCRITERIA OR MAIN CRITERIA

For example, the pairwise comparison matrix of l subcriteria used to evaluate the jth main criteria is represented by (1). Similar matrix of the main criteria is also constructed.

\[
A_j = \left( a_{jk} \right)_{l \times l}
\]

where \( C_{jl} \) are l inspection subcriteria to evaluate the main criteria \( j \); \( a_{jk} \) denotes the comparative importance of subcriterion \( jk \) against subcriterion \( k \); \( a_{jk} = 1 \) when \( k = \hat{k} \); and \( a_{jk} = 1/a_{kk} \) for \( j = 1, \ldots, m \) and \( k = 1, \ldots, l \).

A pairwise comparison scale from 1 (the two criteria are equally preferred) to 9 (one criterion is extremely preferred against subcriterion \( jk \)) is used to check the consistency of the pairwise comparison by calculating the consistency ratio (CR) using (6).

\[
CR = \frac{\lambda_{\text{max}} - 1}{(l - 1)}
\]

where \( \lambda_{\text{max}} \) is the maximum eigenvalue of \( A_j \) and \( l \) is the order of the matrix.

3) CONSTRUCTION OF THE NORMALIZED MATRIX

The normalized matrix \( (a^*_{jk}) \) and the priority vector \( (W) \) are calculated for criterion \( j \). The priority vector is the final vector of weights of the subcriteria that are subsequently used in the TOPSIS calculations.

\[
a^*_{jk} = \frac{a_{jk}}{\sum_{k=1}^{l} a_{jk}}
\]

4) CALCULATION OF THE \( \lambda_{\text{max}} \)

The value \( \lambda_{\text{max}} \) which is the maximum eigenvalue of \( A_j \) is calculated by solving the matrix equation

\[
A_j W_j = \lambda_{\text{max}} W_j
\]

\( \lambda_{\text{max}} \) is an important validating parameter in AHP and is used to check the consistency of the pairwise comparison.

\[
RI = \frac{(\lambda_{\text{max}} - 1)/(l - 1)}{RI}
\]

where \( W_j \) is a random index depending on the order of the pairwise comparison matrix. The values of \( RI \) as a function of the order of the matrix are presented in Table 4. If \( CR \leq 0.1 \), the pairwise comparison is consistent.

F. USING TOPSIS FOR EVALUATING FIRMS WITH RESPECT TO MAIN AND SUBCRITERIA

The TOPSIS method is used to prioritize firms for inspection based on their relative closeness coefficients \( C_i^a \). The relative closeness coefficient is an important parameter for the proposed model in two ways:

1) The weights of each set of subcriteria (which are calculated by AHP) and their scores (from 1 to 5) are used in a first cycle of TOPSIS calculations to obtain the \( C_i^a \) for each firm with respect to the relevant main criteria.

2) The scores of the main criteria (calculated as \( C_i^a \)) and their weights (calculated by AHP) are used again through a second cycle of TOPSIS calculations to obtain the overall relative closeness coefficients of the problems.
firms \((C^*_j)\). The new \(C^*_j\) values represent the overall OSH performance of the firms, which can be further used as determinant of the subsequent inspection schedule considering firms with higher \(C^*_j\) values for earlier inspections than those with lower ones.

The following TOPSIS steps were followed to calculate both \(C^*_j\) (first TOPSIS cycle) and \(C^*_n\) (second TOPSIS cycle) of the firms. The first TOPSIS cycle is explained in these steps.

1) ESTABLISHMENT OF THE DECISION MATRIX
If the \(i\)th inspected firm \((F_i)\) is scored with respect to the \(k\)th subcriterion belonging to the main criterion \(j\) (i.e., \(C_{jk}\)) using the scoring criteria presented in Table 1 (i.e., \(f_{ijk}\)), the following decision matrix for criterion \(j\) is formed.

\[
D_j = (f_{ijk})_{l \times n} = \begin{bmatrix}
F_1 & C_{j1} & C_{j2} & \cdots & C_{jl} \\
F_2 & f_{j11} & f_{j12} & \cdots & f_{j1l} \\
\vdots & \vdots & \vdots & \ddots & \vdots \\
F_n & f_{nj1} & f_{nj2} & \cdots & f_{njl}
\end{bmatrix}
\]  

(7)

where \(i\) (firm number) = 1, \ldots, \(n\); \(j\) (main criterion number) = 1, \ldots, \(m\); and \(k\) (subcriterion number) = 1, \ldots, \(l\).

2) CALCULATION OF THE NORMALIZED DECISION MATRIX
The normalized decision matrix is represented as \(R = [r_{ijk}]\), where \(r_{ijk}\) is the normalized value of the inspection score of the \(i\)th firm regarding the \(k\)th subcriterion used to evaluate the \(j\)th main criterion. In this model, it is calculated by the norm proposed by García-Cascales and Lamata [77] represented by (8) for eliminating the problem of rank reversal when new firm data are entered to the calculation model.

\[
r_{ijk} = \frac{f_{ijk}}{\text{Max}_k(f_{ijk})}
\]

(8)

Max\(_k\) \((f_{ijk})\) is the maximum score given for the firms regarding the \(k\)th subcriterion of the \(j\)th main criterion. Despite many norms were proposed to overcome rank reversal, the norm presented in (8) was selected as it was successfully evaluated for benefit criteria by Jahan and Edwards [90]. All the criteria proposed in this model are benefit criteria with respect to the priority for inspection. A firm given high score in subcriteria during an inspection will have high \(C^*_j\) and, therefore, should have higher priority for inspection in the future.

3) CALCULATION OF THE WEIGHTED NORMALIZED DECISION MATRIX
The weighted normalized decision matrix is represented as \(W_j = [w_{ijk}]\), where \(w_{ijk}\) is calculated using (9).

\[
w_{ijk} = w_{jk} \times r_{ijk}
\]

(9)

As previously mentioned in (3), \(w_{jk}\) represents the weight of the \(k\)th subcriterion of the \(j\)th decision criterion, and \(i = 1, 2, \ldots, n\) and \(j = 1, 2, \ldots, m\).

4) DETERMINING THE PIS \((A^+_j)\) AND THE NIS \((A^-_j)\) FOR THE MAIN CRITERION \(j\)
\(A^+_j\) and \(A^-_j\) represent the maximum and minimum weighted normalized values, respectively, of firm scores in subcriteria \(1, \ldots, l\) of the main criterion \(j\), as defined in (10) and (11).

\[
A^+_j = \left\{ W^+_j, W^+_{j2}, \ldots, W^+_{jl} \right\} = \left\{ \text{Max}W_{ijk} | j \in J \right\}
\]

(10)

\[
A^-_j = \left\{ W^-_j, W^-_{j2}, \ldots, W^-_{jl} \right\} = \left\{ \text{Min}W_{ijk} | j \in J \right\}
\]

(11)

\(J\) is associated with the positive factors (benefit criteria) and \(J'\) is associated with the negative factors (cost criteria).

5) MEASURING THE SEPARATION DISTANCE OF EACH ALTERNATIVE (FIRM) TO THE PIS \((D^+_j)\) AND THE NIS \((D^-_j)\)

\[
D^+_j = \sqrt{\sum_{k=1}^{l} (W^+_{ijk} - W^-_{jk})^2}, \quad i = 1, 2, \ldots, n
\]

(12)

\[
D^-_j = \sqrt{\sum_{k=1}^{l} (W^-_{ijk} - W^+_{jk})^2}, \quad i = 1, 2, \ldots, n
\]

(13)

6) CALCULATION OF THE RELATIVE CLOSENESS COEFFICIENT
\(C^*_ij\) for firm \(i\) regarding criterion \(j\) is calculated using (14).

\[
C^*_ij = \frac{D^-_j}{D^+_j + D^-_j}
\]

(14)

The values of \(C^*_ij\) represent evaluation scores of each inspected firm with respect to each main criterion. These scores are accurately calculated using AHP-TOPSIS approach rather than being subjectively evaluated. If the same TOPSIS steps are applied to the main criteria using their calculated scores (in this case \(C^*_j\)) and their weights previously calculated by AHP, the overall closeness coefficients of firms \((C^*_j)\) can be obtained.

The calculated closeness coefficient \((C^*_j)\) is considered as an overall evaluation of firm regarding the aforementioned OSH inspection criteria. It is, therefore, a prioritization index for subsequent safety inspections. Based on \(C^*_j\) value, the time to the next inspection of a firm can be determined by the inspectorate in charge provided that a relationship between \(C^*_j\) and the time to the next inspection is available. This type of relationships is determined mainly by the minimum and maximum times between two consecutive inspections of a firm that are targeted by the inspectorate. Once the schedule of inspections within a period of time is constructed, the inspection agency can determine staff and other resources requirements during the period of interest.

III. EXAMPLE CASE STUDY
In this section an example is presented to show the application of the proposed model for calculating the closeness coefficient \((C^*_j)\) of firms as the priority index to schedule
subsequent regulated OSH inspections. The case assumes that 1500 firms were subjected to first-time inspections where they were assessed with respect to the subcriteria presented in Table 1. The assessment data of the firms were used as the input to the proposed decision support model to calculate the priority indexes of the 1500 firms so that the inspectorate in charge can decide on their priorities for subsequent inspection scheduling. To make sure that the highest and the lowest priority indexes (i.e., closeness coefficient) have values of 1.0 and 0.0, respectively, two hypothetical firms were added where the first one (F1501) has scores of 1 in all subcriteria and the second one (F1502) has scores of 5 for all subcriteria.

In order to prove the advantage of the proposed DH-TOPSIS model, it is compared with the GWS-TOPSIS method that uses the global weights of the subcriteria. For this purpose, several sets of assessment scores of the firms regarding the thirteen subcriteria were used to test the performance of the model under different distributions of scores. Seven sets of score ranges are used for evaluation: 1–4, 2–5, 2–4 and four ranges of 1–5 with different distributions (uniform, normal, right-tailed and left-tailed). Three replicates of each set are randomly generated and the mean values of the comparison parameters are calculated.

### A. AHP CALCULATIONS

Using Delphi approach, the experts agreed about the pairwise comparisons of the main criteria presented in Table 4 and the subcriteria presented in Tables 6–9. These tables show also the priority vectors for each set of criteria or subcriteria as calculated by (2–4), the global weights of subcriteria (product of criterion weight and subcriterion local weight), and the consistency ratio (CR) as calculated by (6).

#### TABLE 5. AHP calculations for weights of main criteria.

|   | C1 | C2 | C3 | C4 | Priority vector (Criteria weight) |
|---|----|----|----|----|----------------------------------|
| C1 |  1 |  4 | 1/3|  2 | 0.224                            |
| C2 | 1/4|  1 | 1/7| 1/3| 0.060                            |
| C3 |  3 |  7 |  1 |  6 | 0.587                            |
| C4 | 1/2|  3 | 1/6|  1 | 0.128                            |

\(\lambda_{\text{max}} = 4.09, \text{RI} = 0.882, \text{CR} = 0.033\)

#### TABLE 6. AHP calculations for weights of subcriteria of the main criterion C1 "Compliance history", weight = 0.224.

|   | C11 | C12 | C13 | Priority vector (Local weight) | Global weight |
|---|-----|-----|-----|---------------------------------|---------------|
| C11|  1  | 1/4 | 1/5 | 0.098                           | 0.022         |
| C12|  4  |  1  | 1/2 | 0.334                           | 0.075         |
| C13|  5  |  2  |  1  | 0.568                           | 0.127         |

\(\lambda_{\text{max}} = 3.025, \text{RI} = 0.525, \text{CR} = 0.024\)

#### TABLE 7. AHP calculations for weights of subcriteria of the main criterion C2 "Complaint history", weight = 0.060.

|   | C21 | C22 | C23 | Priority vector (Local weight) | Global weight |
|---|-----|-----|-----|---------------------------------|---------------|
| C21|  1  | 1/4 | 1/5 | 0.098                           | 0.006         |
| C22|  4  |  1  | 1/2 | 0.334                           | 0.020         |
| C23|  5  |  2  |  1  | 0.568                           | 0.034         |

\(\lambda_{\text{max}} = 3.025, \text{RI} = 0.525, \text{CR} = 0.024\)

#### TABLE 8. AHP calculations for weights of subcriteria of the main criterion C3 "Injury records", weight = 0.587.

|   | C31 | C32 | C33 | Priority vector (Local weight) | Global weight |
|---|-----|-----|-----|---------------------------------|---------------|
| C31|  1  | 1/4 | 1/6 | 0.089                           | 0.052         |
| C32|  4  |  1  | 1/3 | 0.324                           | 0.190         |
| C33|  6  |  2  |  1  | 0.587                           | 0.345         |

\(\lambda_{\text{max}} = 3.01, \text{RI} = 0.525, \text{CR} = 0.009\)

#### TABLE 9. AHP calculations for weights of subcriteria of the main criterion C4 "Industry characteristics", weight = 0.128.

|   | C41 | C42 | C43 | C44 | Priority vector (Local weight) | Global weight |
|---|-----|-----|-----|-----|---------------------------------|---------------|
| C41|  1  | 1/5 | 1/7 |  2  | 0.078                           | 0.010         |
| C42|  5  |  1  | 1/3 |  8  | 0.303                           | 0.039         |
| C43|  7  |  3  |  1  |  9  | 0.573                           | 0.073         |
| C44| 1/2 | 1/8 | 1/9 |  1  | 0.046                           | 0.006         |

\(\lambda_{\text{max}} = 3.01, \text{RI} = 0.525, \text{CR} = 0.009\)

### B. TOPSIS CALCULATIONS

The remaining calculations are performed according to the first and second TOPSIS cycles of the DH-TOPSIS model using (8–14). To calculate \(C_{ij}^{+}\) of the subcriteria in the first TOPSIS cycle, Table 10 represents the decision matrix \(D_j\) of each subcriterion described by (7). These decision matrices are normalized using (8) to avoid rank reversal and to be sure that the value of \(C_{ij}^{+}\) or \(C_i^{-}\) for each firm remains constant with addition of more firms to the database of the model. On the other hand, the values of \(C_{ij}^{-}\) are used as the decision matrix \(D_j\) of the main criteria.

The next step is to construct the weighted normalized matrices (\(W_{ij}^{jk}\)) using (9). The weights expressed as priority vectors of the subcriteria presented in Tables (6–9) are used as \(w_{jk}\). From these matrices, the PIS (\(A_j^{+}\)) and the NIS (\(A_j^{-}\)) for the subcriteria are determined based on (10) and (11). The last step of the first TOPSIS cycle is to determine the separation distance of each firm to the PIS (\(D_j^{+}\)) and the NIS (\(D_j^{-}\)), and to calculate \(C_{ij}^{+}\) with respect to subcriteria using (12–14). Table 11 shows example calculations of first TOPSIS cycle based on firm inspection data similar to that presented in Table 10.
Similar calculations are performed for the main criteria in the second TOPSIS cycle except that the evaluation scores of the main criteria are the $C_i^*$ values that are calculated in the first TOPSIS cycle. The final outcome is the overall values of $C_i^*$ that are used for prioritization of firms for subsequent programmed inspections. Table 12 shows example calculations of the second TOPSIS cycle.

### C. COMPARISON OF THE DOUBLE-HIERARCHICAL TOPSIS WITH THE SINGLE TOPSIS METHOD

For comparison purpose, three replicates of seven sets of assessment score ranges were randomly generated for 1502 firms (including the two hypothetical ones) regarding the thirteen subcriteria. The $7 \times 3$ sets were used to run the proposed DH-TOPSIS model and the commonly used GWS-TOPSIS method.

The comparison is made regarding the probability that the best alternative (in this case the firm with the highest priority for inspection) is not the closest to the ideal solution or not the farthest to the negative ideal solution.

Let $N_{D_i^+ < D_i^*}$ be the number of incidents where the preceding alternatives to an alternative $i$ have farther distance to the positive ideal solution, $N_{D_i^- > D_i^-}$ be the number of incidents where the preceding alternatives to an alternative $i$ have shorter distance to the negative ideal solution, and $N_p$ be the sum of the number of alternatives that precede all alternative $i$ for $i = 1, 2, \ldots, n$, where $n$ is the number of all alternatives (or firms), then the overall probability that the best alternative does not have the shortest distance to the ideal positive solution, $P (D_i^+ < D_k^+)$, and the overall probability that the best alternative does not have the farthest distance to the negative ideal solution, $P (D_i^- > D_k^-)$, are calculated by (15) and (16), respectively as follows:

$$P (D_i^+ < D_k^+) = \frac{N_{D_i^+ < D_k^+}}{N_p}$$

$$P (D_i^- > D_k^-) = \frac{N_{D_i^- > D_k^-}}{N_p}$$

where $N_p = 0 + 1 + 2 + \ldots + n - 1$.

Table 13 presents a comparison between the DH-TOPSIS and the GWS-TOPSIS in terms of the mean value of $C_i^*$, the number of incidents with change in rank of firms, and the mean magnitude of rank change per firm. The rank of the vast majority of alternatives is different from one method to the other. The mean magnitude of change in the rank of individual alternatives is small (5.3–21.8) relative to the total number of alternatives (1502) with maximum magnitudes of 33–182, depending on the pattern of alternative scores with respect to the subcriteria. It is obvious that the overall mean $C_i^*$ is the same in both methods despite being different on the individual alternative level. It is probable that the type of distribution or score pattern in combination with the large number of alternatives make the mean value of $C_i^*$ constant regardless of the TOPSIS method used.

Comparing the proposed DH-TOPSIS model to the GWS-TOPSIS method regarding the probability that the best alternative does not have the shortest distance to the ideal positive solution, Table 14 shows that the proposed DH-TOPSIS method decreased the probability to values in the range 0.011–0.036 compared to 0.016–0.095 when using the GWS-TOPSIS, which means reduction of the probability by up to 66.2% when using the proposed method. In line with this, the proposed DH-TOPSIS method decreased the probability that the best alternative does not have the farthest distance to the ideal negative solution to values in the range 0.011–0.039 compared to 0.017–0.096 when using the GWS-TOPSIS, which means reduction of the probability by up to 67.4%.

A sensitivity analysis was performed by changing main criteria and subcriteria weights in 7 runs using a uniform score range of 1–5 of the firms with respect to subcriteria. The results of the sensitivity analysis are presented in Table 15. Both the GWS-TOPSIS and DH-TOPSIS methods performed similarly regarding the mean and maximum change in alternative rank although the rank of individual firm differs in the two methods as aforementioned. Fig. 2 shows an overall view of the change in the rank of firms after three runs where the weights of the main criteria and the subcriteria of C33 are changed as compared to the ranks obtained from the weights presented in Tables 5–9 (Run 1). Not all the 7 runs are

#### TABLE 10. Example firm assessment scores with respect to the model subcriteria.

| Firm code | C1 (weight = 0.224) | C2 (weight = 0.060) | C3 (weight = 0.587) | C4 (weight = 0.128) |
|-----------|---------------------|---------------------|---------------------|---------------------|
|           | C11 | C12 | C13 | C21 | C22 | C23 | C31 | C32 | C33 | C41 | C42 | C43 | C44 |
| F0001     | 4   | 4   | 4   | 1   | 4   | 3   | 3   | 5   | 5   | 5   | 4   | 5   | 5   | 3   |
| F0002     | 2   | 1   | 5   | 5   | 1   | 1   | 5   | 5   | 5   | 5   | 4   | 5   | 5   | 2   |
| F0003     | 4   | 5   | 4   | 5   | 2   | 5   | 1   | 5   | 5   | 4   | 1   | 4   | 5   |
| F0004     | 5   | 5   | 4   | 2   | 3   | 5   | 4   | 5   | 5   | 2   | 1   | 2   | 1   |
| F0005     | 3   | 2   | 5   | 3   | 3   | 5   | 2   | 5   | 5   | 4   | 1   | 3   | 2   |
|           | :   | :   | :   | :   | :   | :   | :   | :   | :   | :   | :   | :   | :   |
| F1501     | 1   | 1   | 1   | 1   | 1   | 1   | 1   | 1   | 1   | 1   |
| F1502     | 5   | 5   | 5   | 5   | 5   | 5   | 5   | 5   | 5   | 5   | 5   | 5   | 5   | 5   |
### TABLE 11. Example of first TOPSIS cycle calculations for some firms regarding subcriteria.

| TOPSIS step | Equation/Table | Firm | C1   | C2   |
|-------------|---------------|------|------|------|
| Weights \((w_{jk})\) | Tables VI–IX  |      | 0.098 | 0.334 |
| Maximum score \((\text{Max}_{jk}(f_{ijk}))\) | | | 0.50 | 5.0 |
| Weighted normalized decision matrix \((W_{ijk})\) \((8)\) and \((9)\) | F0001 | | 0.0786 | 0.2671 |
| | F0002 | | 0.0393 | 0.6686 |
| | F0003 | | 0.0786 | 0.3339 |
| | F0004 | | 0.0982 | 0.3339 |
| | F0005 | | 0.0589 | 0.1336 |
| | F1501 | | 0.0196 | 0.0668 |
| | F1502 | | 0.0982 | 0.3339 |
| PIS \((A_{ij}^+)\) \((10)\) | | | 0.0982 | 0.3339 |
| NIS \((A_{ij}^-)\) \((11)\) | | | 0.0196 | 0.0668 |

| | C1   | C2   |
| | \(D_{ij}^+, D_{ij}^-, C_{ij}\) \((12)\)–\((14)\) |      |      |
| F0001 | 0.1332 | 0.3996 |
| F0002 | 0.2736 | 0.4547 |
| F0003 | 0.1153 | 0.4370 |
| F0004 | 0.1136 | 0.4400 |
| F0005 | 0.2042 | 0.4609 |
| F1501 | 0.5328 | 0.0000 |
| F1502 | 0.0000 | 0.5328 |

| TOPSIS step | Equation/Table | Firm | C3   | C4   |
|-------------|---------------|------|------|------|
| Weights \((w_{jk})\) | Tables VI–IX  |      | 0.089 | 0.324 |
| Maximum score \((\text{Max}_{jk}(f_{ijk}))\) | | | 5.0 | 5.0 |
| Weighted normalized decision matrix \((W_{ijk})\) \((8)\) and \((9)\) | F0001 | | 0.0536 | 0.3238 |
| | F0002 | | 0.0893 | 0.3238 |
| | F0003 | | 0.0179 | 0.3238 |
| | F0004 | | 0.0714 | 0.3238 |
| | F0005 | | 0.0357 | 0.3238 |
| | F1501 | | 0.0179 | 0.0648 |
| | F1502 | | 0.0893 | 0.3238 |
| PIS \((A_{ij}^+)\) \((10)\) | | | 0.0893 | 0.3238 |
| NIS \((A_{ij}^-)\) \((11)\) | | | 0.0179 | 0.0648 |

| | C3   | C4   |
| | \(D_{ij}^+, D_{ij}^-, C_{ij}\) \((12)\)–\((14)\) |      |      |
| F0001 | 0.0357 | 0.5374 |
| F0002 | 0.0000 | 0.5410 |
| F0003 | 0.0714 | 0.5363 |
| F0004 | 0.0179 | 0.5389 |
| F0005 | 0.0536 | 0.5366 |
| F1501 | 0.5410 | 0.0000 |
| F1502 | 0.0000 | 0.5410 |
TABLE 12. Example of second TOPSIS cycle calculations for some firms regarding main criteria.

| TOPSIS step | Equation/Table | Firm     | Main criteria |
|-------------|---------------|----------|---------------|
| Weights \(w_j\) | Tables VI–IX | F0001    | C1: 0.224, C2: 0.060, C3: 0.587, C4: 0.128 |
| Maximum score \(\text{Max}_j(f_{ij})\) |          | F0002    | C1: 0.1767, C2: 0.0332, C3: 0.5508, C4: 0.1228 |
| Weighted normalized decision matrix \(W_{ij}\) | (8) and (9) | F0003    | C1: 0.1396, C2: 0.0078, C3: 0.5874, C4: 0.1133 |
|            |          | F0004    | C1: 0.1769, C2: 0.0423, C3: 0.5184, C4: 0.0726 |
|            |          | F0005    | C1: 0.1777, C2: 0.0462, C3: 0.5686, C4: 0.0275 |
|            |          | F1501    | C1: 0.1549, C2: 0.0468, C3: 0.5341, C4: 0.0528 |
|            |          | F1502    | C1: 0.2236, C2: 0.0605, C3: 0.5874, C4: 0.1285 |
| PIS \((A_i^+)^*\) | (10)    |          | C1: 0.0000, C2: 0.0000, C3: 0.0000, C4: 0.0000 |
| NIS \((A_i^-)^*\) | (11)    |          | C1: 0.2236, C2: 0.0605, C3: 0.5874, C4: 0.1285 |
| \(D_i^+, D_i^-, C_i^*\) | (12–14) | F0001    | C1: 0.0724, C2: 0.5897, C3: 0.8906, C4: 3 |
|            |          | F0002    | C1: 0.1003, C2: 0.6144, C3: 0.8597, C4: 9 |
|            |          | F0003    | C1: 0.1020, C2: 0.5542, C3: 0.8446, C4: 14 |
|            |          | F0004    | C1: 0.1134, C2: 0.5982, C3: 0.8406, C4: 19 |
|            |          | F0005    | C1: 0.1160, C2: 0.5606, C3: 0.8285, C4: 24 |
|            |          | F1501    | C1: 0.6444, C2: 0.0000, C3: 0.0000, C4: 1502 |
|            |          | F1502    | C1: 0.0000, C2: 0.6444, C3: 1.0000, C4: 1 |

TABLE 13. Comparison between GWS-TOPSIS and the proposed DH-TOPSIS regarding alternative rank change.

| Score range | Mean \(C_i^*\) ±SD | Number of incidents with rank change (Mean ±SD) | Firm rank displacement (Mean ±SD) | Max |
|-------------|----------------------|-----------------------------------------------|----------------------------------|-----|
| 2 - 4       | GWS-TOPSIS: 0.502±0.124, DH-TOPSIS: 0.502±0.124 | 1353±17.8                                   | 5.3±5.1                          | 33  |
| 1 - 4       | GWS-TOPSIS: 0.405±0.155, DH-TOPSIS: 0.406±0.155 | 1440±9.2                                    | 10.0±10.0                        | 74  |
| 2 - 5       | GWS-TOPSIS: 0.601±0.151, DH-TOPSIS: 0.600±0.151 | 1422±5.1                                    | 10.1±10.3                        | 72  |
| 1 - 5U      | GWS-TOPSIS: 0.504±0.173, DH-TOPSIS: 0.505±0.173 | 1437±9.5                                    | 15.0±15.9                        | 115 |
| 1 - 5R      | GWS-TOPSIS: 0.380±0.113, DH-TOPSIS: 0.380±0.114 | 1454±16.7                                   | 21.8±24.7                        | 162 |
| 1 - 5L      | GWS-TOPSIS: 0.623±0.115, DH-TOPSIS: 0.623±0.116 | 1439±6.1                                    | 20.1±24.1                        | 182 |
| 1 - 5N      | GWS-TOPSIS: 0.500±0.132, DH-TOPSIS: 0.500±0.133 | 1440±6.1                                    | 12.7±12.8                        | 81  |

TABLE 14. Comparison between GWS-TOPSIS and the proposed DH-TOPSIS regarding probability that the best alternative does not have the shortest distance to the ideal positive solution and the probability that it does not have the longest distance to the negative ideal solution.

| Score range | \(P(D_i^+ < D_i^-)\) | \(P(D_i^- > D_i^+)\) |
|-------------|------------------------|------------------------|
| GWS-TOPSIS  | DH-TOPSIS              | GWS-TOPSIS  | DH-TOPSIS |
| Mean ±SD    | % Reduction by DH-TOPSIS | Mean ±SD | % Reduction by DH-TOPSIS |
| 2 - 4       | 0.016±0.0007           | 0.011±0.0001          | 31.8     | 0.017±0.0014           | 0.011±0.0004          | 35.4     |
| 1 - 4       | 0.033±0.0009           | 0.014±0.0006          | 57.1     | 0.052±0.0003           | 0.022±0.0003          | 58.0     |
| 2 - 5       | 0.052±0.0003           | 0.021±0.0003          | 59.5     | 0.034±0.0011           | 0.014±0.0004          | 57.8     |
| 1 - 5U      | 0.059±0.0036           | 0.022±0.0001          | 62.7     | 0.060±0.0018           | 0.022±0.0003          | 63.3     |
| 1 - 5R      | 0.077±0.0034           | 0.026±0.0006          | 66.2     | 0.096±0.0046           | 0.039±0.0005          | 59.4     |
| 1 - 5L      | 0.095±0.0034           | 0.036±0.0015          | 62.0     | 0.077±0.0014           | 0.025±0.0005          | 67.4     |
| 1 - 5N      | 0.049±0.0013           | 0.019±0.0009          | 62.1     | 0.049±0.0010           | 0.019±0.0005          | 61.3     |

shown in Fig. 2 to avoid complexity of the figure. Generally, the rank displacement increases as the weights of main or subcriteria are sharply changed. The displacement was more observable with changing the local weights of C3 subcriteria than the weight of the main criteria. This applies for both the GWS-TOPSIS and DH-TOPSIS methods.
TABLE 15. Sensitivity analysis of the GWS-TOPSIS and the proposed DH-TOPSIS methods using 7 runs with change in main criteria and subcriteria weights.

| Run  | Mean ±SD GWS-TOPSIS | Mean ±SD DH-TOPSIS | P(D_i^+ < D_k^+) | % Reduction by DH-TOPSIS | P(D_i^- > D_k^-) | % Reduction by DH-TOPSIS |
|------|----------------------|---------------------|------------------|--------------------------|------------------|--------------------------|
| 1    | 0                    | 0                   | 0.059            | 62.7                     | 0.060            | 62.7                     | 61.7                     |
| 2    | 28±19.7              | 86                  | 27±19            | 63.6                     | 0.056            | 65.1                     | 65.0                     |
| 3    | 13±9.4               | 47                  | 14±9.7           | 63.6                     | 0.056            | 65.1                     | 65.0                     |
| 4    | 12±9.4               | 60                  | 12±9.2           | 63.6                     | 0.062            | 65.1                     | 65.0                     |
| 5    | 205±150              | 641                 | 206±152          | 63.6                     | 0.084            | 74.9                     | 74.6                     |
| 6    | 153±117              | 411                 | 147±114          | 63.6                     | 0.079            | 80.0                     | 79.9                     |
| 7    | 29±216               | 678                 | 282±208          | 63.6                     | 0.063            | 64.5                     | 65.3                     |
| 8    | 15±119               | 383                 | 149±116          | 63.6                     | 0.072            | 81.3                     | 81.0                     |

1 The main criteria C1–C4 weights for runs 1–8 are (0.224, 0.060, 0.587, 0.128), (0.256, 0.062, 0.549, 0.133), (0.204, 0.059, 0.612, 0.125), (0.224, 0.060, 0.587, 0.128), (0.354, 0.076, 0.373, 0.196), (0.224, 0.060, 0.587, 0.128), (0.224, 0.060, 0.587, 0.128) and (0.19, 0.059, 0.628, 0.123), respectively. The subcriteria C31–C33 weights for runs 1–8 are (0.089, 0.324, 0.587), (0.089, 0.324, 0.587), (0.098, 0.334, 0.568), (0.089, 0.324, 0.587), (0.111, 0.444, 0.444), (0.123, 0.557, 0.320), (0.123, 0.557, 0.320). All other subcriteria were kept constant.

2 Rank displacements were calculated taking Run 1 as a reference.

Although the absolute values of change in firm ranks seem to be large compared to the results of sensitivity analysis in other published work, such as [39], [42], [91], [92], it may be considered acceptable relative to the large number of alternatives. In the other published applications, the number of alternatives is usually small. Running the same trials of the current application on a small number of firms (12 firms) revealed that the change of firm ranks was in the range of 0–8 which is similar to other applications.

Fig. 2 shows also that the least change in alternative rank is found with both the highest and lowest prioritized alternatives. For instance, in Run 2 of the DH-TOPSIS method, the average rank displacement of the first 100 and the last 100 ranked firms is 9.75 and 9.24, respectively, whereas the average rank displacement of the firms originally ranked between 300 and 1200 is 31.4. This indicates that the firms with the poorest OSH performance will remain highly prioritized for inspection even with moderate change in criteria weights.

On the other hand, regarding the two probabilities \( P(D_i^+ < D_k^+) \) and \( P(D_i^- > D_k^-) \), the DH-TOPSIS method still achieves high percentage reduction of them, indicating that the ranks obtained by DH-TOPSIS are more consistent with the human expectation that the best alternative is the one that has the shortest distance to the ideal solution and the farthest distance to the negative ideal solution, as compared to the GWS-TOPSIS.

IV. DISCUSSION

A. THE MAIN AND SUBCITERIA FOR PRIORITIZATION

The current model presents a decision support system that is based on a mixed approach of Delphi-AHP-TOPSIS. This hybrid approach was used for decision making in many other applications [59]–[62], [68]. However, the literature on its application for supporting decisions in regulated safety inspections is missing.

Using Delphi method, the criteria and subcriteria for prioritizing safety inspections were determined. Before doing this, the firm targeting criteria in some countries were reviewed. Based on this review, it was concluded that OSH inspection targeting based on firm level injury rates [10], [93] was recently preferred over targeting based on industry level injury rates. However, this approach was criticized for finding that the inspected firms did not always have the highest injury rates [93]. This is mainly because the prioritization is based on one criterion which is the injury rate. For increasing the probability of targeting firms with the lowest safety performance, more criteria were included in this model (C1–C4).

Most of the subcriteria included in this model are firm-level rather than industry-level ones. Only one subcriterion is based on the industry-level which is the hazard level of the industry sector that the firm belongs to (C43).

When pairwise comparisons of the main criteria were conducted, the experts involved in the decision making judged the importance of the main criteria in this order \( C3 > C1 > C4 > C2 \). The rationale behind this is that injuries and illnesses are the ultimate undesirable outcomes of any industrial activity and all efforts are made to prevent them. So, it makes sense to assign the highest importance to injury records (C3) relative to other criteria. Occupational injuries and illnesses are expected to be reduced by compliance to OSH regulations and standards. For this, the importance of compliance history (C1) was judged to be next to injury records and higher than the remaining two criteria. The industry or firm characteristics (C4) that can be considered as indicators of the OSH conditions are given relative importance that is lower than C3.
and C1 and higher than C2. This judgment was justified by the reported evidence that hazardous industries are those with the highest injury rates and many inspectorates design their inspection model based on this [10] whereas those applying OSH management systems achieve better safety performance [82], [84]. Furthermore, firms with large numbers of employees and vulnerable workers are extensively targeted by inspectorates for inspection worldwide [6], [8], [88], [89]. Finally, the complaint history (C2) was given the least relative importance because of the drawbacks associated with depending on it for prioritization [4]–[6], [9]. In spite of these, complaint history should not be eliminated from the list of criteria since it represents an indicator of OSH performance, but rather it is assigned lower relative importance than other criteria.

The selection of subcriteria to evaluate the firms for inspection priority was made on the basis that they can be easily measured. The subcriteria can be measured and scored using the data that are assumed to be available to all inspectorates provided that the inspectorate has access to a database of safety and health records and other relevant databases. Unless these data are available, it will be difficult to the inspectorate to plan inspections based on the proposed or any other model. For this reason, data availability initiatives and information management are crucial for the effectiveness of such prioritization model and the inspection system as a whole [9], [94]. Example for this is the OSHA Integrated Management Information System [10] and the OSHA Data Initiative [93].

B. THE AHP-TOPSIS HYBRID APPROACH
The number of main criteria and subcriteria in the presented prioritization approach are small enough to avoid large number of pairwise comparisons [39]. This plays an important role in minimizing inconsistency and, hence, assuring successful application of AHP method for determination of their relative weights. This is evident by the low values of consistency ratio presented in Tables 5–9. Furthermore, the decision problem is structured in a way that results in minimum variation in the number of subcriteria under each main criterion (the number of subcriteria is 3 or 4). This is important to avoid overweighting of the main criteria that encompass large number of subcriteria if existing [35].

Many authors reported that addition or removal of alternatives to or from the decision matrix results in change of $C_i^*$ and, subsequently, causes rank reversal [77], [90], [95]. As mentioned earlier, a normalization method proposed by García-Cascales and Lamata [77] was used to avoid this problem. In order to check the effectiveness of this normalization method, the calculations of the two TOPSIS cycles were performed by adding 100 firms stepwise and checking the effect of adding new firms on the values of $C_i^*$ and relative order of the previously added firms. With all additions, no change was observed in the values of $C_i^*$ and relative order of the previously added firms. This proves that the proposed approach is appropriate for applications where unlimited number of firms is covered in the inspection planning without rank reversal.

C. THE DH-TOPSIS APPROACH
Many of the decision problems are structured in multiple levels of hierarchy using AHP method. Apart from the first level (goal) and the last level (alternatives), the intermediate levels include the criteria and subcriteria (or attributes). The AHP method determines the weights of both the criteria and subcriteria using a pairwise comparison approach. In most of the previous research, the global weights of the subcriteria are determined by multiplying the local weight of the subcriteria and the weight of the criteria they belong to, where the sum of the resulting global weights is 1 [61], [71]–[73]. In these methods, the global weights are used in a single TOPSIS calculation cycle to rank the alternatives.

In the proposed method, instead of using the global weight of the subcriteria, the local weight is used in a first TOPSIS calculation cycle to calculate a priority index for each of the alternatives with respect to each main criterion. Using the priority indexes of the alternatives as performance scores along with the weights of the main criteria, a second TOPSIS cycle is performed to determine the final priority of the alternatives. This way, the TOPSIS method is applied for each level of
the intermediate hierarchical levels of the decision problem. In the presented decision problem (i.e., OSH inspections), there are two levels of criteria and the TOPSIS method is, therefore, applied twice.

As compared to the commonly used GWS-TOPSIS, the proposed DH-TOPSIS method achieved sharp decrease in the probability that the distance of an alternative to the positive ideal solution is farther than those of the following ones and the probability that the distance of the alternative to the negative ideal solution is shorter than those of the following ones. The use of this criterion for proving the effectiveness of the proposed method should be useful because the classical TOPSIS method was criticized in that the best alternative is not necessarily the one with the shortest distance to the positive ideal solution [46].

The improved performance of the proposed DH-TOPSIS method is attributed to two main reasons. Firstly, the method avoids building the ranking procedure completely on the ordinal scores given to the alternatives with respect to the subcriteria (in this study a 5-point Likert scale). Instead, it uses the ordinal scores only once to produce a more accurate evaluation scale for the alternatives with respect to the main criteria. This evaluation scale is represented by the relative closeness coefficient of alternatives with respect to each main criterion, which has values in the range 0–1. The new evaluation scores, which are continuous rather being ordinal, are used in a second TOPSIS run to prioritize alternatives with respect to the main criteria. The ordinal Likert scale is widely used to measure attributes associated with opinions, valuations or ratings [96]. Despite having some advantages, such as good reliability, easiness of generation and the possibility of using their outcomes in statistical analysis, Likert scales have the disadvantage of their limitation in estimating intervals of ordinal data [97], [98]. To overcome this disadvantage, a number of authors proposed using fuzzy Likert scale that is capable of capturing the lost information and regulating the distorted information arising from the closed-form scaling and the ordinal nature of the scale [98], [99]. The proposed DH-TOPSIS method overcomes the same disadvantage by applying the classical TOPSIS calculations twice (as described previously) instead of applying it once as in the case where global weights of the subcriteria are used. The first cycle transforms the ordinal evaluations of the alternatives with respect to the subcriteria into infinite number of potential evaluation values of the alternatives with respect to the main criteria.

Secondly, eliminating the need to use global weights of the subcriteria reduce uncertainty enlargement associated with the multiplication of both criteria weights and the local subcriteria weights. It is known that the weights of criteria are common sources of uncertainty in decision making [74]–[76].

D. USING THE PROPOSED APPROACH FOR INSPECTION PLANNING

The inspection authority that intends to apply the proposed approach has two options to plan subsequent inspections based on the results of the prioritization model. The first option is to rely on firm ranking for scheduling subsequent inspections. This is implemented by considering individual firms on a daily basis according to their rank and depending on the number of available inspectors until all firms are scheduled for inspection within a predetermined planning period. For instance, when 1500 firms are scheduled for inspection within a 2-year inspection plan, the firm ranked 1 is inspected in the first day and that ranked 1500 is inspected in the last day of the timeframe of the plan. However, the drawback of this option is that every established list of firms will be ranked and inspected independent of the others and, therefore, will be planned throughout a timeframe following that of the previously prioritized list. In other words, this option limits the possibility of overlapping two consecutive inspection plans. In this case, if a firm in the new prioritized list has higher priority than others in the previous list, there is no chance for that firm to be scheduled before the ones with the lower priority as far as they belong to the oldest list. On the other hand, the second option is to schedule subsequent inspections of prioritized firms based on an appropriate relationship between the time of subsequent inspection of a firm and its priority index (i.e., $C_i^*$). In this case, overlapping between more than one list will be possible and a firm with high priority in a latter planning list can be scheduled before another one from a former list and having much lower priority. The need for a performance (or priority) index to develop a relationship between the firm underlying OSH conditions and the time to next inspection is the reason for selecting TOPSIS over other MCDM methods.

E. LIMITATIONS OF THE RESEARCH

Despite the current research presents a prioritization model that encompasses the most important criteria that should be considered for prioritization of firms for OSH inspection, it encounters few limitations that should be mentioned. The proposed main and subcriteria and their weights were decided by Saudi experts and their views might have been influenced by the local conditions in Saudi Arabia. In spite of this, these criteria are expected to undergo limited modification if applied in other countries. For instance, the inspectorates in many countries may establish a special hazard inspection program such as that implemented by OSHA [86]. This specific hazard may, thus, be included as a subcriterion belonging to the main criterion “industry characteristics”. Similarly, in countries where workers unions have significant role in OSH improvement [7], [100], unionization can be included as a subcriterion. If up-to-date data of the firm business activity is available to the inspectorate, the business cycle can be included in the decision model as well since business cycle has impact on injury rates as found in previous research [101], [102].

The proposed DH-TOPSIS method was used to improve the performance of the inspection prioritization model by eliminating the use of the global weights of the subcriteria and to transform the ordinal Likert scale that represent
firm evaluation regarding subcriteria into a more expressive and infinite scale representing the firm evaluation regarding the main criteria. A comparison between the proposed DH-TOPSIS method and the commonly used GWS-TOPSIS method was performed to prove the improvement obtained by the proposed method. Despite it was found performing better than the GWS-TOPSIS regarding the relative importance of the distance to PIS and PNS, the proposed method needs to be further compared with other approaches, such as fuzzy TOPSIS or VIKOR. Furthermore, various forms of firm assessment may be studied, such as using the raw assessment data of the criteria in their original units of measurement or evaluation.

Apart from the normalization method, the proposed DH-TOPSIS method does not change the TOPSIS calculation procedure itself. Instead, it suggests using the TOPSIS method twice or more, depending on the number of criteria hierarchies in the decision model. This way, the proposed method minimizes the possibility that the best alternative is not the closest to the ideal solution. However, it does not completely eliminate it. The relative importance of the distances to the ideal positive and to the ideal negative solutions in TOPSIS remains an open question [46].

Finally, the research does not provide a proposed scheduling model based on the priority index. This topic needs further research to study the potential scheduling techniques that should be developed based on the priority index and, at the same time, considers the inspectorate capabilities and targeted timeframes. Currently, a funded research is in process to handle this topic and the results will be published in a later stage.

V. CONCLUSION
Prioritization of firms for OSH inspections is a critical issue in the success of country efforts to enforce OSH regulations. Unless the prioritization criteria and methods are properly identified, the probability of inspecting industries with high injury rates at the right time will be lower and, accordingly, more injuries and illnesses will occur. Most of the OSH inspectorates rely on one or two criteria for prioritization of firms for inspection such as the hazard level of the industrial sector, the size of industry and the degree of unionization. The result of this is less effective inspection plans. Furthermore, in spite of being an important strategic element in OSH enforcement effort, using MCDM approaches such as AHP-TOPSIS in firm prioritization is scarce.

The current research proposes a prioritization model based on a four-criterion decision making model addressing compliance history, complaint history, injury records and industry characteristics. Each one of the main criteria is evaluated via a number of measurable subcriteria that can be assessed by information from previous inspection results and/or updated database containing relevant information of all firms included in the inspection plans. The decision main and subcriteria as well as their relative comparisons were decided by a group of experts through a Delphi methodology. In addition, the weights of the main and subcriteria were determined using AHP method. These weights in addition to the assessment scores of subcriteria from inspections were used in a two-cycle TOPSIS procedure named the DH-TOPSIS method to determine the overall priority index or the closeness coefficient ($C_i^*$) of firms which are proposed to be used by the OSH inspectorate to schedule subsequent inspections of the firms. This method is capable of handling large number of firms in one calculation cycle without rank reversal or without a change in the values of $C_i^*$. This allows for using a meaningful and fair scheduling basis to target the firms with the worst underlying OSH conditions first.

As compared to the commonly used GWS-TOPSIS, the proposed DH-TOPSIS method performed better with respect to the probability that the distance of an alternative to the positive ideal solution is shorter than that of the following ones and the probability that the distance of an alternative to the negative ideal solution is farther than that of the following ones. It is assumed that minimization of the uncertainty associated with global weights in addition to the transformation of the ordinal Likert scale into infinite number of potential evaluation values of the alternatives are main contributors to the improved performance of the proposed DH-TOPSIS method.

This research provides a systematic, yet dynamic approach based on AHP-TOPSIS integration for prioritizing firms for OSH inspections. Combining this approach with an appropriate scheduling methodology is expected to significantly improve the effectiveness of OSH inspection plans and, thus help leveraging enforcement practices and providing safe workplaces.

To sum up, the main contributions of this paper are summarized in the following points:

1. The paper presents a new MCDM model for regulated OSH inspections based on a hybrid AHP-TOPSIS approach. To the knowledge of the author, the application of this model to regulated OSH inspections is not reported in the literature despite being used for solving risk assessment problems on an individual organization level. The model uses an extended TOPSIS method where the classic method is applied twice on each hierarchical level of criteria, therefore, named DH-TOPSIS. The proposed method has better performance than the GWS-TOPSIS one as it improves the TOPSIS performance regarding the relative importance of the distance to the ideal solution. This makes the results of the method more consistent with the natural human choice. The proposed model is a dynamic one that handles large number of firms for prioritization, which is the case that all OSH inspectorates deal with. The model accepts adding or removing firms to or from the list without any change in the prioritization index of each firm because of elimination of the rank reversal problem.

2. The model proposes four main criteria comprising 13 subcriteria for prioritization instead of using only one or two criteria as commonly practiced by OSH inspectorates worldwide. The proposed criteria assist...
targeting much more industries than the currently applied limited-criteria approaches worldwide. The proposed criteria can be quantitatively assessed from available firm data. Even though some criteria are qualitative in nature, they can be easily assessed by using appropriate Likert scale based on well-defined conditions. This is expected to minimize the subjectivity in evaluating the firms against the criteria, making the use of an easy-to-apply method such as the AHP-TOPSIS a reasonably practicable approach in contrast to the more complex approaches such as fuzzy MCDM methods which are preferred when the criteria are subjectively assessed.

3. The presented model proposes a prioritization index (i.e., relative closeness coefficient) which can be used as an overall quantitative measure of the underlying OSH conditions. This index can be utilized by the inspectors for further analysis and inspection planning. For instance, if a relationship between the priority index and the time of next programmed inspection of a firm is found, planning and scheduling inspection activities will be easier and more efficient.

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