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| **Vendor Risks and N-Order Effects** | |
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| ***Sponsor:* Defense Logistics Agency** | ***Thrust Area:* Supply Chain** |
| ***Keywords:*** risk analysis, supply chain | |
| ***Problem in Context:*** The main goal of this project is to develop a methodology for measuring supply chain risk associated with items and vendors within different supply chains. | |
| ***Technical Approach:*** data analysis and modeling, multi-objective decision analysis, risk assessment. | |
| ***Broader Value to CELDi Members:*** This research has the broader impact of illustrating how to measure risk based on operationally obtained data elements. Similar measures can be used for other CELDi members and supply chain entities other than items and vendors. | |

# OVERVIEW OF METHODOLOGY AND RISK METRICS

In this section, we present an overview of the methodology to be used to develop supply chain risk indices. We build on the ideas presented in the Rand report by using operational data to formulate risk indices; however, the proposed methodology overcomes many of the shortcomings of the approach taken in the Rand report by using the concepts of multi-objective decision analysis (MODA).

## MODA Modeling of Risk Indices

This section overviews the basic components and steps within the multi-objective decision analysis (MODA) methodology applied to the risk index development process. Decision making with multiple objectives have been long studied within the field of decision analysis, which is a well-established discipline of systems engineering. The basics of the MODA methodology are fairly standardized as laid out in the *Handbook of Decision Analysis* (Parnell, et al. 2013). The key step of this process that is applicable to this project is crafting the decision objectives and value measures (or value function hierarchy):

*“Craft the decision objectives and value measures: During this step, the outcome-related issues are grouped from the framing into a hierarchy. Decision criteria become numbers via a metric to measure them and a value function to normalize them, including returns to scale. Criteria are ranked against each other and the results recorded in a swing weight matrix.”*

This process provides stakeholders with a common framework for considering the risk and identifies the most relevant factors that may influence risk. In this project, we apply the MODA methodology to the development of risk indices.

The first step in the MODA process is to define attributes and risk/importance measures. For our purposes, the purpose of this step is to define ways to measure risk. Within the MODA methodology, a Value Function Hierarchy (VFH) is the major tool to structure multiple characteristics into independent and non-overlapping groups of criteria. The VFH starts with the ultimate goal at the top (e.g. measure vendor risk) and identifies characteristics that contribute to the overall goal. The next layer involves characteristics that are involved in this main goal. Characteristics are composed of attributes, which make up the next layer. Finally, metrics are created for each attribute. The VFH can be composed either top-down, by asking what goes into the vision statement and so on, or bottom-up, by grouping and discussing risk issues that arise during the hierarchy framing process. The VFH represents a value tree that encapsulates the NIIN and vendor risk and importance characteristics. Figure 1 illustrates a notional value hierarch tree for conceptualizing risk measurement involving NIINs and vendors. At the lowest level of the tree we see possible attribute attributes that may be used to represent risk or importance within the overall NIIN or vendor measure.

Figure 2 Notional Value Hierarchy Tree

As illustrated in Figure 1, the attributes associated with specific supply chain characteristics involving items and vendors serve as the traditional decision objectives for the application of the MODA methodology. The values of the attributes (as observed from entity data instances) serve as the raw attribute values that will be normalized to a common measurement scale by the specification value functions. The value functions represent a mapping from observed values to a scale (0-100) that represents the risk or important of the attribute within the supply chain risk context. This is discussed further in the following paragraphs.

Once the value function hierarchy (VFH) or value tree is developed, we need to develop value functions for the risk or importance measures. As previously noted, a risk or importance measure is an attribute that we have designated to measure the risk or the importance of the supply chain characteristic. For example, the attribute (annual demand quantity) for NIIN has been designated as an importance measure for analyzing NIINs because we assume that the more an item is demanded, the more important the item within the supply chain analysis. Value functions convert different scales of measures to a common scale that ranges from 0 to 100. This determines an overall *value* for each risk index by adding up its scores across the value measures.

Each value function has an *x*-axis and a *y*-axis, where the *x*-axis is the scale of the value measure (e.g., production lead time) and the *y*-axis is a standard unit-less scale from 0 to 100. Continuous value functions typically follow four basic shapes of linear, concave, convex, and S curve as illustrated in Figure 3. Depending on the impact of each value measure, value functions could be either monotonically increasing, as indicated in Figure 1, or decreasing. As suggested in Kirkwood (1996), the shape of value functions is determined by consulting with subject matter experts. Once the general shape is determined, the experts identify the increase/decrease in value from a specific incremental increase in the measure scale. Repeating this multiple times up to the maximum on the measure scale produces a piecewise linear function. The functions illustrated in Figure 3 were produced in a linear piecewise fashion.

Thus each attribute has raw value based on its natural scale, , which is then standardized to a common scaled by applying a value function, , where

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| --- | --- |
|  | be the score of measure on the *x*-axis of the value function |
|  | be the value of measure on the *y*-axis of the value function |

For example, let us assume that we have a risk index with 4 attributes or measures. Then, we would have , …, raw scores that correspond to the four measures. Value functions would then convert , …, scores to , …, values that all have common scales (i.e. [0, 100]). As noted each metric has its own range of values, which often differs radically from other metrics. Production lead time, for instance, ranges from 1 to 365 days, while material availability may range from 0.7 to 1.0. A value function, therefore, maps the value of the metric to a standardized scale, commonly 0-100 for comparison purposes. Furthermore, the value functions have different shapes. This is because not all changes to metrics are created equal. For example, increasing material availability from 0.75 to 0.85 is much more valuable that increasing it from 0.85 to 0.95 for most items. Once the raw scores have been translated to a common scale, we need a method to combine the values into an overall value. In the methodology presented here, we call the combined overall value an index. To combine the individual values, we use weights and an additive model.

Typically, decision makers do not view all value measures equally. Measure weights () are supposed to capture the importance of the measures to the decision makers and incorporate the individual components into an overall value model as illustrated in (Equation 1).

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The weights depend on both the importance of the value measure and the impact of varying the score of value measures. A swing weight matrix is one of the well-known methods to determine the weights. This method assesses measure weights by “swinging” the value measure score from its worst to its best. Parnell and Trainor (2009) discusses this method in detail with examples. There are various ways besides the swing weight matrix to elicit weights from stakeholders which are discussed in (Clemen and Reilly, 2001; Kirkwood, 1996). Once the weights are determined, we can evaluate supply chain entity instances using a value model that generates total *value* for each entity (Equation 1). A value model is a mathematical expression that provides trading off value among objectives. The MODA methodology has many different relationships to do this but we will use the most common method called the *additive value model* to calculate the overall risk indices as illustrated in Equation 1. A higher total value indicates more risk for the entity (NIIN or vendor) for the given weights, value functions and its measure scores. After the value functions have been specified, the attribute criteria can be ranked against each other and the results recorded within a swing weight matrix so that an overall risk index can be formed.

To summarize, using the MODA methodology as outline here enables the evaluation the risk based on multiple characteristics that influence the overall interpretation of risk from operational data sources. The process starts with specifying a value function hierarchy (i.e. selecting the component measures (leaves of the tree). After the value function hierarchy (VFH) tree has been specified, data is collected, and normalized, and then mapped to indices (for risk and importance). Finally, a deterministic analysis can be completed based on the results. In this step the scores for NIINs and vendors can be analyzed. The purpose of this step is to guide further work by identifying assumptions, criteria, parameters, and factors that are important to the overall analysis of risk. The risk index value is represented as a single numerical score, the output of an additive value function based on the value functions and the swing weights applied to each entity (NIIN or vendor). After performing an analysis of the risk scores for various supply chain grouping criteria, a sensitivity analysis of the weights and scores can be performed.

We can gain valuable insights by performing a sensitivity analysis on the elements of the MODA model and observe how the results change. Weights and value functions are the elements that can be subject to sensitivity analysis to gain further insights on the riskiest entities and their influence on overall supply chain risk. The application of the MODA methodology to the building of risk indices mitigates one of the problems associated with the approach suggested within the RAND report by providing a rational and well-established basis for combining measures that have different scales and importance within the context of measuring supply chain risk.

In the following section, we provide guidance for analysts to select and interpret value functions.

## Value Functions

A value function is how the MODA methodology models the relationship between the amount of an attribute and its worth. Value functions are necessary because attributes have their own natural scales within the operational data. When each attribute has its own scale, though, levels cannot be directly compared across attributes.

The purpose of a value function is to translate the amount of an attribute into terms that can be compared across attributes. A value function does this by converting the amount of the attribute into its value. To a decision maker, value is a concept that encapsulates the inherent worth or utility of the attribute to the overall determination of value that encompasses all (multi-objective) attributes used in the problem context. In this project, the amount of each attribute is translated to a risk or importance score between 0 and 100. An overall risk score represents the “common value” translation across the attributes included in the risk measure. Similarly, an overall importance score represents the “common value” translation across the attributes included in the importance measure. This translation from amount to value can be complicated because the relationship between the amount of an attribute and its value (in this project, its risk or importance) is not necessarily linear or even increasing.

For example, consider two NIINs, A and B. Assume that both NIINs are similar in unit cost, criticality, lead time, etc. Their only difference lies in annual demand. The demand for NIIN A averages about 100 units per year; the demand for NIIN B averages about 300 units per year – three times higher. Most people agree that NIIN B is more important than NIIN A. The question is, how much more important is NIIN B? Does having three times more demand make B three times as important, 50% more important, or a whopping nine times more important than A? Does the answer change if the demand for A and B are 1 and 3 items per year, or 1 million and 3 million?

As the annual demand example above shows, the relationship between amount of each variable and its level of importance (or risk) is not always linear. The relationship is not always increasing, either, unlike the annual demand example in the previous paragraph. For instance, consider three vendors, V1, V2, and V3 who are each competing for their second long term contract (LTC). V1’s first LTC contract expired four years ago, V2’s expires in five years, and V3’s expired two months ago. The Vendor model quantifies the time to expire in the attribute max\_remaining\_days variable, which measures how many days lie between the present and the latest expiration date across a vendor’s contracts. The value is negative for contracts that have already expired and positive for ones that are still in force. A reasonable analyst could argue that the closer that the expiration date of a vendor’s final LTC lies to the present, the less risky it is to award them another LTC, implying that the relationship between max\_remaining\_days and risk could be U-shaped. Risk decreases as max\_remaining\_days gets less negative, reaches a minimum at 0, and increases as max\_remaining\_days gets more positive. In other words, awarding the LTC to V1 with a max\_remaining\_days of -1460 days is almost as risky as awarding it to V2 with 1825 days until its contract expires. The vendor with the lowest risk is V3 given their max\_remaining\_days value of [-54 days]. The considerations discussed in the previous paragraph would then apply to relative level of risk incurred by awarding to vendors V1, V2, and V3.

The rest of this section discusses what value functions are available for users of the tool and how to choose among them. The first subsection contains a gallery of value functions and discusses how they translate raw amounts into risk or importance scores. The subsection ends with a guide to choosing value functions.

Shape, polygon

Description automatically generated

Figure 3 Value Function Direction/Shape and Mathematical Forms

## Interpreting Value Function Shape and Direction

Each variable in the risk and importance indexes must be assigned a value function. Value functions are defined by specifying a shape and a functional form in the VF\_Def tab of the model definition template workbook. Four shapes and five functional forms are implemented in the SAS tool, for a total of 20 possibilities. Figure 3 displays the available value functions. The gallery is organized into rows for each direction/shape and columns for each functional form.

The four directions are:

1. Increasing: This shape is used when more relates to higher value. For example, in the case of risk, a higher value of the attribute implies a higher risk.
2. Decreasing: This shape is used when less relates to higher value. For example, in the case of risk, low values of the attribute imply a higher risk.
3. Peak: This shape is used when increasing values of the attribute relate to increasing value (risk, importance) and after reaching some maximum peak, increasing values of the attribute cause decreasing value (risk, importance).
4. Valley: This shape is used when the extremes are to be avoided. That is, value decreases to a middle point, after which value increases, as the value of the attribute increases.

The direction of a value function depends on how the risk/importance changes in response to an increase in amount. There are four directions implemented in the tool: increasing, decreasing, peak, and valley. Direction does not determine *how much* the value changes when the amount increases. Direction just indicates the direction the value moves.

The simplest direction is increasing. Increasing direction means that whenever the amount of an attribute increases, so does the value (aka risk or importance). How much the value goes up by depends on the functional form of the value function– see next subsection – but any increase in amount, no matter how small, always results in an increase in value (possibly even smaller, but an increase nonetheless.) An increasing value function is used when more relates to higher value. This is the most common direction for a value function.

The next direction is decreasing. Risk variables often have decreasing value functions. A decreasing direction means than whenever the amount increases, the value decreases. As with increasing value functions, how much the value goes down by depends on the functional form – see next subsection – but any increase in amount, no matter how small, always results in a decrease in value (possibly even smaller, but a decrease nonetheless.) A decreasing value function should be used when less relates to higher value.

The last two directions/shapes are compounds of increasing and decreasing. As the amount increases, a peak value function increases as well, until the midpoint of the amount range (i.e. a peak value function increases with the amount up to the median amount), and then it switches to decreasing from the midpoint of the amount range to the maximum. In a peak value function, the maximum value occurs at the median amount.

The valley or U-shaped value function is the opposite of the peak value function. This is used when the extremes of the amount range are considered bad. If the peak value function is trying avoid the middle, then the valley value function is trying to be in the middle. This might be useful when having the exact right amount of a variable minimizes risk and the further from the middle cause increased risk. For a non-DLA example, consider predicted annual rainfall in natural disaster risk index: very low means drought with concomitant crop failure and wildfire risks and very high means floods. Average rainfall is the low risk because infrastructure, farming practices, flora and fauna are all adapted to handle it.

The tool provides five functional forms for a value function, which are:

1. Linear: The amount of the attribute and the related value increase at the same rate.
2. Logarithmic: Value increases more slowly than the amount of the attribute.
3. Exponential: Value increases more quickly than the amount of the attribute.
4. Sigmoid: At first, value increases more quickly than the amount of the attribute. After the midpoint, value increases more slowly than amount.
5. Inverse Sigmoid (Logit): At first, value increases more slowly than the amount of the attribute. After the midpoint, value increases more quickly than the amount of the attribute.

The functional form of a value function depends chiefly on the marginal value of the variable. The paramount question is not, “How much is this amount worth to you?” but instead is, “How much is this next increment of amount worth to you?”. It is useful to think in terms of levels. In project terms, the questions to ask are:

* If we go from none to a little, does the risk change a lot, hardly at all, or a little?
* If we go from not much to some, does the risk change a lot, a little, or about as much as the amount does?
* If we go from some to a lot, does the risk change a more than the about as much as the amount does?

This concept is summarized in Table 1.

Table 1 Conceptualizing Change in Risk or Importance

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| --- | --- | --- | --- |
|  | Starting Amount | Ending Amount | The Risk or Importance Changes |
| 1 | None | A little | r A. Less than the amount changes (aka hardly at all)  r B. As much as the amount changes  r C. More than the amount changes |
| 2 | A little/not much | Some | r A. Less than the amount changes  r B. As much as the amount changes  r C. More than the amount changes |
| 3 | Some | A lot | r A. Less than the amount changes  r B. As much as the amount changes  r C. More than the amount changes |
| 4 | A lot | As much as possible | r A. Less than the amount changes  r B. As much as the amount changes  r C. More than the amount changes |

Using the insides gained from Table 1, the analyst has a basis for selecting a shape. For example:

* If all answers are B: Linear. This is the simplest value function, and probably a good choice if the answers to all of the above are “I do not know, how would you even tell?”, as well as resources that do not have lots of constraints or competing uses and proportional output. This choice is useful as the default.
* Exponential: Choose exponential if each additional increment makes all the increments that came before it more valuable. Or if every time an additional increment is added, it generates more incremental value than the increment before. For example, going from 0-10 gives you 1, then going from 10-20 gives you 2 more (for a total of 3), going from 20 to 30 gives you 4 (total of 7) etc. This is obviously increasing, but it works similarly in reverse: you lose more value going from 0 to 10 than from 10 to 20, and from 10 to 20 than from 20 to 30, etc. This is also true for the peak case with going out from the center or in from the edges (valley). Thus, for decreasing, the value drops each time you add 1 to the amount, but it drops less than it did last time. Or, for decreasing, every time the amount drops by 1, the value increases more than it did the last time the amount dropped by 1. This is probably a good value function to consider when having more makes it easier to get more (like family fortunes/the rich getting richer).
* Logarithmic: Choose logarithmic if, every time you add 1 to the amount the value increases less than it ever has before, but still increases. That’ is for increasing. For decreasing, every time you take 1 away an increment the value increases, but less than what it did before. Or, for decreasing, each time you add 1 to the amount, the value decreases more than it did last time. Analogous responses happen with peak and valley. This is a good value function to use when a resource has maybe usage costs (e.g. holding cost for inventory – more may be better but not that much better, and you must store and monitor the inventory), or for any situation where it is easy to accumulate more than you can use. Basically, the increasing function is good for anything with diminishing returns. If returns start out increasing and do not begin diminishing until halfway through the range, then sigmoid (next one) may be a better model.
* Sigmoid: This curve basically grows exponentially up to the midpoint, then logarithmically thereafter. It is a classic for resources that start empty but have capacity constraints, so sigmoid is a good value function to consider for variables with constraints on their output. The sigmoid is a good choice for modeling thresholds—that is, variables which are not worth much until you have “enough” (which the tool constrains to the midpoint of the amount range), but once you do have enough, diminishing returns set in rapidly. The PEAK version gives a nice bell curve.
* Logit or inverse sigmoid: This curve grows logarithmically until the midpoint of the amount range, and exponentially thereafter. This value function shape is good for variables that have an okay region in the middle of their range. Logit tends to be useful for variables where you need at least a little, but ample amounts open up possibilities. In risk terms logit can be useful for modeling variables (like, say, contamination) where normal operations can filter out standard background levels, medium levels require mitigation but it is doable, and high levels must be avoided at all cost.

Note that to implement direction, there is a mathematical relationship that can be used. The decreasing, peak, and valley value functions can all be mapped to the increasing value function using the some mathematical relationships. The four value functions are:

* is the increasing value function.
* is the decreasing value function. The decreasing value function is just the increasing value function reflected about . Therefore, the relationship between the and is given by: and
* is the peak value function.
* is the valley value function.

The SAS tool exploits the relationships between the value functions by implementing functions that use these relationships to simplify implementation. By converting the scaled variable values to their increasing equivalent using these relationships, the SAS tool can implement all 20 value functions from gallery in Figure 3 by implementing only 6 user functions in PROC FMCP in the script value\_fns.sas: v\_linear(x), v\_log(x), v\_exp(x), v\_sigmoid(x) and v\_logit(x) for the shapes, plus normalize(x, direction $) to handle the shapes by transforming all scaled variables to their equivalent increasing value. The SAS code to implement the value functions can be found in the Appendix.

In the approach that follows, we develop separate indices to measure 1) importance within the supply system, and 2) risks within the supply system. Importance provides some measure of whether the element should be prioritized within supply chain operations, but that importance does not necessarily (alone) measure the inherent risk associated with the element. That is, we believe that it is useful to analyze supply chain elements based on two criteria 1) their operational importance, and 2) their operational risk. An element may be important but pose little risk. Our interest should be in finding elements that are both important to supply chain operations and pose high risk to supply chain operations. Thus, within the following sections, when we analysis NIIN risk and vendor risk, we include indices for both importance and risk, which are then combined into an overall index.

The next two sections illustrate the application of the MODA methodology to the development of NIIN and vendor importance and risk indices. After that presentation, we provide illustrative examples of the application and interpretation of the indices.

## Modeling NIIN Importance and Risk

This section presents the operational fields used in developing the NIIN indices as well as how the fields are combined into an overall index. Fields within DLA operational information systems were reviewed for relevance and availability for use within the NIIN risk analysis. Sets of possible fields based on the reviewed literature and DLA information systems were proposed and evaluated as to their contribution to indicating three main characteristics: 1) fields that facilitate grouping and analysis, 2) fields that indicate the importance of the item and 3) fields that indicate some notional of operational risk. DLA subject matter experts (SMEs) assisted in reviewing and collecting example data on the possible fields.

First, we present mathematical notation to represent the general components of the risk and importance indexes for analyzing NIINs. Then, the selected fields will be discussed based on DLA data instances. Keep in mind that there will be additional fields included in the analysis called “grouping fields” that are not represent mathematically since they are not translated to index values.

* Let be the number of risk components in the NIIN risk index.
* Let be the value of risk component i for NIIN j
* Let be the weight of risk component i for NIIN j
* Let be the risk contribution for component i for NIIN j
* Let be the risk index for NIIN j, where:
* Let be the proportion of the total risk contributed by component i for NIIN j

The value of for a given NIIN j is the key output from the MODA risk computations. The analyst has the ability to choose which components are included in the risk computation as well as the weight associated with each component.

As noted in the previous section, we develop a separate index to represent the importance of the factor to the supply chain. Thus, a NIIN that has high risk and high importance would be identified for further investigation and control. The mathematical notation for the importance index is as follows.

* Let be the number of importance components in the NIIN importance index.
* Let be the value of importance component i for NIIN j
* Let be the weight of importance component i for NIIN j
* Let be the component importance contribution for component i for NIIN j
* Let be the importance index for NIIN j, where:
* Let be the proportion of the total importance contributed by component i for NIIN j

The value of for a given NIIN j is the key output from the MODA importance computations. The analyst has the ability to choose which components are included in the importance computation as well as the weight associated with each component.