DSMs for Organization Design: Incorporating Additional Criteria in Clustering Algorithms

Runar Solberg[1], Ali Yassine[2], Nicolay Worren[1,3], Kim Soldal[3], Tore Christiansen[3]
[1]Norwegian University of Life Sciences
[2]Stevens Institute of Technology
[3]Reconfig AS

Abstract: The Design Structure Matrix (DSM) is a useful tool for improving systems, including organizations, by grouping interdependent elements (such as roles) to reduce coordination costs. However, traditional DSM algorithms, like the Minimum Description Length (MDL) approach, are primarily used to optimize systems based on a single criterion: interdependencies between elements. In this paper, we extend the MDL algorithm by adding resource utilization as an additional criterion to improve its relevance for organizational design. We introduce a modified MDL fitness function to account for consolidation errors, implemented through a genetic algorithm. Furthermore, to guide organizational change management, we introduce a classification matrix for diagnosing problems related to coordination and resource constraints. Finally, we demonstrate our approach on a hypothetical case involving radiologists in a hospital. Results show improved fitness scores, reflecting better clustering and resource utilization. Future work includes the refinement of parameters through sensitivity analysis and empirical validation.

Keywords: Design Structure Matrix (DSM), organization design, clustering, resource consolidation, genetic algorithm

1 Introduction

In organization design, the main criterion for grouping roles into units is to minimize coordination costs (Thompson, 1967). Indirectly, this criterion also simplifies interfaces between units (Baldwin and Clark, 2000; Sanchez, 1995) and enhances accountability by creating focused units (Kilmann, 1983). Minimization of coordination costs is also the most widely used criterion when using the Design Structure Matrix (DSM) to examine and improve the structure of teams or organizations (Eppinger and Browning, 2012). Rigorous techniques have been developed to automate the identification of DSM clusters using a Minimum Description Length (MDL) metric and a genetic algorithm (Worren et al., 2020; Yu et al., 2007).

However, scholars have pointed out that more than one criterion can be used to group roles. In particular, roles can also be grouped by skills or knowledge to improve learning (Sosa and Mihm, 2007), by market segment to improve customer orientation (Homburg et al., 2000; Lee et al., 2015; Van Witteloostuijn and Boone, 2006), or by function to achieve economies of scale and scope (Yassine et al., 2021), as when consolidating resources into a shared services unit (Bondarouk, 2014).

In this paper, we focus on the latter criterion, although our approach may also be extended to other criteria. As the standard MDL algorithm only includes a single criterion (related to interdependencies between elements), it does not incorporate potential synergy effects from sharing of resources across units. This is problematic because most organizations are critically dependent on effective resource utilization (Bower and Gilbert, 2007; Teece, 1980), and it limits the applicability of current DSM-based clustering methods in situations involving consideration of multiple criteria (which may be the norm for organization design).

Hence, in this study, we pursued the following research question: *How can incorporating additional criteria in clustering algorithms help managers design organizations?*

We address the research question by augmenting the approach proposed in Yassine et al. (2021) to incorporate resource consolidation as an additional criterion in the MDL algorithm. More specifically, we provide an updated MDL fitness function to account for consolidation errors, and we implement the optimization using the same genetic algorithm (GA) as in Yu et al. (2007). As an example of resource consolidation, we consider the question of how to organize radiologists in a hospital, as illustrated in Figure 1. Currently, the radiologists are organized into two separate units (A and B). Each of the units consists of a core team of a nurse practitioner, supported by a radiologist and an anesthesiologist.

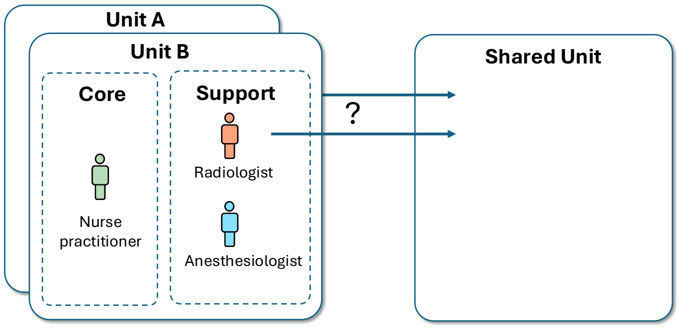

Figure 1. Illustrative example involving the organization of radiologists in a hospital

Depending on the constraints the hospital faces, the hospital managers must consider multiple criteria, such as the need for coordination within and across units and effective resource utilization. In healthcare, such resource utilization challenges are quite common, making the example particularly relevant (see e.g., Fagefors et al., 2024).

In the following, we use this example to provide a simple demonstration with a synthetic data set. It is worth noting that although we focus on resource utilization in this paper, our proposed approach is a general one, which, in principle, may be used with any combination of criteria, as long as they can be captured quantitatively in the same manner as we show below.

2 Theory and Existing Methods

Recent research on DSMs treats modularization as a multi-criteria trade-off rather than a single-criterion optimization. Using a DSM-based Pareto search, Sanaei et al. (2015) show how intra-cluster (cohesion) and inter-cluster (interface) costs trade off, allowing designers to select non-dominated modular product architectures. Building on this idea, Otto et al. (2020) proposed a set of "field-effect" guidelines that treat zones of heat, pressure, magnetics, etc., as constraints on module boundaries, ensuring that field-sensitive components are separated from harmful fields while still supporting innovative relocations of functions across those boundaries. Worren and Pope (2024) describe comparable functional conflicts in organization design. A third line of work examines how firms can simultaneously lower coordination costs and capture synergy from shared resources across business units (Solberg et al., 2024; Yassine et al., 2021). Despite these advances, as far as we know, no study has extended the widely used Minimum Description Length (MDL) clustering algorithm to incorporate multiple criteria. In the following, we describe the existing MDL metric in more detail.

2.1 The Existing Minimum Description Length (MDL) Metric

The Minimum Description Length Metric (MDL) metric, introduced by Yu et al. (2007), is an information-theoretic approach to evaluating the modularity of complex systems. It builds on the principle that an efficient system should require less information to describe its content and structure. When applied to the DSM for evaluating the modularity of complex systems, the MDL metric calculates the total "description cost" of a modularization. Specifically, the MDL metric assesses the amount of information needed to describe the size of modules within the DSM (i.e., the number of elements) as well as the connectivity between and within these modules. It can also assess more complicated architectures like those with bus modules as well as those with overlapping clusters. Buses are typically elements that interact with most other elements or system-level integrating components, such as integration teams (Browning, 2009; Sharman and Yassine, 2004). Although the algorithm introduced by Yu et al. (2007) can identify such buses, this is fundamentally different from grouping based on resource consolidation. While such consolidated units would look the same in a DSM, the underlying grouping criterion is based on potential value (e.g., improved resource utilization or learning), not on current interactions from interdependencies. Resource consolidation potential refers explicitly to the anticipated improvement in resource utilization—such as reducing idle capacity—achieved by grouping particular roles in a single organizational unit. Therefore, decisions to consolidate resources must be based on additional information regarding this potential value.

The original MDL metric from Yu et al. (2007) is shown in Equation (1).

$$f_{DSM}(M) = (1-\alpha-\beta)\left(n_c \log n_n + \log n_n \sum_{i=1}^{n_c} cl_i\right) + \alpha[|S_1|(2\log n_n + 1)] + \beta[|S_2|(2\log n_n + 1)] \quad (1)$$

The terms α and β are weights that the system architect selects and takes on values between 0 and 1. These are used to match the preferences of human experts. As suggested by the authors, the simple approach is to set these values to 1/3, thereby giving each component of the metric an equal weight. The term n_c is the number of clusters, n_n is the number of rows or columns in the DSM, and cl_i is the size of module i. The S_1 and S_2 terms account for data mismatches, which are undesirable structural features, such as overlapping clusters or bus modules, which are often encountered in real-world systems. These penalties help penalize complex or inefficient architectures.

A fundamental principle of organizational design is to cluster interdependent elements together, a concept that underpins the use of the DSM for identifying modular groupings such as teams. The MDL metric, used in conjunction with the DSM, enables the systematic detection of these clusters based on patterns of interdependence. There are many situations where decision makers need to consider more than one design criterion. One example is when the anticipated benefits of consolidating resources—such as increased efficiency, flexibility, or economies of scope—outweigh the potential savings in coordination costs typically achieved through modular organization.

The standard MDL metric includes terms for module size encoding, interconnections, and mismatch penalties. To incorporate the benefit of consolidating resources, Yassine et al. (2021) suggested augmenting the MDL formula by adding a new term to the original MDL equation that reflects how important consolidation is relative to coordination, as shown in red in Equation (2).

$$f_{DSM}(M) = w_1 f_1 + w_2 f_2 + w_3 f_3 + w_4 f_4 \qquad (2)$$

This term refers to type III mismatches: elements that should have been consolidated but were not. The first term denotes model complexity, the second type I errors (hypothesized marks that the model description misses), and the third type II errors represent real marks that the hypothesized model description misses.

Returning to our example of organizing radiologists in a hospital, as illustrated in Figure 1. Imagine that the hospital manager has identified that the current capacity is not fully utilized. The radiologists are idle some of the time, because the workload within the different units is unpredictable and varies with the number of patients that are admitted. However, since radiologists currently belong to local units, it is difficult to utilize these existing resources fully across units. Therefore, the manager is considering consolidating the radiologists into a shared common unit (i.e., a resource pool). Assume we have an initial mapping of roles and their interactions and consolidation potential, as shown in Figures 2a and 2b, respectively.

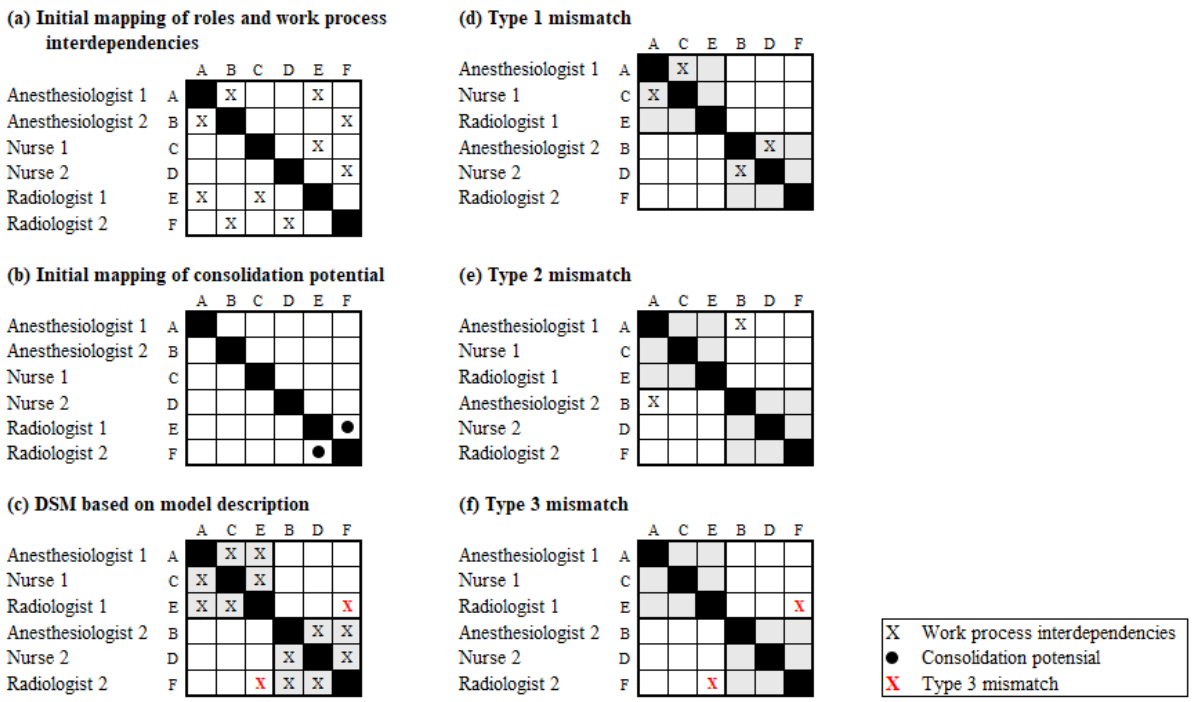

Figure 2a-f. Modified MDL metric with Type III mismatches applied to the example of consolidating radiologists in a hospital, adapted from Yassine et al. (2021), with alternative joint representation of interactions and consolidation potential

Suppose we have a suggested model description as shown in Figure 2c. In this particular case, when compared to the DSM in Figure 2a, the model description has three types of mismatches (see Table 1 for definitions of the three mismatches). In addition to the classical type I and type II mismatches, as shown in Figures 2d and 2e, the model description also has type III mismatches, denoted in red in Figures 2c and 2f.

2.2 Visualization of Complex Information in the DSM

A significant issue with the DSM relates to handling the large amounts of data associated with complex system architectures while maintaining its usability and readability. Approaches to address the large amounts of data associated with complex systems with many interfaces include the use of a DSM with sub-cells (Helmer et al., 2010).

The original MDL focuses on structural relationships (i.e., who connects to whom). It could be expanded to include semantic or functional relationships, such as the similarity of tasks, roles, or component functions. This would allow the metric better to reflect functional cohesion, not just structural compactness. For example, even if two components (or roles within the organization) are not directly connected, they might serve similar constraints or functions and could be grouped accordingly, for instance, to realize a potential for improved resource utilization.

3 Proposed Approach

3.1 Modified MDL Fitness Function and Optimization

The premise for including consolidation in the fitness function is that consolidation should be weighed against other organizational design priorities and is not an absolute decision. In clear-cut cases, one can simply optimize for a single dominant criterion. However, there will be situations where one needs to balance multiple criteria (see e.g., Solberg et al., 2024). A classic example is when considering implementing a matrix organization (Davis and Lawrence, 1977; Worren, 2017). To account for type III mismatches, we extend the original MDL fitness function described in Equation (1) with the additional term and parameter as shown in red in Equation (3), also highlighting each term in brackets.

$$f_{DSM}(M) = \overbrace{(1-\alpha-\beta-\gamma)\left(n_c \log n_n + \log n_n \textstyle\sum_{i=1}^{n_c} cl_i\right)}^{\text{Model description}} + \overbrace{\alpha[|S_1|(2\log n_n+1)]}^{\text{Type I mismatches}} + \overbrace{\beta[|S_2|(2\log n_n+1)]}^{\text{Type II mismatches}} + \overbrace{\gamma[|S_3|(2\log n_n+1)]}^{\text{Type III mismatches}} \quad (3)$$

In addition to the previous α and β parameters, we incorporate the parameter γ, as defined in **Fehler! Verweisquelle konnte nicht gefunden werden.**. The S_3 term accounts for type III mismatches.

Table 1. Definition and explanation of the α, β and γ parameters of the fitness function

Parameter	MDL technical definition	Practical implications for organization designer
α	The weighting parameter that penalizes Type I mismatches—connections hypothesized inside clusters in the model description that do not exist in the mapped interactions (false positives within clusters).	A higher α (relative to the other parameters) means the organization designer prioritizes within-unit interactions. It puts pressure on the algorithm to optimize for tight coordination and cohesion within units/teams.
β	The weighting parameter that penalizes Type II mismatches—connections that exist between clusters but are missed in the model description (false negatives between clusters).	A higher β (relative to the other parameters) means the organization designer prioritizes between-unit interactions. It puts pressure on the algorithm to optimize for coordination between units/teams, also referred to as system-level interactions.
γ	The weighting parameter that penalizes Type III mismatches—failure to group resources that are recognized to have an increased effectiveness if grouped together.	A higher γ (relative to the other parameters) means the organization designer prioritizes consolidation of resources that naturally belong together in the same unit to achieve a form of synergy potential, such as improved resource utilization.

3.2 Constraint Matrices and DSM Visualization

Consolidation decisions require additional information beyond the interactions contained within a traditional DSM. The potential value from consolidation can be represented in an additional DSM (see Figure 2b). However, a method is needed to capture the meaning of the marks in the two DSMs. These marks differ qualitatively from those indicating interactions due to interdependencies—they represent value potential rather than dependencies.

We propose to use a constraint matrix to capture this information. in our example involving organizing the radiologists in the hospital, we need to express both the current (as-is) and desired target state (to-be) in terms of criteria and elements (i.e., roles or units). Figure 3a-b shows the corresponding constraint matrices against the two criteria of minimizing coordination costs and maximizing resource utilization for a) the current organization (as is) without any consideration of consolidation potential, and b) the preferred future state of consolidating the radiologists in the same unit to maximize resource utilization.

(a) Current organization (as-is)

	Roles					
Design criteria	Anesthesiologist 1	Nurse 1	Radiologist 1	Anesthesiologist 2	Nurse 2	Radiologist 2
Minimize coordination costs	x	x	x	x	x	x
Maximize resource utilization						

(b) Target organization (to-be)

	Roles					
Design criteria	Anesthesiologist 1	Nurse 1	Radiologist 1	Anesthesiologist 2	Nurse 2	Radiologist 2
Minimize coordination costs	x	x	x	x	x	x
Maximize resource utilization			x			x

Figure 3. Design matrices between the design and the DSM elements (e.g., roles in the organization) for the current organization (a) and the desired target organization (b)

Notably, in Figure 3b, both radiologists have marks for both design criteria. This is an important point as it signifies that we need to balance the two criteria; if the radiologists were to satisfy only the criterion of maximizing resource utilization, they could simply be frozen or excluded from the optimization. However, as they also need to satisfy the criteria of minimizing coordination costs, the optimization must try to strike a balance between the two.

For visualization and reconciliation of the dual information in a single DSM, we suggest applying a simple rule for aggregation similar to what is described by Helmer et al. (2010) and Solberg et al. (2023). Using a multi-criteria decision-making method such as AHP (Saaty, 1990), we can identify a priority vector representing the relative weight of importance of the design criteria between 0 and 1. We can use a rule that states that any higher-level value within one cell will always supersede any quantity of lower-level values, as illustrated in Figure 4c within a certain threshold of tolerance τ around the center of 0.5 (e.g., 0.2). In our simple binary example, we only have one consolidation group. However, to be flexible, our proposed solution supports the definition of multiple consolidation groups. We propose that this consolidation group information can be visualized using different colors in one single DSM, as illustrated in Figure 4d, with a second hypothetical consolidation group consisting of the two anesthesiologists (Figure 4d, upper left) with a dominant criterion of resource utilization. This approach could be used on multiple levels (e.g., on a unit level) to signal the dominant criterion for that group of elements.

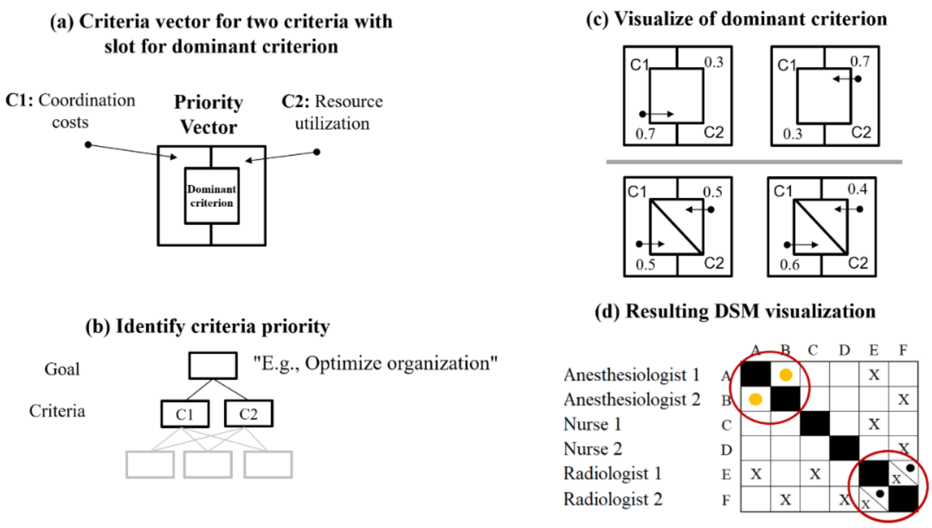

Figure 4a-d. Alternative visualization of interdependencies and consolidation potential in a single matrix

In our example we have a non-trivial case with marks for both criteria for the radiologists (Figure 3b and Figure 4d, bottom right). For such conflicting cases with close scores, manual adjustments can be made to prioritize criteria, leveraging extra contextual details for better decisions. The dominant criteria could be visualized in the DSM, while the detailed information could be stored in the design matrices, accessible to the user by clicking on the respective cell. The design matrices shown in Figure 3 could also store numerical data to signal the strength or intensity of the relationship.

3.3 Problem Diagnosis and Classification of Current and Desired Organizational States

Based on our two criteria, the organization can face two main types of problems: The first is a coordination problem, which arises when interdependent organizational units or team members fail to effectively align their tasks, interactions, or communication, resulting in reduced efficiency or compromised organizational outcomes. Organizations with this problem are primarily coordination-constrained, with a high coordination cost. The second main problem is a resource utilization problem, which arises when scarce organizational resources (e.g., personnel, knowledge, tools, or assets) are inefficiently grouped, allocated, or deployed, resulting in redundancy, resource underuse, overuse, or diminished operational effectiveness. Such organizations are primarily resource utilization-constrained.

Building on these two main types of problems, we propose a classification matrix as shown in Figure 5. This classification matrix can be a practical tool to identify the current state ("as-is") situation, the desired future state ("to-be"), the gap, as well as a choice of strategy to close the gap. The matrix shows four main quadrants: (1) efficient and balanced (balanced effectiveness with strong internal alignment and optimized resource utilization), (2) coordination-constrained, yet efficient resource utilization (strong in resource management, but needs clearer coordination and improved synchronization), (3) resource utilization-constrained, yet strong coordination, and (4) chaotic and dysfunctional, that is both coordination and utilization-constrained. The green arrows represent possible strategies to close the gap. Here, we assume we have access to additional data to assess the degree of resource constraint.

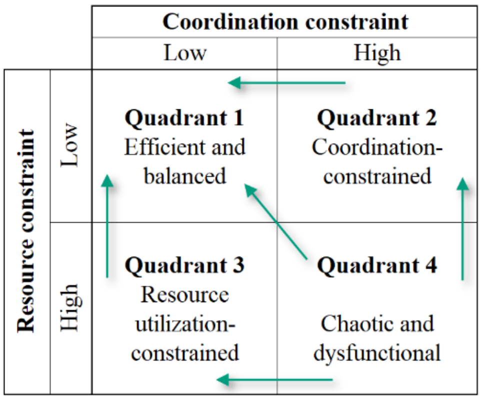

Figure 5. Classification matrix as a useful tool for problem diagnosis (identify current state), future state, gap as well as choice of strategy to close the gap

3.4 GA Implementation

The provided code is a Python implementation of a Genetic Algorithm (GA) designed for optimizing Design Structure Matrices (DSMs). The algorithm takes as input an Excel sheet with a DSM containing interactions and a list of resource groups that should ideally be consolidated. The key steps of the algorithm are:

1. Initialize a population of random candidate solutions.
2. Evaluate and rank the fitness of each candidate solution based on Equation 3.
3. Apply selection, crossover, and mutation operators to the candidate solutions to create a new population of candidate solutions so that characteristics from higher-ranked candidates are more likely to be included in the next generation.
4. Evaluate the stop criteria, and if not met, go back to step 2 with the new population of candidate solutions.

The objective is to find the model that minimizes the fitness function described in Equation 3. Visualization is employed to illustrate the convergence of the algorithm through a fitness plot. For detailed exploration, access the complete implementation in the public git repository here. Our Python implementation does not support overlap of clusters in order to limit computational complexity.

3.4.1 Example 1: Consolidation of Radiologists in a Hospital (Small Organization)

Continuing the hypothetical example involving the radiologists, imagine we have an initial DSM with two units (clusters), as shown in Figure 6a.

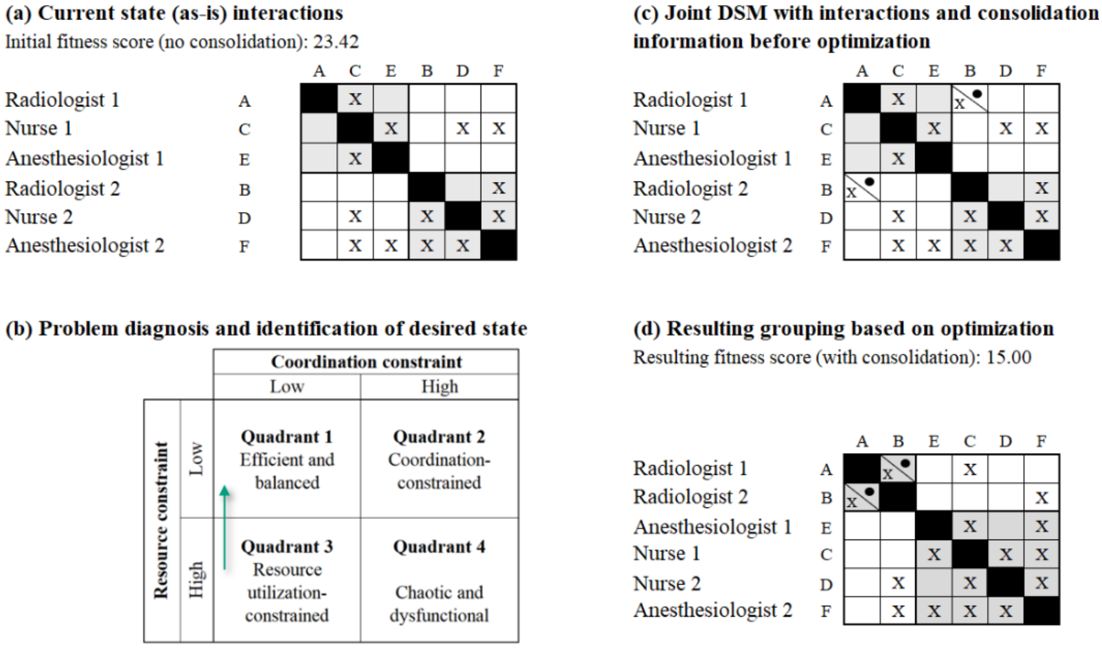

Figure 6a-d. Simple DSM example of current interactions

This current-state (as-is) organization was constructed to illustrate two interdisciplinary teams each team consisting of one radiologist, one nurse and one radiologist. The interactions marks show a balance between interactions across and within the two teams.

The manager in charge of organizing the radiologists applies the classification table to diagnose the problem. The manager thinks the main problem is one of resource constraint (Quadrant 3) and seeks a desired state of “efficient and balanced” as shown in Figure 6b (Quadrant 1). To close this gap, he is considering consolidating the two radiologists, as specified in the design matrices (see Figure 3), which results in a joint DSM as shown in Figure 6c. As we have not done a sensitivity analysis of the α, β and γ parameters, we use a simple heuristic of setting them each to 0.25, and n_c (max number of clusters) = 3. Running the optimization results in a fitness plot as shown in Figure 7. The resulting optimized fitness score (which we seek to minimize) was 15.00 compared to the original fitness score (without consolidation) of 23.42.

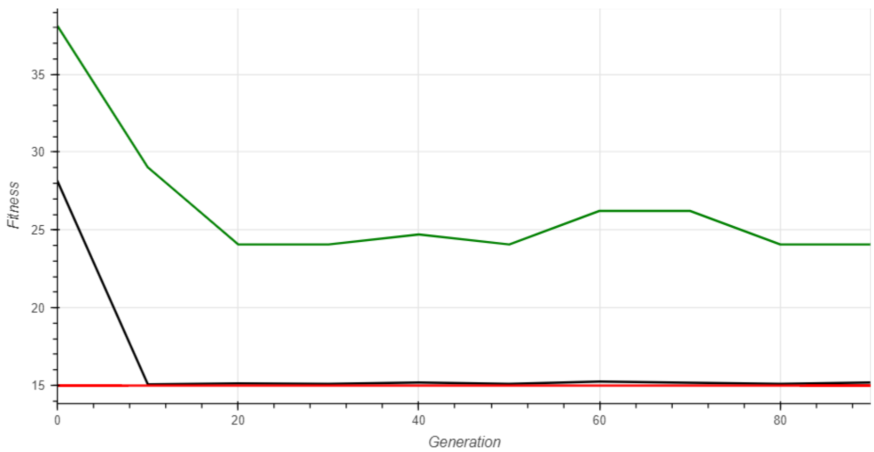

Figure 7. Fitness convergence plot with minimum (red), average (black), and maximum (green) fitness

3.4.2 Example 2: Consolidation of Radiologists in a Hospital (Medium-sized Organization)

Now, consider a hypothetical medium-sized organization with two main emergency units as shown in Figure 8d. This current-state (as-is) organization was constructed to depict a situation where none of the radiologists are currently consolidated in a common unit, representing a potential for economies of scope through sharing of radiologists across units.

Using our classification matrix to diagnose the current problem, imagine the hospital manager diagnoses the current organization to be in Quadrant 4 “Chaotic and dysfunctional”. Currently, the radiologists are dedicated to three different units. The manager has identified a potential to improve the radiologists' utilization due to seasonal demand variability. To alleviate this resource constraint, he is considering consolidating Radiologists 1,2, and 3 in a common unit. This consolidation group is visualized with yellow circles. By tuning the three main α, β, and γ parameters, we can use our algorithm to provide three different target organizations. This makes it possible to consider different strategies as stipulated by the green arrows in Figure 8. For instance, it the hospital manager ultimately seeks to achieve a target-state of “Q1: Efficient and balanced” (the diagonal green line) but his short-term main concern is to alleviate resource constraints, he could consider an intermediate step to reach Quadrant 2 as an intermediate state before continuing to the final target state in Quadrant 1.

At least a couple of observations are interesting when examining the DSMs and the corresponding values of the α, β, and γ parameters. First, in Quadrant 2 (Figure 8b), we see, as expected, that all the radiologists are consolidated into the same unit, alleviating the resource constraints experienced by the manager. Also, the number of units is reduced from four to three. However, we also see a large number of interactions outside the units, especially in the center unit, with only one mark inside the cluster. In Quadrant 3 (Figure 8c), which favors optimizing for within or between unit coordination with no emphasis given to resource utilization (γ = 0), the resulting DSM still has two of the radiologists in the same unit. We see fewer marks across clusters and more marks within clusters. Finally, in Quadrant 1 (Figure 8b), we see that two of the radiologists are in the same unit, with a balanced distribution of marks within and across units, with four equally sized units.

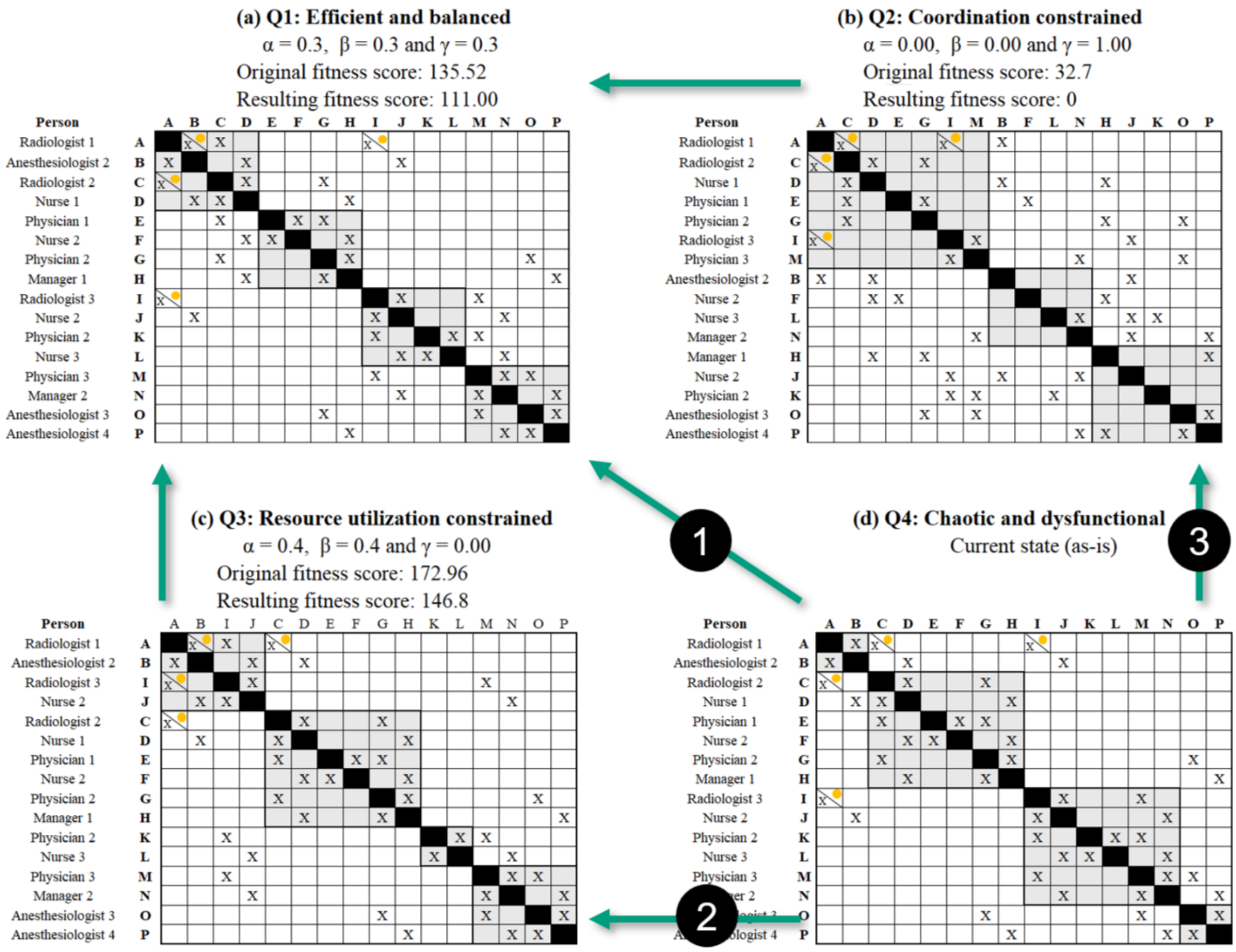

Figure 8. Example 2 – Consolidation of radiologists in a medium-sized organization with α, β, and γ parameters and fitness scores and alternative change strategies

Through such an interactive approach, the manager can consider various organizational designs, using the reduction in fitness score as a quantitative measure of improvement, and tune the α, β, and γ parameters as well as other parameters such as the maximum number of clusters (here it was fixed to 4). This approach can also help the manager plan the organizational change. For instance, to get from Quadrant 4 to Quadrant 1, the manager can consider three different change strategies, as highlighted by the numbered circles in Figure 8. The first path, on the diagonal, is to go directly to the desired state in Quadrant 1. In certain situations, this is a necessary strategy to realize the inherent benefits. However, a strategy of going through intermediate states, as illustrated by paths 2 and 3, can also be considered. Such intermediate steps might be necessary depending on the various priorities and constraints faced by the organization, e.g., to quickly achieve intermediate benefits along a roadmap of two separate stages.

4 Summary and Conclusion

This study has addressed an important gap in existing DSM-clustering methodologies by showing how multiple criteria—particularly resource utilization—can be incorporated into the MDL algorithm by extending the fitness function. By adding a term for consolidation potential, the approach provides a more applicable clustering tool for organization designers who must consider multiple criteria, such as coordination costs and resource utilization. We illustrated the proposed method through a practical example involving hospital radiologists, showing clear benefits in terms of improved fitness scores. Additionally, we introduced a visual and diagnostic tool in the form of a classification matrix combined with a novel DSM visualization technique to facilitate an interactive decision-making process in complex organizational contexts. The simplified parameter selection (α, β, and γ) serves demonstration purposes. Future research should involve an extensive sensitivity analysis to identify the Pareto-efficient frontier. Also, we suggest empirical validation across different organizational scenarios to refine parameter values and ensure robust practical recommendations. While demonstrated using two criteria and binary values, the approach can, in principle, be used with any combination of criteria and numerical values that represent the strength of interdependencies.

References

Baldwin, C.Y., Clark, K.B., 2000. Design rules: The power of modularity. MIT press.

Bondarouk, T., 2014. Shared Services as a New Organizational Form. Emerald Group Publishing. https://doi.org/10.1108/s1877-6361_2014_0000013015

Bower, J.L., Gilbert, C.G., 2007. From Resource Allocation to Strategy.

Browning, T.R., 2009. Using the Design Structure Matrix to Design Program Organizations. Handb. Syst. Eng. Manag. 1401–1424.

Davis, S.M., Lawrence, P.R., 1977. Matrix, First. ed, Reading, Mass. Addison-Wesley Publishing Company, Inc.

Eppinger, S.D., Browning, T.R., 2012. Design Structure Matrix Methods and Applications, Design Structure Matrix Methods and Applications. MIT press. https://doi.org/10.7551/mitpress/8896.001.0001

Fagefors, C., Lantz, B., Rosén, P., Siljemyr, L., 2024. Staff pooling in healthcare systems–results from a mixed-methods study. Heal. Syst. 13, 31–47. https://doi.org/10.1080/20476965.2022.2108729

Helmer, R., Yassine, A., Meier, C., 2010. Systematic module and interface definition using component design structure matrix. J. Eng. Des. 21, 647–675. https://doi.org/10.1080/09544820802563226

Homburg, C., Workman, J.P., Jensen, O., 2000. Fundamental changes in marketing organization: The movement toward a customer-focused organizational structure. J. Acad. Mark. Sci. 28, 459–478. https://doi.org/10.1177/0092070300284001

Kilmann, R.H., 1983. The costs of organization structure: Dispelling the myths of independent divisions and organization-wide decision making. Accounting, Organ. Soc. 8, 341–357. https://doi.org/10.1016/0361-3682(83)90048-X

Lee, J.Y., Sridhar, S., Henderson, C.M., Palmatier, R.W., 2015. Effect of customer-centric structure on long-term financial performance. Mark. Sci. 34, 250–268. https://doi.org/10.1287/mksc.2014.0878

Otto, K., Hölttä-Otto, K., Sanaei, R., Wood, K.L., 2020. Incorporating Field Effects into Functional Product-System Architecting Methods. J. Mech. Des. Trans. ASME 142. https://doi.org/10.1115/1.4044839

Saaty, T.L., 1990. How to make a decision: The analytic hierarchy process. Eur. J. Oper. Res. 48, 9–26. https://doi.org/10.1016/0377-2217(90)90057-I

Sanaei, R., Otto, K., Hölttä-Otto, K., Luo, J., 2015. Trade-Off Analysis of System Architecture Modularity Using Design Structure Matrix. https://doi.org/10.1115/detc2015-46403

Sanchez, R., 1995. Strategic flexibility in product competition. Strateg. Manag. J. 16, 135–159. https://doi.org/10.1002/smj.4250160921

Sharman, D.M., Yassine, A.A., 2004. Characterizing complex product architectures. Syst. Eng. 7, 35–60. https://doi.org/10.1002/sys.10056

Solberg, R., Yassine, A., Worren, N., 2023. Using net benefit analysis to value costs and benefits of re-grouping in organization design, in: Proceedings of the 25th International DSM Conference (DSM 2023). pp. 39–47. https://doi.org/10.35199/dsm2023.05

Solberg, R., Yassine, A., Worren, N., Christiansen, T., 2024. Process Versus Knowledge Interdependencies: Balancing Alternative Grouping Criteria, in: DS 134: Proceedings of the 26th International DSM Conference (DSM 2024), Stuttgart, Germany. pp. 98–107. https://doi.org/10.35199/dsm2024.11

Sosa, M.E., Mihm, J., 2007. Organization design for new product development, in: Handbook of New Product Development Management. Routledge, pp. 165–198. https://doi.org/10.4324/9780080554402-12

Teece, D.J., 1980. Economies of scope and the scope of the enterprise. J. Econ. Behav. Organ. 1, 223–247.

Thompson, J.D., 1967. Organizations in action: social science bases of administrative theory. McGraw-Hill, New York.

Van Witteloostuijn, A., Boone, C., 2006. A resource-based theory of market structure and organizational form. Acad. Manag. Rev. 31, 409–426. https://doi.org/10.5465/AMR.2006.20208688

Worren, N., 2017. The matrix as a transitory form: the evolution of FMC technologies 2001–2016. J. Organ. Des. 6. https://doi.org/10.1186/s41469-017-0023-0
Worren, N., Christiansen, T., Soldal, K.V., 2020. Using an algorithmic approach for grouping roles and sub-units. J. Organ. Des. 1–19. https://doi.org/10.1186/s41469-020-0069-2
Worren, N., Pope, S., 2024. Connected But Conflicted: Separating Incompatible Roles in Organizations. Acad. Manag. Rev. 49, 6–31. https://doi.org/10.5465/amr.2021.0054
Yassine, A., Worren, N., Christiansen, T., 2021. Dedicated vs. shared resources in organizations: Modifying the Design Structure Matrix (DSM) to support consolidation decisions, in: Proceedings of the 23rd International Dependency and Structure Modeling Conference, DSM 2021. pp. 10–20. https://doi.org/10.35199/dsm2021.2
Yu, T.-L., Yassine, A.A., Goldberg, D.E., 2007. An information theoretic method for developing modular architectures using genetic algorithms. Res. Eng. Des. 18, 91–109. https://doi.org/10.1007/s00163-007-0030-1

Contact: R. Solberg, Norwegian University of Life Sciences, School of Economics and Business, Department of Strategy, Organization and Leadership, Postboks 5003 NMBU 1432, Ås, Norway, ruso@nmbu.no.