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# Analysis of the Relationship between Mobilization Uncertainty and Flexibility Based on the "Effective Response Dimension" Framework

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**Abstract:** Modern social mobilization systems are becoming increasingly complex, leading to significant uncertainty in the mobilization process. This paper introduces the concept of "Effective Response Dimension" to quantify the complexity of mobilization systems, namely the number of key decision-making nodes in the mobilization system (truncation dimension, kt) and the order of collaboration among mobilization departments (superposition dimension, ks). Utilizing flexibility's ability to quickly adapt to changes and modularly reorganize resources, this study reduces the effective response dimension or provides compensation, conducts more comprehensive simulation assumptions for resource allocation, process regulation, and social collaborative mobilization, suppresses the growth of uncertainty, and generates more accurate mobilization decisions.

**Keywords:** Mobilization; Effective Response Dimension; Uncertainty; Flexibility

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## 1. Introduction

Mobilization refers to responding to sudden events that disrupt social order during social development, such as natural disasters, financial crises, and supply chain disruptions. National mobilization systems are increasingly large and complex. Liu Jia [1] argues that mobilization-based governance has become one of the necessary means for the whole society to jointly respond to sudden public crises. Wu Chunxiao [2] points out that the resources that government governance needs to mobilize include three aspects: human resources, organizational resources, and material resources. Yong Linyi [3] notes that the formation of resource mobilization capacity relies on the collaborative support of multiple conditions. Traditional mobilization models have evolved into comprehensive supply chain mobilization involving universal participation, gradually forming a comprehensive mobilization system with cross-field, cross-departmental, and even transnational coordination. A refined mobilization simulation process can form an ideal mobilization plan. However, in the actual implementation of mobilization, the reliability of mobilization actions lacks reference data from social practice for verification. In the absence of a standard scope, overly idealized mobilization processes increase complexity and uncertainty risks, making it difficult to effectively control mobilization effects.

## 2. Analysis of Uncertainty Factors in Mobilization Actions

Mobilization refers to a series of activities in which the state, in response to the needs of the overall development strategy, mobilizes resources from various social fields into an emergency state, unifies the will of the whole people, transforms social potential into comprehensive strength, and coordinates the allocation of resources required for the development strategy. Usually, it constitutes a complete social mobilization process from mobilization preparation to mobilization implementation and then to demobilization. In this overall mobilization process, the uncertainty factors arising in the mobilization preparation stage, mobilization implementation stage, and mobilization demobilization stage are mainly analyzed.

### 2.1. Main Uncertainty Factors in the Mobilization Preparation Stage

Insufficient planning and anticipation capabilities to address deep uncertainty: Adequate social mobilization preparation lies in the prediction and planning of uncertainty. How to respond to uncertainty is a common challenge faced by mobilization planning in countries around the world. The state not only needs to overcome the risks brought by uncertainty but also balance risks and cost expenditures to avoid resource waste or social unrest caused by excessive planning. However, in general, there is a lack of sufficient planning and anticipation capabilities to cope with deep uncertainty.

Failure to break through the limited scope of traditional mobilization: At present, China's social development is in an upward stage with a stable development trend and few fluctuations. The thinking for formulating mobilization plans cannot break away from traditional mobilization scenarios and models, fails to fully combine specific scenarios for uncertainty analysis of varying degrees, and cannot fully guarantee and represent expected change needs. In a stable development period, traditional mobilization preparations can play a certain backup role, but in the future under special development trends, especially unprecedented changes dominated by the rapid development of emerging technologies, the problem of lacking the ability to break through traditional mobilization will become more prominent.

### 2.2. Main Uncertainty Factors in the Mobilization Implementation Stage

Short-term and long-term mobilization needs are constrained by mobilization plan budgets: In the process of mobilization implementation, most of the budget expenditures for both short-term and long-term mobilization needs are irretrievable. Due to the difficulty in identifying changes in long-term development strategy needs, mobilization tends to invest most of the budget in short-term demand adjustments and social operations under long-term development planning schemes. Although budget expenditures are scientific, continuous, and developmental, from the perspective of the overall development strategy, the lack of long-term planning means uncertainty in future development.

Rigid mobilization procedures lead to strong delay in development: The existing mobilization system and structural framework have long-standing certainty and continuity. However, it is precisely this fixed procedure and model that are more vulnerable to targeted attacks and destruction, becoming a fatal weakness. An overly certain mobilization system has inert links, weak update capabilities, and hinders the overall process, resulting in a lack of flexibility and adaptability in the system. It cannot confront flexible and variable systems, leading to fatal consequences.

### 2.3. Main Uncertainty Factors in the Mobilization Demobilization Stage

Lack of sound institutional guarantees: The temporary nature of mobilization may lead to such actions being carried out in certain areas without institutional guarantees, resulting in problems such as disorderly division of powers and responsibilities, difficulty in fund settlement, and easily leading to unfinished tasks, shirking of responsibilities, or resource misallocation, which affects the subsequent promotion of mobilization.

Lack of effective feedback mechanisms: In the demobilization process, there is a lack of timely collection of actual demands, operational difficulties, and relevant suggestions during the implementation process, leading to the lack of dynamic evaluation of demobilization effects and summary of review experience. The lack of a closed loop generates uncertainty.

## 3. The "Effective Response Dimension" Analysis Framework

The mobilization system introduces the "Effective Response Dimension" analysis framework to quantify the mobilization process through "effective dimensions", measure the connection between the complexity and uncertainty of each mobilization node, help formulate flexible measures according to the application background and purpose, adjust the mobilization process, and ensure the relative stability of the mobilization process lacking practical experience data.

### 3.1. Core Connotation

It reflects system complexity through the truncation dimension kt and superposition dimension ks, providing a quantitative and structured tool for the operation and evaluation of mobilization systems and other similar complex management systems. The truncation dimension kt is the number of key elements in the system. Minor changes in key elements will significantly affect the core output of the system, such as the completion time of mobilization tasks and the quantity and quality of mobilized materials, reflecting how many non-negligible driving factors exist in the system and the complexity of these driving factors. The superposition dimension ks is the highest order of collaborative effects that must be considered to explain most of the system's behaviors, reflecting the complex, non-linear interactions between various departments and units as well as the connection complexity of the system.

### 3.2. Core Idea

It reflects that the essential complexity of a system is determined by its "effective response dimension" rather than the actual number of component structures; whether the uncertainty of the system can be effectively controlled depends on the allocation of the "effective response dimension" by flexibility, and the effectiveness of flexible measures is reflected through quantitative analysis.

### 3.3. Main Objectives

The application of this concept is consistent with the reality of insufficient experience in mobilization actions. In the absence of sufficient data verification, it judges whether an increasingly complex mobilization system has become more accurate or merely more uncertain and difficult to control. By quantitatively evaluating the actual complexity of the mobilization system, tracing the source of output uncertainty, and using flexible means for regulation, the stable operation of the mobilization system is achieved.

### 3.4. Mathematical Principles of Complexity and Uncertainty

In mathematical models, the number of parameters and their connection modes are the main factors affecting the complexity of mathematical models [4]. For models lacking verification data, such as those for trend prediction, exploring the potential impact of emerging technologies, and predicting potential risks in the natural environment, by focusing on the number of model components and their connection modes, we can establish the correlation between model complexity and uncertainty based on statistical principles with the help of the Analysis of Variance (ANOVA) decomposition framework and the concept of effective dimension [4]. In the ANOVA decomposition framework, parameters are regarded as random variables, and their uncertainty is described by probability distributions—these distributions reflect the statistical errors, natural variations, inherent randomness, and subjective judgments of parameters.

Given the form $y = f(x)$, $x = (x_1, x_2, \ldots, x_i, \ldots, x_k) \in R^k$, where y is a scalar output and $x_1, x_2, \ldots, x_i, \ldots, x_k$ are k independent parameters, the proportion of variance transmitted by each parameter to y is calculated, namely the first-order effect Si, the interaction between parameter pairs (second-order effect $S_{\{i,j\}}$), the interaction between parameter triples (third-order effect $S_{\{i,j,l\}}$), and so on up to the k-th order interaction.

For a model with only three parameters, its variance decomposition formula is $S_1 + S_2 + S_3 + S_{\{1,2\}} + S_{\{1,3\}} + S_{\{2,3\}} + S_{\{1,2,3\}} = 1$. This variance decomposition method is applicable to functions f(x) that are square-integrable within the domain, and its theoretical basis is derived from Sobol's functional decomposition theory—which decomposes f(x) into the sum of 1-dimensional, 2-dimensional, and up to k-dimensional subfunctions.

In multi-dimensional or computationally intensive models, it is often difficult to estimate interactions up to the k-th order. The calculation of the total-order effect $T_i$ can be considered to capture the proportion of variance transmitted to y by the first-order effect of xi and its interactions up to the k-th order. Taking $x_1$ in a three-parameter model as an example, its total-order effect can be expressed as $T_1 = S_1 + S_{\{1,2\}} + S_{\{1,3\}} + S_{\{1,2,3\}}$, and the same applies to $x_2$ and $x_3$. Based on this, we now introduce the concept of effective dimension.

#### 3.4.1. Effective Dimension in the Superposition Sense (ks)

Let $\lambda = \{1, 2, \ldots, k\}$. For any subset $u \subseteq \lambda$, let |u| denote its cardinality. In the "superposition sense", the effective dimension of the model f is defined as the smallest integer ks that satisfies the following condition:

$$\sum_{0<|U|\leq k_5} Su \geq p \tag{1}$$

where $0 < p < 1$. The preset threshold p is artificially set, and here we assume $p = 0.99$. Taking a three-parameter model as an example, we calculate up to which order of interaction effects can capture most of the variation P in the model output. That is, the sum of Sobol indices from the first order to the ks-th order accounts for p (99%) of the total variance. All its variance components are:

First-order effects: $S_1$, $S_2$, $S_3$ (impact of individual parameters)

Second-order interaction effects: $S_{\{1,2\}}$, $S_{\{2,3\}}$, $S_{\{1,3\}}$ (interaction impact between two parameters)

Third-order interaction effect: $S_{\{1,2,3\}}$ (joint interaction impact of three parameters)

The cumulative calculation is performed step by step from the first order to the third order until the cumulative sum meets or exceeds P, indicating that this order is the effective dimension of the model.

If the sum of first-order, second-order, and third-order effects still does not meet or exceed P, it means that a large amount of variation is hidden in interactions of the fourth order and above. Due to the high computational difficulty, the model can be directly determined as a complex model.

[Figure: Operational Flowchart of Effective Dimension in the Superposition Sense]

Start Effective Dimension Analysis → Estimate Sobol indices through Monte Carlo and other numerical methods → Obtain specific numerical estimation results of Sobol indices → Calculate the sum of first-order effects ($S_1 + S_2 + \ldots + S_k$) → Is the sum of first-order effects ≥ p? → Yes: Determine effective dimension ks = 1; No: Calculate the sum of first-order + second-order effects (ΣSi+ΣS{i,j}) → Is the sum of first-order + second-order effects ≥ p? → Yes: Determine effective dimension ks = 2; No: Calculate the sum of first-order + second-order + third-order effects (ΣSi+ΣSi,j+ΣSi,j,l) → Is the sum of first-order + second-order + third-order effects ≥ p? → Yes: Determine effective dimension ks = 3; No: Determine effective dimension ks ≥ 4 → Output the final effective dimension.

### 3.4.2. Effective Dimension in the Truncation Sense (kt)

Now consider the total-order index vector T = {T1, T2, ..., Tk}. In the truncation sense, the effective dimension of the model f is defined as the smallest integer kt that satisfies the following condition:

$$kt = |C| = \{Ti \in T \mid Ti > q\} \tag{2}$$

where |C| denotes the cardinality of the subset C, which is composed of elements $T_i$ in T that satisfy $T_i > q$. This study assumes q = 0.05 as the screening threshold, which is a commonly used critical value in sensitivity analysis to distinguish “influential parameters” from “non-influential parameters”—that is, the dividing line between parameters that can transmit uncertainty to y and those that cannot. Models with a higher effective dimension in the truncation sense often contain a large number of influential parameters, thus presenting a larger kt value.

Generally speaking, the hierarchical relationship k ≫ kt ≫ ks will appear in the model, which stems from the low-order effect dominance characteristic and Pareto principle generally existing in mathematical models. The model actually exists in the space defined by kt and ks, rather than the space nominally defined by k—when the model contains a considerable number of non-influential parameters, the k value may be artificially inflated. The space defined by kt and ks cannot be simplified without changing the model behavior, and has irreducible complexity. Therefore, more complex models usually present higher effective dimensions in terms of kt and ks, and this growth will exacerbate output uncertainty. The larger the ks dimension, the smaller the sum of first-order indices $S_i$. With the gradual increase of influential parameters, these high-order effects are activated. This is because the output variance of more complex models is increasingly driven by high-order effects.

## 4. Analysis of the Relationship between Flexibility and Uncertainty and Countermeasure Suggestions

In the information age, the random uncertainty of mobilization is mainly constrained by complex factors such as elements, structure, function, and operation. Complex conditions lead to increased uncertainty, while flexibility can effectively respond to uncertainty.

## 4.1. Complexity and Uncertainty of the Mobilization System

Although the mobilization process is specifically divided into three major steps: mobilization preparation, mobilization implementation, and demobilization, with corresponding institutional measures, the more detailed the expansion of action nodes in the actual mobilization process, the more likely it is to be carried out without standardization and normalization. This is because it is impossible to determine whether the added nodes can improve the efficiency of mobilization actions. We take the gradual complexity of emergency material supply chain mobilization as an example to illustrate the above relationship.

Model A: A simple central warehousing-direct distribution model. Its uncertainty mainly comes from transportation time and demand forecasting, with low kt and ks values.

Model B: On the basis of Model A, multiple regional distribution centers are added. The scheduling level and inventory capacity of multiple centers become new key parameters, increasing the system's kt value. The ks value may also increase due to the coordination needs between centers, leading to increased uncertainty.

Model C: On the basis of Model B, real-time path optimization algorithms and complex multi-modal transportation are introduced. Adding state parameters of transportation modes, as well as the coordination of transportation mode switching, information flow, and physical flow, achieves a high-order system with significantly improved kt and ks values. The output uncertainty reaches the highest level.

Flexibility Intervention: Implement flexible regulation in Model C, establish a sharing mechanism for transportation resources to reduce dependence on specific transportation tools, thereby reducing kt; deploy dynamically modular transportation units that can be flexibly reorganized to quickly adapt even under high-order path planning and compensate for high ks. After flexible transformation, the output uncertainty of Model C will be significantly lower than that of the rigidly designed Model C, and may approach Model B after continuous optimization.

Therefore, it is suggested to regard the specific node parameters of the mobilization system, such as resource stock, response time, coordination efficiency, and their information interaction, collaboration links, and collaboration relationship models, as key input factors of system complexity. By focusing on the number of system nodes and their connection and collaboration relationships, Sobol's functional decomposition and variance analysis are used to link system complexity with uncertainty.

## 4.2. Flexibility as a Regulator of Uncertainty

Flexibility refers to the ability of a system to quickly respond to and effectively adapt to uncertain changes in the environment [5]. Within the framework of effective dimension, flexibility regulates uncertainty through two main ways:

Flexibility reduces kt: Modular and standardized resource units and general processes can reduce the number of key parameters required in specific scenarios. On the premise of achieving goals, the set of key parameters should be simplified as much as possible.

Flexibility optimizes ks: Authorized decision-making, flattened structures, and information sharing mechanisms can decompose high-order, unpredictable global interactions (high ks) into multiple low-order, more controllable local interactions (low ks). This is equivalent to introducing a "decoupling mechanism" in the system design, reducing the overall model management interaction complexity.

Therefore, it is suggested to use flexibility as a regulator. A mobilization system with high flexibility does not mean that the system is redundant, complicated, or simple. Instead, it actively or passively switches itself to an operation mode with lower “effective dimension”, more certainty, and more controllability when facing uncertainty through effective and orderly regulation of uncertainty, so as to maintain the certainty of the mobilization system.

### 4.3. Focus on the Application of Flexibility in Each Node of Mobilization

The relationship between flexibility and uncertainty lies in its recognition of the inherent connection between complexity and uncertainty, and complex system management is carried out based on this. Its ultimate goal is not to pursue absolute certainty, but to use flexibility to establish reliable response capabilities in an uncertain mobilization environment. By improving the structure, rules, and decision-making power of the system, we can actively shape and optimize its “effective response dimension”.

Apply the evaluation of complex effective dimensions and the principle of flexible regulation to the planning and process upgrading of the mobilization system. It can help decision-makers better judge whether the new nodes increase uncontrollable interactions (increase ks) or endow the system with dimension reduction capabilities.

Mobilization Preparation Stage: By simulating different architectural schemes, select the scheme with lower (kt, ks) values while meeting functional requirements.

Mobilization Implementation Stage: After each new function or department is added, recalculate (kt, ks). If the growth of dimensions is much greater than the performance gain, the necessity of this upgrade should be questioned, or flexible design should be enhanced simultaneously.

Demobilization Evaluation Stage: Compare the (kt, ks) values of different mobilization schemes or different institutions to evaluate their inherent complexity and potential risks.

Therefore, it is suggested to innovate the mobilization mechanism, establish a regular assessment mechanism for the effective response dimension in all links of the operation of the mobilization system, identify the “critical point” where ks rises sharply in the system, focus supervision priorities and resources before the critical point, and formulate more robust and executable safety standards to ensure that the complexity of the system matches the uncertainty of its environment, thereby building a flexible mobilization system that remains stable in changes.

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