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Abstract

This paper develops a simulation model to compare the performance of two stylized manufacturing networks: the lead factory network (LFN) and the archetype network (AN). The model identifies the optimal network configuration and its implications for coordination mechanisms. Using an NK simulation model to differentiate between exogenous factors (configuration) and endogenous factors (coordination), we find low complexity of the production process, low transfer costs and high search costs, as well as a larger number of manufacturing plants benefit LFN compared to AN. Optimally coordinating the chosen network configuration of LFN might require to fully transfer knowledge in the short run but to transfer nothing in the long run. Moreover, a late knowledge transfer from the lead factory to the plants increases the pre-transfer performance of LFN but results in a larger performance drop, yielding a lower short-run but a higher long-run performance of LFN.

Keywords Manufacturing network, Manufacturing plant, Global operations management, Lead factory, Knowledge transfer

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1 Introduction

Managers of large, multinational manufacturing firms face the complex problem of configuring and coordinating global manufacturing networks (Porter, 1986). Configuration determines the allocation of manufacturing activities and process competencies across plants (Kulkarni et al., 2004). Coordination refers to the question of how to link these activities and competences in order to maximize value creation (Meijboom and Vos, 1997). In short, configuration determines the structure of global manufacturing networks, while coordination defines the processes which link the activities within the network (Colotla et al., 2003).

According to Meijboom and Vos (1997), configuration and coordination are usually addressed separately in the literature and are rarely integrated. The contribution of this paper is to combine both dimensions by examining how to optimally configure and coordinate global manufacturing networks. We compare the performance of two stylized network configurations: the lead factory network and an archetype network. To simulate the performance of the manufacturing networks, we utilize the NK model applied to the manufacturing environment (McCarthy 2004).

In lead factory networks, one of the manufacturing plants serves as the central knowledge hub of the network. This plant, which acts as an intermediary between the R&D department and the other manufacturing plants, is called a "lead factory" (Vereecke and van Dierdonck, 2002, Ferdows, 1997). The lead factory generates essential production knowledge by closely cooperating with the R&D department and transfers this knowledge to the other manufacturing plants (Ferdows 1997; Roth and Morrison 1992). The lead factory network (LFN) is widely applied in practice. For example, many Japanese original equipment manufacturers (OEM), such as Daihatsu, Honda, and Toyota test production processes in their Japanese plants and replicate them within US and European plants (Simon et al., 2008).

Manufacturing networks that favor market- or product-oriented specialization of the plants do not organize their network according to different strategic roles (Johansen and Riis, 2005). We refer to such a network, which consists of an R&D department and internationally distributed manufacturing plants, as the archetype network (AN). In the AN configuration, R&D transfers its knowledge directly to each plant.

Vereecke and van Dierdonck (2002) and Shi (2003) argue that there is a need for understandable models of international manufacturing systems that help managers configure and coordinate their global manufacturing networks. So far, researchers have focused on the description of different plant roles and the differences between plants (e.g., Vereecke, 2002, 2006; Simon et al., 2008). An exception is Deflorin et al. (2012), who show in a static analytical model which factors positively or negatively influence the performance of a lead factory network. However, their model does not combine configuration and coordination aspects. We respond to the call for more research in this area by developing an NK simulation model to analyze the optimal configuration and coordination of archetype and lead factory networks.

As proposed by McCarthy (2004), we regard manufacturing firms as complex adaptive systems and take his paper as a starting point for our simulation model. In his conceptual paper, McCarthy proposes an innovative model of manufacturing fitness and shows that the NK model framework can be applied to the process of manufacturing strategy formulation.

In this paper, we simulate and compare the performance of the lead factory network and the archetype network. We show how exogenous factors (parameters) such as the complexity of the production process, the number of manufacturing plants, the heterogeneity between the manufacturing plants as well as the magnitude of the transfer and search costs determine the optimal configuration choice between a lead factory network and an archetype network. Endogenous factors such as the timing and depth of the knowledge transfer relate to coordination aspects and determine the decisions of a production manager to optimally coordinate the network. Because our simulation model allows us to analyze the underlying dynamics of the production process, we can differentiate between short-term and long-term results regarding the optimal configuration and coordination of global manufacturing networks.

This paper is structured as follows. In Section 2, we provide an overview of the literature on manufacturing network configuration and coordination. Section 3, introduces our simulation model. Section 4 presents our results. Finally, the simulation results are discussed and further implications of our results are derived in Section 5.

2 Literature Review

From the late 1970s to the early 1990s operations management research moved from the focus on a single plant to a multi-plant focus and finally towards networks (Rudberg and Olhager, 2003). Shi and Gregory (1998) define a manufacturing network as a plant network with matrix connections. Each node (i.e. plant) influences other nodes and hence cannot be managed in isolation. Within the analysis of manufacturing networks, two dominant areas exist: configuration and coordination.

2.1 Network configuration

The firm's network can serve as a source of sustainable competitive advantage as it allows plants to access key resources from its environment, such as information, access, capital, goods and services (Gulati, 1999). However, a firm's network configuration may lock a firm into undesirable strategic situations (Gulati et al., 2000). Therefore, each company must define which network configuration best supports its aim for achieving competitive advantage. The choice of a suitable configuration is especially important because managing the network involves using appropriate governance mechanisms, developing inter-firm knowledge sharing routines, making appropriate relations-specific investments, and initiating necessary changes to the partnership as it evolves (Dyer and Singh, 1998). To design an appropriate network configuration, which factors render it more or less efficient need analyzation. The network configuration is analyzed through the relationship between the plants, specifically through each plant's strategic role within the manufacturing network.

Possible roles in such networks have been studied over the past three decades by multiple researchers from different perspectives. For example, Bartlett and Ghoshal (1987, 1990), Ferdows (1989, 1997), Roth and Morrison (1992), Surlemont (1996, 1998),Vereecke and van Dierdonck (2002) studied subsidiary roles from the perspective of competencies and strategic relevance within the network. Gupta and Govindarajan (1991, 1994), Frost et al. (2002), Vereecke et al. (2006) and Enright and Subramanian (2007) used capability creation and knowledge in- and outflow as their lens of analysis. Despite the different perspectives, two similar roles emerge: Subsidiaries that are close to the market and subsidiaries that centrally advance the development of products, processes, and/or technologies and spread the newly gained knowledge throughout the network. Based on Ferdow's (1997) categorization, we label the subsidiaries where new products and processes are developed lead factories.

The lead factory transfers production know-how to the geographically distributed manufacturing plants, which fulfill the network's aim for market proximity and low cost production. Depending on the need for capacity, there can be many knowledge receiving plants (Rudberg and West, 2008). While the literature agrees that many networks have implemented an intermediary between R&D and plants, different roles can be found concerning the receiving plants. To understand the impact of the lead factory on the whole network, we focus our analysis on this special plant and do not consider further strategic roles of the receiving plants. This simplification is supported by Fusco and Spring (2003), who conclude that automotive manufacturers of world products concentrate on two of Ferdow's six strategic plant roles. Their analysis shows that each network consists of a lead factory and source plants. Source plants have access to low-cost production but similar to the lead factory, they have high site competences (Ferdows, 1997). Site competences refer to improvements in the production process, logistics and procurement as well as in minor design issues. It follows that the receiving plants are able to further improve their performance after they have received the production know-how from the lead factory. We label such a network configuration a lead factory network (LFN); it consists of a lead factory and multiple receiving source plants. Because the lead factory concept is a commonly implemented network configuration, it is especially important to understand which factors influence the performance of the LFN.

Despite the growing relevance of the lead factory concept, many companies favor market- or product-oriented specialization (Johansen and Riis, 2005). Within such a so-called archetype network (AN), R&D transfers its knowledge directly to each of the plants and cannot take advantage of an intermediary. There is no strategic difference between the plant located at headquarters and the other plants.

Although Hayes et al. (2005) indicate that different network configurations have different strengths and weaknesses and a given network cannot do everything equally well, which factors determine the network configuration remains unclear. To exploit the strengths and weaknesses of a network configuration, one has to understand how certain exogenous factors determine the performance of network configurations. This leads us to our first research question:

> RQ1: How do exogenous factors determine the relative performance of LFN as compared to AN?

2.2 Network coordination

Coordination refers to the organization, linkage and integration of the production facilities to achieve strategic business objectives (Gupta and Govindarajan, 1994). It addresses the management of the physical and non-physical flows between the network's plants. It also covers the establishment of rules and control mechanisms for interaction between the plants. In recent years, the literature has also addressed the issue of balancing decision responsibility between plants and headquarters (Feldmann and Olhager, 2009, Maritan et al., 2004).

A central theme within the coordination literature is the transfer and diffusion of production technologies and knowledge between plants (Vereecke et al., 2006, Ernst and Kim, 2002). Dynamic forms of communication and coordination between the plants develop to synchronize the activity of each plant to the activities of the whole network (Nassimbeni, 1998). Because one of the main reasons for the existence of multinationals is the possibility to acquire, create, and use technological assets across different boundaries, it is commonly accepted that knowledge flow is an important task of networks (Dunning, 1993). The ability to transfer knowledge through the multinational's network is crucial for attaining a competitive advantage, therefore we focus our analysis on the mechanism of the knowledge transfer.

Although there is common agreement on the importance of knowledge transfer within networks, the literature in operations management mainly focuses on configuration studies. Less attention is devoted to coordination; even less is given to aligning coordination activities to specific configurations (Meijboom and Vos, 1997).

Exceptions are the work of Meijboom and Vos (1997), Nassimbeni (1998) and Rudberg and Olhager (2003). Meijboom and Vos (1997) conclude that it is essential to mix configuration and coordination aspects in order to understand how plants function in their respective international networks. Based on the detailed discussion of four case companies, Meijboom and Vos (1997) pose two questions: (i) Does a certain configuration determine the way the co-ordination is organized? and (ii) Can co-ordination problems alter the configuration? Nassimbeni (1998) presents a classification of three configurations based on Mintzberg (1979), which concern the type of interdependence between the units and, consequently, the prevailing co-ordination mechanisms operating on them. Rudberg and Olhager (2003) analyze manufacturing networks and supply chains from an operations strategy perspective, and present a typology for analysis of network systems resulting in four basic network configurations. They argue that coordination is contingent upon the configuration types and conceptually derive four types of coordination activities: utilize, optimize, synchronize, and harmonize. Cheng et al. (2011) support this view and argue that coordination mechanisms have to be redeveloped when the coordination of manufacturing networks changes.

However, the literature on the coordination of knowledge transfer within networks remains rather superficial. Our contribution is to show how the coordination of knowledge transfer influences the performance of a network configuration. We elaborate on the assumption that all knowledge might not be useful in other contexts (Winter and Szulanski, 2001). Hence, managers have to decide what knowledge to transfer (depth of knowledge transfer) and when to transfer (timing of knowledge transfer). This leads us to our second research question:

> RQ2: How does the coordination of the depth and timing of the knowledge transfer in the LFN influence its performance as compared to the AN?

3 Simulation Model

In order to determine the optimal configuration and coordination of a manufacturing network, we apply the NK model. The NK model is widely accepted and applied in various disciplines. It was initially developed by Stuart Kauffman and his colleagues to the context of evolutionary biology (Kauffman and Levin, 1987; Kauffman, 1993). Levinthal (1997) applied the NK framework to the field of organization science by showing that the existence of interdependencies among firm choices can explain persistent organizational heterogeneity. Since then, research that utilizes the NK framework is flourishing and has been conducted on a broad range of topics such as organizational development and change (Ruef 1997), innovation (Frenken, 2000; Fleming and Sorenson, 2001, Almirall and Casadesus-Masanell 2010), organizational design (Gavetti 2005, Rivkin and Siggelkow 2003, Siggelkow and Levinthal 2003), and strategy (Siggelkow and Rivkin 2005, Csaszar and Siggelkow 2010, Levinthal and Posen 2007). Porter & Siggelkow (2008) provide a comprehensive overview on NK models in the context of organizational search.

As shown by McCarthy (2003, 2004) and McCarthy and Tan (2000), the NK framework can also be applied to operations management research by regarding manufacturing firms as complex adaptive systems. They were the first to relate the fitness landscape theory to the process of manufacturing strategy by developing a conceptual model of manufacturing fitness. We take their work as a starting point and extend it by explicitly simulating the performance of two distinct network configurations with the NK model.

3.1 The NK Model Framework

The starting point of our NK model is an N-dimensional vector $\mathbf{a} = (a_1, a_2, ..., a_N)$ of binary decisions $a_i \in \{0, 1\}$ with $i \in I = \{1, ..., N\}$. This vector represents the set of all relevant decisions made within the production process of a product. Some of these decisions are interdependent and others not. The interdependence is characterized by the parameter $K \in \{0, ..., N-1\}$, which describes the number of binary decisions a_j that (co-) determine the effect of the decision a_i. This effect is characterized by the function $C_i = C_i(a_i, a_{i_1}, a_{i_2}, ..., a_{i_K})$ where $i_1, i_2, ..., i_K$ are K distinct decisions other than i. Without loss of generality, the values of C_i lie within the unit interval. The "performance" of the production process is calculated as the arithmetic mean of the (partial) effects C_i according to the function $\phi(\mathbf{a})$:

$$\phi(\mathbf{a}) = \frac{1}{N} \sum_{i=1}^{N} C_i(\mathbf{a})$$

Starting from a randomly chosen vector $\mathbf{a}$ in period $t = 0$, the firm's management consecutively changes one decision a_i in each period to search for performance improvements. If a new vector improves performance, it is adopted and the search continues from this new vector in period $t + 1$. Otherwise, the next search step starts from the unchanged vector defined in period t. We assume that each change of the vector $\mathbf{a}$ is associated with costs given by $\gamma \in \mathbb{R}_+$. Accumulated search costs in period t amount to

$$c(t) = \gamma \cdot \Gamma(t),$$

where $\Gamma(t)$ denotes the number of changes of the vector $\mathbf{a}$ until period t.

This process may be interpreted as a search for higher points in an $N+1$-dimensional landscape. Each of the N decisions of the vector constitutes a horizontal axis in an N-dimensional space. Each vector on the horizontal space is then associated via the function $\phi(\mathbf{a})$ with a performance value that is plotted on the vertical axis (Siggelkow and Rivkin, 2005).

The search process stops after P periods. During the P periods, the firm can get stuck at a vector (sticking point) whose performance cannot be improved by changing one of its N decisions. In this case, the firm is either at a local or global maximum. A local maximum can be interpreted as a peak. The global maximum is the highest peak in the landscape. As shown by Rivkin & Siggelkow (2002), a firm may get stuck at a sticking point that is not a local peak on the fitness landscape of the overall organization in more complex hierarchical organizations.

In our simulation model, we create thousands of different landscapes representing many different environments for the firm. To compare the results, the performances are normalized on each landscape from the interval $[0; \max \phi]$ to the unit interval, i.e., $\tilde{\phi}(\mathbf{a}) = \phi(\mathbf{a}) / \max \phi$ and then the average performance $\overline{\phi}$ over all landscapes is calculated. We use this normalized mean performance as a measure for "efficiency" of the production process.

3.2 Alternative Manufacturing Networks

3.2.1 The Archetype Network

The archetype network (AN) is composed of E geographically separated manufacturing plants denoted by MP_j, $j \in \{1, ..., E\}$ that operate in different environments. In our model, these plant-specific environments are represented by heterogeneous landscapes. Formally, these heterogeneities in the landscapes are generated through the noise parameter $T \in [0; 1]$ with $\phi(\mathbf{a}) \overset{Noise}{\rightarrow} \phi'_j(\mathbf{a})$, $j \in \{1, .., E\}$ such that the final values $\phi'_j(\mathbf{a})$ stay in the unit interval $[0; 1]$. As shown in the appendix, we develop a technique to guarantee that the distribution of the landscape values remains unaltered through the noise parameter T. Note that $T = 0$ corresponds to a situation without noise addition, yielding $\phi(\mathbf{a})$ unchanged, while $T = 1$ corresponds to the maximum of noise generating a new set of uncorrelated random values for $\phi'_j(\mathbf{a})$.

Each plant MP_j, starts in period $t = 0$ at the vector $a_j = (a_{j_1}, a_{j_2}, ..., a_{j_K})$ in its landscape and searches for improvements in the production process. In each period, MP_j can change one decision. Accumulated search costs are given by in $c_j(t) = \gamma \cdot \Gamma_j(t)$ in $t \in \{1, ..., P\}$. The (normalized) performance of AN in period $t \in \{0, 1, ..., P\}$ is then calculated as

$$\Phi_{AN}(t) = \frac{1}{E}\left[\sum_{j=1}^{E}\{\bar{\phi}_j(\mathbf{a}_j(t)) - c_j(t)\}\right]$$

3.2.2 The Lead Factory Network

In the lead factory network (LFN), one plant is assigned the role of a lead factory denoted by LF. We denote the remaining $E - 1$ plants by MP_j with $j \in \{1, \ldots, E - 1\}$. Again, all plants, including the lead factory, operate on heterogeneous landscapes similar to the archetype network.

Contrary to AN, only the lead factory is searching for improvements in the production process during the first R periods with $t \in \{0, ..R\}$. In $t = R$, the lead factory (partially) transfers instantaneously its knowledge about the production process to all other plants after its search step. Formally, this knowledge transfer is characterized through the number of decisions $S \in \{0, .., N\}$ that are transferred from the lead factory's vector $a^*_{LF} = (a^*_{LF,1}, .., a^*_{LF,N})$ in $t = R$ to the other plants. We assume that this knowledge transfer results in one-time transfer costs given by

$$r(S) = \rho \cdot S,$$

where ρ characterizes marginal transfer costs. The more decisions are transferred from the lead factory to the other plants the higher are the transfer costs. It should be noted that our results do not depend on the functional form of the transfer cost function. We have chosen a linear specification to keep the model simple.

After the knowledge transfer period, each MP_j improves its production process starting from the vector $(a^*_{LF,1}, .., a^*_{LF,S}, a_{j,S+1}, ..., a_{j,N})$ in $t = R + 1$. Each plant can change all N decisions during the remaining $P - R$ periods. In particular, MP_j can also change $(a^*_{LF,1}, .., a^*_{LF,S})$. In periods $t \in \{R+1, ..., P\}$, the lead factory acts as a normal plant and continues to improve its production process by changing its vector $(a^*_{LF,1}, .., a^*_{LF,N})$. Our results would not change qualitatively if we assumed that the lead factory only transfers knowledge and does not transform into a manufacturing plant.

As in AN, each change in the vector a_j costs γ such that accumulated search costs in $t \in \{1, ..., P\}$ amount to $c_j(t) = \gamma \cdot \Gamma_j(t)$. In the first $R - 1$ periods only the lead factory is active and the performance $\Phi_{LFN}(t)$ of LFN in each period $t \in \{0, .., R - 1\}$is given by

$$\Phi_{LFN}(t) = \phi_{LF}(\mathbf{a}_{LF}(t)) - \frac{1}{E} c_{LF}(t).$$

We assume that the search costs of the lead factory are beard by the firm (i.e., the E plants of the network), and therefore we divide the search costs of the lead factory by the number E of plants in the network to calculate the performance of LFN. The long-run results would not change if we did not divide the search costs by the number of plants and hence calculated the performance as $\Phi_{LFN}(t) = \phi_{LF}(\mathbf{a}_{LF}(t)) - c_{LF}(t)$.

In $t \in \{R, ..., P\}$ all E manufacturing plants are active, including the lead factory such that the performance of LFN is calculated as

$$\Phi_{LFN}(t) = \frac{1}{E} \left[\phi_{LF}(\mathbf{a}_{LF}(t)) - c_{LF}(t) + \sum_{j=1}^{E-1} \{\phi_j(\mathbf{a}_j(t)) - c_j(t) - r(S)\} \right].$$

4 Results and Discussions

We simulate and compare the performance of LFN and AN. At the beginning of each simulation run, we create new landscapes and place firms on random locations on them. We base our results on the average performance over $50'000$ independent runs (i.e., landscapes) of the simulation model to guarantee that the simulations are not the results of a stochastic process but reflect the structure of our model. Without loss of generality and in line with the literature on NK models, all simulations have $N = 6$, i.e., each firm makes six decisions and is observed for $P = 80$ periods. According to Siggelkow and Rivkin (2005), "a problem space with six decisions is large enough to allow adequate range of parameters in the model." Larger problem spaces would exponentially increase the computational complexity without adding new insights because qualitatively the results would not change.

It suffices to simulate 80 periods because practically all firms in our model achieve a steady state in this period either by reaching a sticking point or by engaging in a repetitive cycling behavior. When we report that a particular firm achieves a higher performance than another firm, the difference in mean performance averaged over the $50'000$ landscapes is statistically significant at the 1% level. We define the short run as the time period immediately after the knowledge transfer in LFN, i.e., $t = R$, and the long run as the time period when the simulation stops, i.e., $t = P$.

First, we show how to coordinate knowledge transfer if the manufacturing network has a lead factory. In a second step, we analyze when such a network configuration is advantageous. Specifically, we show which factors increase the performance of LFN as compared to AN.

4.1 Optimal Coordination of Manufacturing Networks

The success of LFN is dependent upon effective coordination mechanisms. In this section, we show how differences in knowledge transfer depth and timing influence performance. First, we explain the mechanisms behind the knowledge transfer in LFN and then describe two counterintuitive results of this knowledge transfer. Next, we analyze how the optimal number of transferred decisions depend on the transfer cost coefficient ρ. Finally, we determine the optimal time of knowledge transfer R.

4.1.1 Effects of Knowledge Transfer

Knowledge management in international manufacturing networks is complex. For example, the transfer of knowledge is dependent upon the decision about what knowledge may be useful in other contexts (Winter and Szulanski 2001). Winter and Szulanski (2001) distinguish between a broad and narrow scope to be transferred from one unit into the other. In our model, the parameter S describes the depth of the transferred knowledge, defined through the number of transferred decisions.

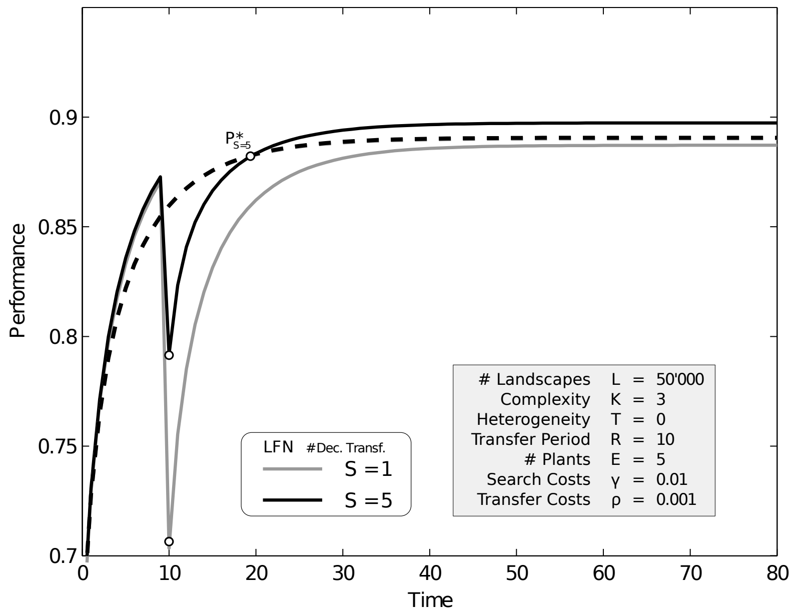
Figure 1 compares the (normalized) performance of AN and LFN for two different values of S (number of transferred decisions) over the first P periods. The dashed line represents the performance of AN. Its performance increases steadily from period to period as each plant acquires additional knowledge to improve its production process. The marginal improvements gradually decrease from period to period until each plant reaches a peak in its landscape.

The performance of LFN is represented by the two bold lines in Figure 1; the dark-shaded (light-shaded) curve depicts the performance for $S = 5$ ($S = 1$). In both cases, LFN benefits from the cost savings of the representative search by the lead factory in the first R periods. Without these cost savings, the performance of both networks would be identical, i.e., we do not assume in our simulation that the lead factory has an advantage, compared to the other plants, in searching for improvements of the production process.

In period $R = 10$, the lead factory (partly) transfers its acquired production knowledge to the other plants. As a result, the performance of LFN drops significantly. The size of this drop depends on two opposed effects: the negative transfer cost effect and the positive knowledge effect. Both effects depend on the depth of knowledge transfer, represented by the number of decisions S that are transferred. A transfer of more decisions from the lead factory to the other plants results in higher transfer costs (transfer cost effect) but also improves the initial performance of the other plants (knowledge effect). On the other hand, if only a small number of decisions is transferred from the lead factory to the other plants, total transfer costs will remain small. A small number of transferred decisions, however, also means that the other plants can benefit from only few of the production improvements which have been realized in the lead factory and. therefore, have to start from lower points within their landscapes. Starting from a lower point in the landscape also implies that a plant will have to incur higher search costs to improve its performance in the remaining periods (search cost effect).

In Figure 1, the performance drop in period $R = 10$ is larger for $S = 1$ than for $S = 5$. For $S = 5$, the knowledge effect compensates for most of the transfer costs and LFN is able to reach a higher performance level than AN after $P^*_{S=5}$ periods. For $S = 1$, the knowledge effect cannot compensate for the transfer cost effect despite lower total transfer costs for $S = 1$ than for $S = 5$. In this case, LFN cannot recover from the resulting performance drop until period P; its performance remains below that of AN. These results show that the relative performance of LFN compared to AN depends on S. Furthermore, the performance drop can be larger for $S = 5$ than for $S = 1$ if the transfer cost coefficient ρ is sufficiently high. However, in this case, LFN can never recover from the resulting performance drop.

Figure 1: Effect of Knowledge Transfer



Moreover, the size of the performance drop depends on the performance difference between the lead factory and the plants because, in general, the performance of the lead factory after the knowledge transfer is higher than that of the plants, i.e., $\phi_{LF}(R) \geq \phi_j(R)$ for $j \in \{1, 2, .., E-1\}$. It follows that the drop increases with the performance difference. First, the partial transfer of decisions to the manufacturing plants (i.e., $S < 6$) completed by some random decisions leads to a lower performance of the manufacturing plants compared to the lead factory in period R. Second, on heterogeneous landscapes (i.e., $T > 0$), the knowledge acquired by the lead factory on its landscape is less effective for the manufacturing plants on their own landscapes and hence decreases their performance.

We summarize that in LFN, the optimal choice of the transferred decisions (S) depends on the heterogeneity of the plants (T), the complexity of the production process (K) and the values of the search and transfer costs (γ and ρ). Since the underlying knowledge effect is a dynamic effect, the optimal choice of S also depends on the time perspective (short run versus long run).

4.1.2 Knowledge Transfer Paradox

In a next step, we present two counterintuitive results behind the knowledge transfer in the case of sufficiently low search and transfer costs. Figure 2 compares the (normalized) performance of AN and LFN over the first P periods. The dashed line represents the performance of AN and the bold lines represent the performance of LFN, where we vary S (number of transferred decisions) in Panel (a) and T (plant heterogeneity) in Panel (b). To isolate the effect of knowledge transfer, we have set the search cost and transfer cost coefficients to zero, i.e., $\gamma = \rho = 0$. Without search costs, AN and LFN have the same performance before the knowledge transfer.

In Figure 2a, landscapes are completely homogeneous, i.e., $T = 0$, with the dark-shaded (light-shaded) curve depicting the performance of LFN for $S = 5$ ($S = 6$). If the lead factory fully transfers its acquired production knowledge to the other plants, i.e., $S = 6$, we do not observe a knowledge drop because landscapes are completely homogeneous and transfer costs are absent.

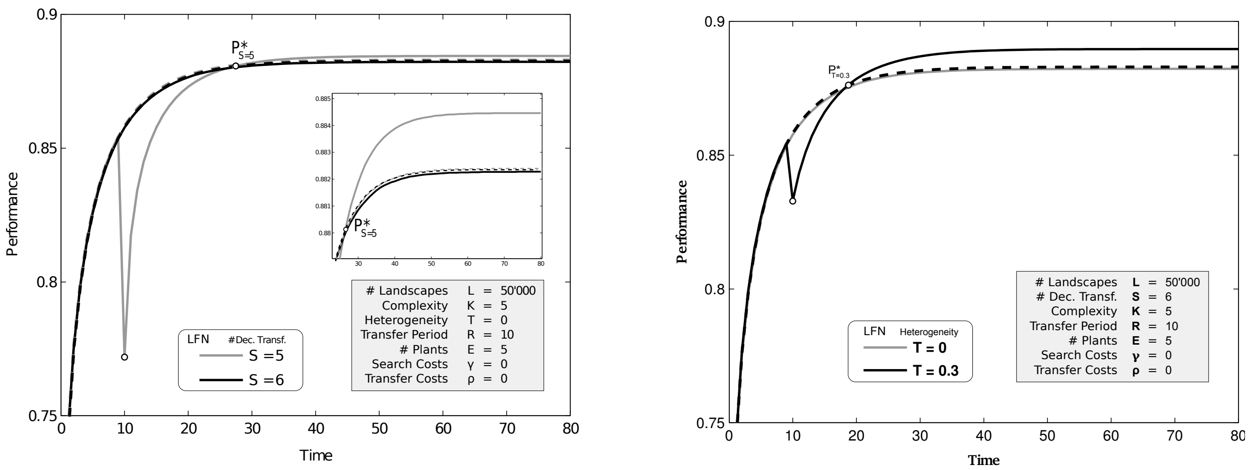
However, if the lead factory only partly transfers its acquired production knowledge, i.e., $S = 5$, we observe a performance drop of LFN. Surprisingly, we find that in the long run the performance of LFN is higher for $S = 5$ than for $S = 6$ although intuition might suggest that transferring more decisions on completely homogeneous landscapes in the absence of transfer costs is more efficient for LFN.

In Figure 2b, we analyze a situation in which the lead factory fully transfers its acquired production knowledge to the other plants, i.e., $S = 6$, with the light-shaded (dark-shaded) curve depicting the performance of LFN for homogeneous (heterogeneous) plants. The light-shaded curve shows that, in the absence of transfer costs, the performance of LFN does not drop after the lead factory has fully transferred its acquired production knowledge to the other homogeneous plants. As expected, the dark-shaded curve shows that the performance of LFN drops for heterogeneous plants because the knowledge acquired by the lead factory becomes less valuable as shown in Section 4.2.1. Again, a counter intuitive result emerges in the case that the lead factory fully transfers its acquired production knowledge to the other plants because the long-run performance of LFN is higher for heterogeneous plants ($T = 0.3$) than for homogeneous plants ($T = 0$).

These two counterintuitive results are caused by what we call the "sticking point effect." In situations in which the knowledge transfer is deterministic, i.e., a full knowledge transfer to homogeneous plants, the sticking points effect emerges through the introduction of randomness. This randomness can either come from plant heterogeneity, in the case of a full knowledge transfer (Figure 2b), or through a partial knowledge transfer, in the case of homogenous plants (Figure 2a). In the case of homogenous plants, a partial knowledge transfer ($S < N$) enables the plants to escape or avoid local maxima (sticking points) in which the lead factory got stuck. Similarly, plants avoid sticking points in the case of a full knowledge transfer to heterogenous plants. In this case, heterogenous plants avoid the lead factory's sticking point because they have to adapt the processes to their own production set-up.

On one hand, the sticking point effect increases with the complexity of production process K due to the presence of more sticking points as shown in Section 4.2.2. On the other, the sticking point effect disappears if search costs become prohibitively high. In this case, the search cost effect overcompensates for the sticking point effect such that LFN can obtain a higher performance in the long run by transferring all decisions. We summarize our results in the following proposition.

Figure 2: Sticking Point Effect



(a) Homogeneous Plants

(b) Full Knowledge Transfer

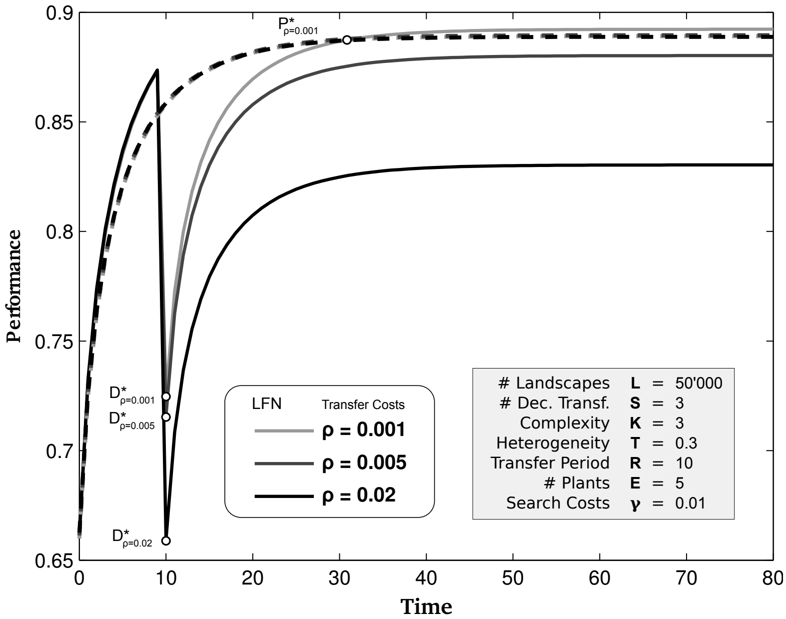
Proposition 1 *Suppose that search and transfer costs are sufficiently low.*
(i) In the case of homogeneous plants, LFN can increase its long-run performance by not fully transferring its decisions from the lead factory to the plants.
(ii) In the case of a full knowledge transfer, LFN can obtain a higher long-run performance by transferring the knowledge to heterogenous plants than to homogenous plants.

4.1.3 Transfer Costs and Optimal Depth of Knowledge Transfer

In this section, we focus on the transfer-cost coefficient ρ and its impact on the optimal depth of knowledge transfer. Teece (1977) highlights the importance of the knowledge transfer and hence, the cost involved in transferring knowledge has to be understood. He finds that the knowledge transfer costs vary significantly and that they are dependent upon the parties involved. In our model, transfer costs result from the transfer of knowledge between the lead factory and the manufacturing plants and thus represent a specificity of LFN.

First, we analyze the impact of the transfer-cost coefficient ρ on the performance in the short and long run and on the period P^* in which LFN eventually outperforms AN. Figure 3 compares the (normalized) performance of AN and LFN over the first $P = 80$ periods for three different values of ρ. As expected, a higher ρ induces a larger performance drop in $t = R$ and a lower long-run performance of LFN. We denote by $D^*_{\rho=\widetilde{\rho}}$ the performance of LFN after the knowledge transfer if the transfer cost coefficient is given by $\widetilde{\rho}$. Because transfer costs have no influence on the performance of AN, a higher transfer cost coefficient therefore increases the time period P^* and deteriorates the relative performance of LFN as compared to AN in the long run. Finally, we observe that if ρ is larger than a critical value then LFN cannot recover from the performance drop until period P, and its performance remains below that of AN.

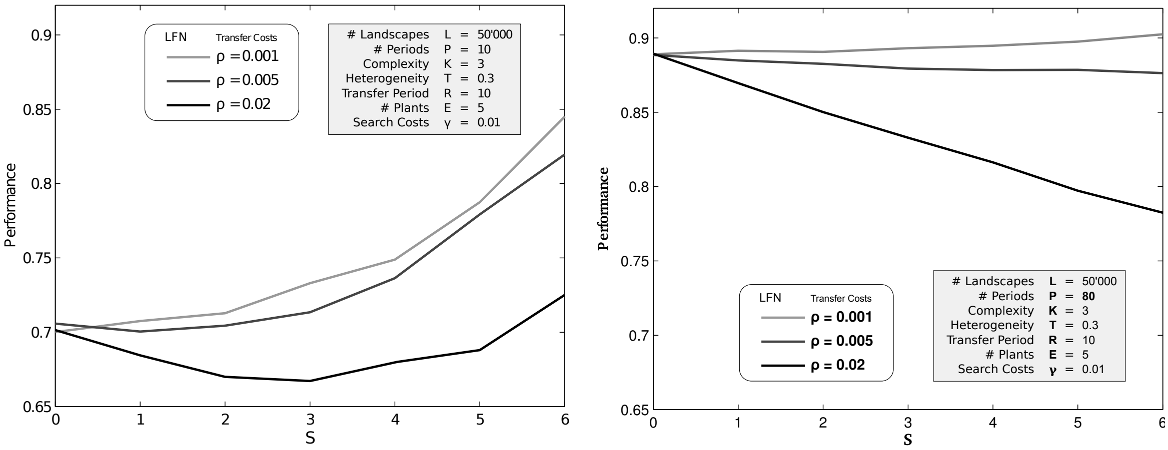
Figure 3: Effect of Transfer Costs (Performance Evolution)



Second, we study the other parameter involved in the transfer cost function $r(S)$, i.e., the number of decisions S that are transferred from the lead factory to the plants. Contrary to the transfer-cost coefficient, S is endogenous and the optimal S is determined by the trade off between the negative transfer cost effect and the positive knowledge effect; search costs have no effect in the short run, i.e., in $t = R$ because the plants have not yet changed their vector of decisions. Figure 4 depicts the performances of AN and LFN in the short and long run as a function of S for different transfer cost coefficients ρ. Panel (a) analyzes the short run ($t = R$) and Panel (b) focuses on the long run effects ($t = P$). The figure shows that the optimal number of transferred decisions is either $S = 0$ or $S = 6$, i.e., it is optimal to transfer either no decision or all decisions.

In the short run, the performance of LFN is a convex function of S. Increasing the transfer-coefficient from $\rho = 0.001$ to $\rho = 0.02$ transforms a strictly increasing convex performance function ($\rho = 0.001$) to a convex performance function ($\rho = 0.02$) with a minimum. This is the consequence of adding a linear decreasing function with an increasingly steep slope ρ to a convex increasing function for $\rho = 0$. It follows that the optimal depth of knowledge transfer is $S = 6$ for small values of ρ and beyond a threshold ρ^*, then the optimal depth of knowledge transfer is $S = 0$. These results show

Figure 4: Effect of Transfer Costs (Short- vs. Long Run)



(a) Short Run (b) Long Run

that, in general, it is not optimal for LFN to partially transfer decisions from the lead factory to sufficiently heterogeneous plants because it results in a worse performance than transferring no decision. However, by transferring no decision from the lead factory to the manufacturing plants, LFN has no advantage compared to AN because LFN behaves like AN (i.e., no knowledge is transferred) but the plants are loosing R periods of time in their development.

There are two limitations: First, in the case of homogeneous plants and sufficiently low search cost, it might be optimal to partly transfer decisions due to the sticking point effect. Second, in the case of a strictly convex transfer cost function $r(S)$, i.e., a polynomial or exponential function with a growth rate depending on the complexity parameter K, a maximum might exist for a value of S between 0 and 6.

Under a long run perspective, the optimal number of transferred decisions is different than under a short run perspective. For example, for $\rho = 0.005$, the optimal depth of knowledge transfer is given by $S = 6$ in the short run (see Panel (a) in Figure 4) and by $S = 0$ in the long run (see Panel (b) in Figure 4). Hence, the threshold ρ^* above which it is better to transfer nothing is smaller in the long- than in the short run because of the relative decreasing importance of the knowledge effect from period to period. The importance of the knowledge effect decreases, because, as an alternative to the knowledge transfer, each plant can search for improvements of its performance and adjust its decision vector accordingly. We summarize our results in the following proposition.

Proposition 2

(i) Lower transfer costs ρ will:

(ia) mitigate the performance drop in LFN through the knowledge transfer.

(ib) reduce the time period P^* at which LFN outperforms AN.

(ic) improve the relative performance of LFN as compared to AN in the long run.

(ii) In the cases of a linear or concave transfer costs function, it is optimal for LFN to transfer either no decision or all decisions from the lead factory to the plants. For small values of the transfer costs coefficient ($\rho < \rho^*$), transferring $S = 6$ decisions is optimal. Beyond a threshold $\rho > \rho^*$, transferring $S = 0$ is optimal. Moreover, the critical value ρ^* is smaller in the long run than in the short run.

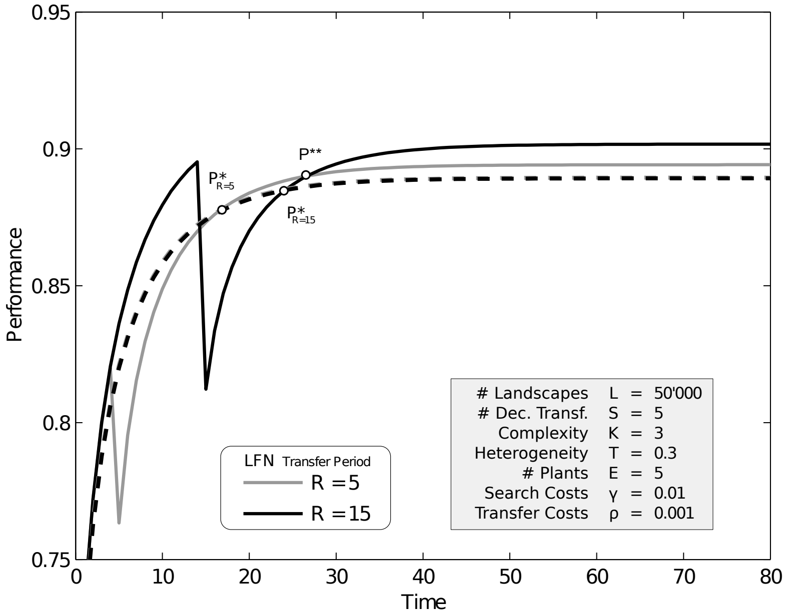
4.1.4 Timing of Knowledge Transfer

When developing new processes another major issue that must be dealt is the timing of its transfer from the lead factory to the plants. The decision, when a process is "ready" to be transferred is often subject to a great debate (Hayes et al., 2005). One philosophy proposes "get it right the first time." This perspective emphasizes minimizing major process changes within the receiving plants after the transfer period. The alternative group argues that it is impossible to anticipate all the problems that may be encountered within a new environment (Hayes et al., 2005). Based on our analysis, we find that it is optimal for LFN to transfer knowledge at the latest possible but such that the plants still have enough time to incorporate the knowledge from the lead factory into their production process. The plants have less time to profit from the transferred knowledge if the product life cycle is short.

A late knowledge transfer means that the production process in the lead factory is relatively mature, represented through a high spot on its landscape yielding a high marginal benefit for each transferred decision. In addition, the later the knowledge transfer, the higher are the cost savings for LFN. This cost-saving advantage of a late knowledge transfer increases with a lower complexity of the production process, more homogeneous plants, and a higher search cost coefficient. On a smooth landscape (low K), on average, a firm changes more decisions (see, e.g., Rivkin and Siggelkow, 2002). Therefore, a low K implies more decision changes before the knowledge transfer.

The performance of LFN is represented by the two bold lines in Figure 5, with the dark-shaded (light-shaded) curve depicting the performance for $R = 15$ ($R = 5$). The figure shows that the long run performance of LFN is higher for a late knowledge transfer ($R = 15$) than for an early transfer ($R = 5$). However, if knowledge is transferred early, LFN is able to reach a higher performance level than AN already in period $t = P^*_{R=5}$ as compared to period $t = P^*_{R=15}$ for a late knowledge transfer. Furthermore, from period $t = P^{**}$ onwards, LFN that has transferred knowledge late reaches a higher performance level than LFN that has transferred knowledge early. Hence, the decision about the optimal time for the knowledge transfer crucially depends on P. If P is sufficiently small (i.e., $P < P^{**}$), then an early knowledge transfer is optimal. Based on these results, we can formulate the following proposition.

Figure 5: Effect of Time of Knowledge Transfer



Proposition 3

(i) A late knowledge transfer R will:

> *(ia) increase the performance of LFN before the knowledge transfer and thus results in a higher performance drop in LFN through the knowledge transfer.*
>
> *(ib) increase the time period P^* at which LFN outperforms AN.*
>
> *(ic) improve the relative performance of LFN compared to AN in the long run.*

(ii) It is optimal for LFN to transfer knowledge the latest possible such that the plants still have enough time to incorporate the knowledge from the lead factory in their production process. Hence, the optimal time for the knowledge transfer decreases in P.

4.2 Optimal Configuration of Manufacturing Networks

In this section, we analyze the advantages and disadvantages of LFN compared to AN with respect to the exogenous model parameters, i.e., the heterogeneity of the plants T, the complexity of the production process K, the search cost coefficient γ and the number of manufacturing plants E. The results of this section might provide guidance to production managers regarding the choice between LFN and AN, i.e., to choose an appropriate network configuration.

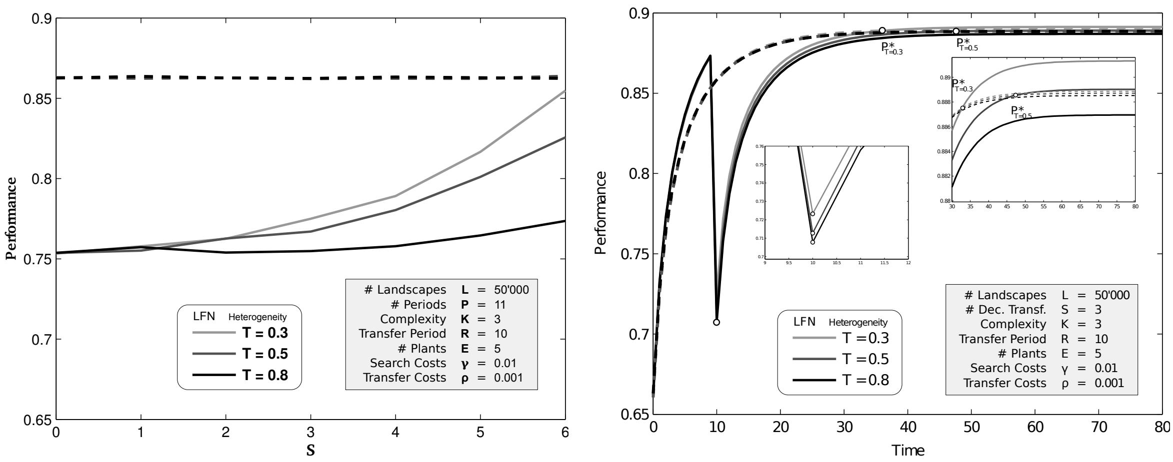
4.2.1 Heterogeneity of the Manufacturing Plants

In this section, we show how plant heterogeneity influences the network configuration choice. In addition to an ongoing trend to specialize in fewer industries, Baldwin et al. (2001) highlight an increase in commodity specialization at the plant level. Despite implementing specialized or one-product focused plants (Skinner, 1974), a multi-plant firm may still face heterogeneity between plants producing the same product. These differences may stem from the level and type of capital equipment used in the plants (Doms 1995).

The comparative advantage of LFN over AN increases as the heterogeneity of the manufacturing plants, denoted by T, decreases. In the extreme case of completely homogenous plants, all plants including the lead factory operate in the same landscape. In this case, the knowledge effect reaches its maximum because the knowledge acquired by the lead factory does not lose any validity when applied by the other plants.

As the heterogeneity of the plants increases, the representative search by the lead factory becomes less valuable because the knowledge acquired by the lead factory (partly) loses its validity when it is transferred to another plant, operating in a different production environment, i.e., in a different landscape. Formally, a higher heterogeneity parameter T decreases the marginal gain from each decision that is transferred from the lead factory to the plants.

Figure 6: Effect of Heterogeneity



(a) Short Run (b) Performance Evolution

Panel (a) in Figure 6 depicts the performance of LFN and AN as a function of the number of transferred decisions S for three different values of T (plant heterogeneity) in the short run, i.e., $t = R$. The figure shows that the slope of the performance function of LFN increases as plant heterogeneity decreases, i.e., the marginal effect of an increase in S on the performance of LFN increases. As a result, a lower heterogeneity mitigates the performance drop through the knowledge transfer. Panel (b) in Figure 6 compares the (normalized) performance of AN and LFN over the first P periods. It shows that a decrease in plant heterogeneity reduces the time period P^* and increases the relative performance of LFN compared to AN in the long run.

Figure 7: Sticking Point Effect

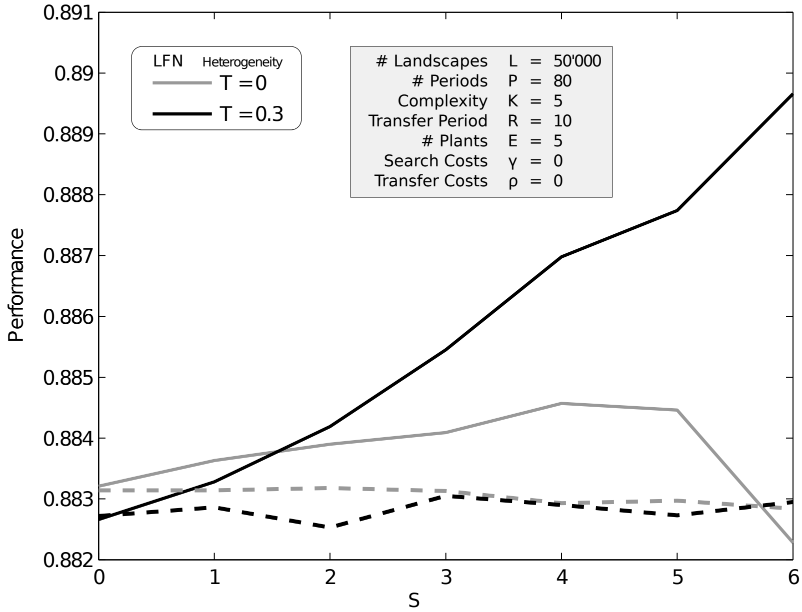


Figure 7 highlights the sticking point effect for homogeneous plants. If transfer costs are sufficiently low such that the performance increases for all S in the case of heterogeneous plants (see dark bold line in Figure 7 for $T = 0.3$) this result does not hold anymore in the case of completely homogeneous plants: if the plants are completely homogeneous, i.e., ($T = 0$), the performance of LFN decreases as the number of transferred decisions increases from $S = 5$ to $S = 6$ (see light bold line in Figure 7 for $T = 0$). The sticking point effect is dominated by the search cost effect if search costs become prohibitively high. In this case, LFN can obtain a higher performance in the long run by transferring all decisions. Our results lead to the following proposition.

Proposition 4

A lower plant heterogeneity T will:

(i) increase the marginal benefit of each transferred decision and thus mitigate the performance drop in LFN through the knowledge transfer.

(ii) reduce the time period P^* at which LFN outperforms AN.

(iii) improve the relative performance of LFN compared to AN in the long run.

4.2.2 Complexity of the Production Process

Several empirical studies support the notion that complexity raises barriers to transferring knowledge (Rivkin 2000). The definition of complexity receives different meanings throughout literature. We adopt the definition of complexity from Simon (1962) and Rivkin (2000) by defining it as the "sheer number of elements in an item of knowledge and the degree of interaction among those elements." We focus on the second aspect of complexity and interpret our model parameter K as a measure for the complexity of the production process. Specifically, a production process with highly interactive process steps has a higher level of complexity than a process with independent process steps. If $K = 0$, the production decisions are independent. If the parameter K increases, the dependency of the production decisions augments, and the production environments of each plant, represented by the respective landscapes, become more rugged (Rivkin and Siggelkow 2003, Siggelkow and Rivkin 2005). As a consequence, the number of local maxima increases such that the plants get stuck more often. Hence, the sticking point effect becomes more important as K increases.

Figure 8: Effect of Complexity

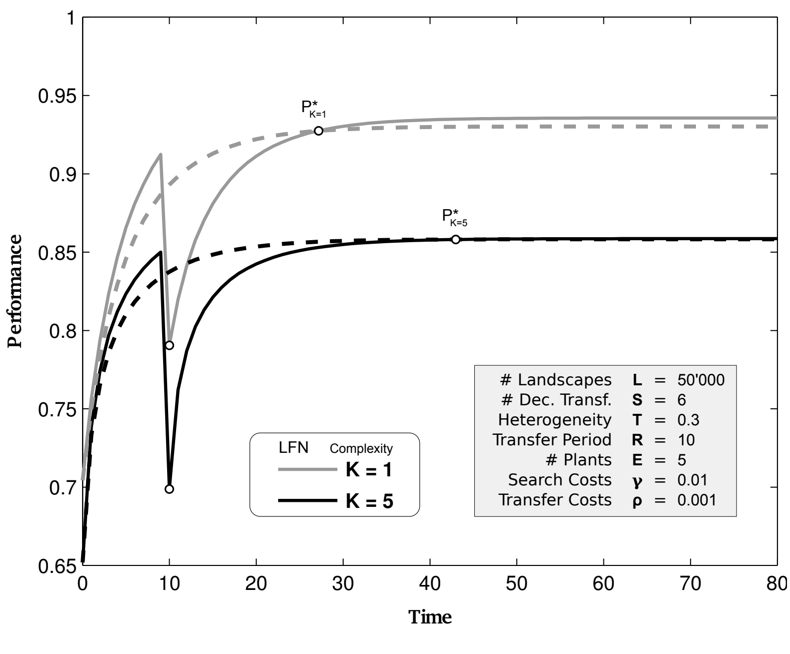


Figure 8 compares the performance of LFN and AN with the dark-shaded (light-shaded) curve depicting the performance for $K = 5$ ($K = 1$). A lower process complexity K leads to an overall better performance of LFN and AN. This general performance increase is due to the presence of fewer sticking points. Since fewer sticking points result in more changes of the decision vector, the search cost advantage of LFN over AN increases as the complexity of the production process decreases. Moreover, lower production process complexity increases the performance difference between LFN and AN before the knowledge transfer.

We further derive that the complexity of the production process affects the size of the performance drop of LFN after the knowledge transfer. A lower complexity K implies a lower dependency between decisions and therefore a lower perturbation of the production process through the knowledge transfer. As a result, ceteris paribus, a lower K increases the marginal benefit for each decision that is transferred from the lead factory to the plants and therefore results in a smaller performance drop. Moreover, the time period P^* at which LFN outperforms AN is an increasing function in K. We establish the following proposition.

Proposition 5

A lower complexity K will:

(i) increase the performance difference between LFN and AN before the knowledge transfer and mitigate the performance drop in LFN through the knowledge transfer.

(ii) reduce the time period P^* at which LFN outperforms AN.

(iii) improve the relative performance of LFN compared to AN in the long run.

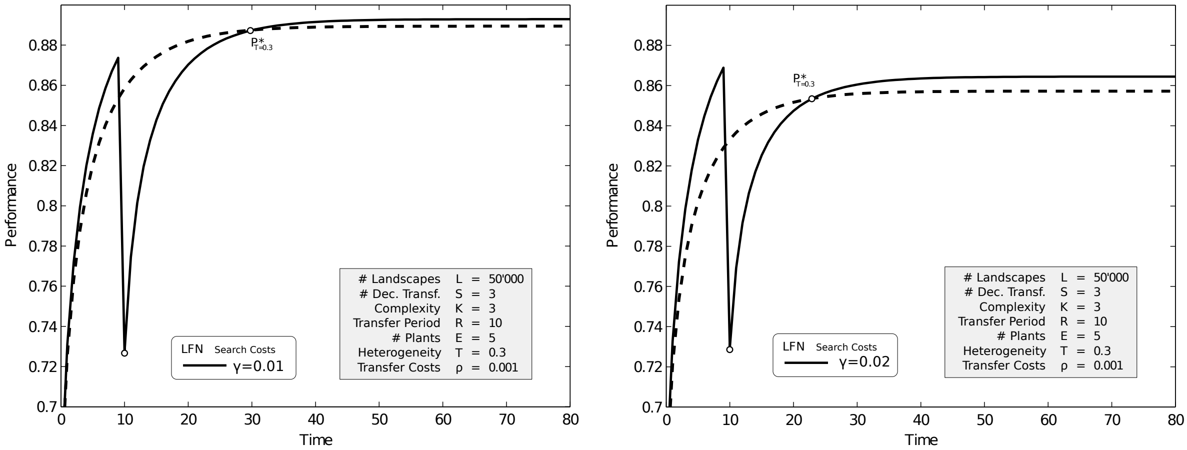
4.2.3 Search Costs

The idea that companies should continuously invest time and resources to improve has become a central tenet of operations management research. The success of large Japanese companies over the last twenty years has triggered this interest (Delbridge and Barton, 2002).

Continuous improvement enables a plant to reach a new performance level. In our model, the related search costs have a positive impact on the relative performance of LFN as compared to AN because LFN economizes on search costs by avoiding a multiplication of search costs in each plant. As a result, the difference in performance between LFN and AN increases in the search cost coefficient before the knowledge transfer. Figure 9 illustrates this result, where Panel (a) represents the scenario with low search costs and Panel (b) depicts the scenario with high search costs. It makes sense to differentiate between the absolute performance drop and the performance drop relative to AN. The size of the absolute performance drop, in general, depends on the level of the lead factory's performance before the knowledge transfer. If its performance is low then the corresponding drop is low and inverse, because the performance of LFN after the knowledge transfer is an average of the performances of the lead factory and the plants. The size of the relative performance drop depends on the difference between LFN and AN.

After the knowledge transfer, the effect of search costs on the performance of LFN is characterized by a trade-off as shown in Figure 9. Lower search costs result in a larger

Figure 9: Effect of Search Costs



(a) Low Search Costs

(b) High Search Costs

absolute and relative performance drop (as compared to the performance of AN), but a faster performance increase after the knowledge transfer. As the performance of LFN before the knowledge transfer decreases in the search costs, the absolute drop decreases with higher search costs. As the difference in performance between LFN and AN increases in the search costs, the relative drop decreases with higher search costs. Moreover, the performance of LFN increases faster after the knowledge transfer, the lower are the search costs. Because each transformation in the vector of decisions is costly, lower search costs imply a faster performance increase. Our results lead to the following proposition.

Proposition 6
Higher search costs γ will:

(i) decrease the overall performance of LFN and AN but increase the performance difference between LFN and AN before the knowledge transfer. Hence, higher search costs result in a lower (relative and absolute) performance drop in LFN through the knowledge transfer but they slow the performance increase in LFN after the knowledge transfer.

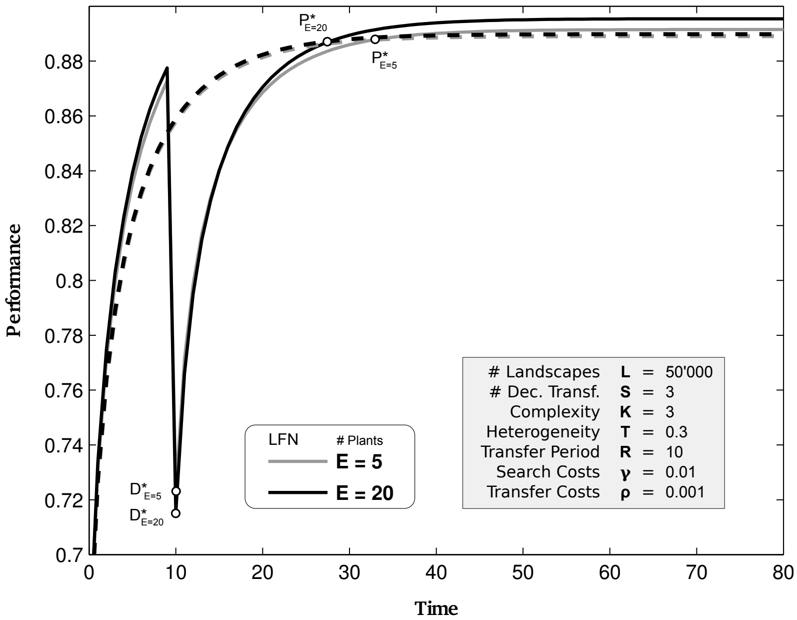
(ii) reduce the time period P^* at which LFN outperforms AN.

(iii) improve the relative performance of LFN compared to AN in the long run.

4.2.4 Number of Manufacturing Plants

To describe a manufacturing network, it is crucial to consider how many plants the network comprises. This is especially important when knowledge transfer is taken into consideration (Rudberg and Olhager, 2003). Our simulation shows that before the knowledge transfer, the difference in performance between LFN and AN increases with a higher number of plants. A higher number of receiving plants within LFN leads to a higher performance of LFN because search costs can be shared among more plants. This cost-saving advantage increases with a delay of the knowledge transfer, a lower complexity of the production process, and a higher search cost coefficient. A larger number of plants also increases the performance drop resulting from the knowledge transfer. Individual performances of the plants are lower than that of the lead factory after the knowledge transfer and the performance of LFN is calculated as the average of these performances. These results are highlighted in Figure 10. The bold curves represent the performance of LFN with the dark-shaded (light-shaded) curve depicting the performance for $E = 20$ ($E = 5$).

Figure 10: Effect of Number of Plants



We conclude that increasing the number of plants increases the performance drop and thus decreases the relative performance of LFN in the short run. Moreover, a higher number of plants reinforce the effects of the parameters that influence the relative performance of LFN compared to AN. Based on our previous results, we derive that the following factors increase the performance difference between the lead factory and the plants after the knowledge transfer and therefore deteriorate the performance of large LFN in the short run: a high complexity of the production process, high transfer costs, a low number of transferred decisions, and a high plant heterogeneity.

In the long run, the individual expected performances of the plants catch up with the expected performance of the lead factory, i.e., $\phi_{LF}(t) \simeq \phi_i(t)$ for $i \in \{1, .., E-1\}$ and $t \gg R$. It follows that due to the search cost savings, a higher number of manufacturing plants improves the performance of LFN in the long run. We establish the following proposition.

Proposition 7
A larger number of plants E will:

> *(i) increase the performance of LFN compared to AN before the knowledge transfer and thus result in a higher performance drop in LFN through the knowledge transfer.*
>
> *(ii) reduce the time period P^* at which LFN outperforms AN.*
>
> *(iii) improve the relative performance of LFN compared to AN in the long run.*

5 Conclusions

5.1 Summary

This paper addresses the question of how to optimally configure and coordinate global manufacturing networks. We have developed an NK computational model to simulate and compare the performance of two alternative forms of network configurations: the lead factory network (LFN) and the archetype network (AN). In AN, the R&D department and the manufacturing plants are organizationally separated. In LFN, management assigns the role of a lead factory to one of the manufacturing plants. The lead factory acts as an intermediary between the R&D department and the other manufacturing plants. By closely cooperating with the R&D department the lead factory generates essential production knowledge and transfers this knowledge to the other manufacturing plants.

Our model shows that compared to AN, LFN has a general cost advantage and disadvantage. Both result from the search by the lead factory for improvements in the production process. The search conducted within the lead factory eliminates the multiplication of search costs. This cost advantage increases in the number of manufacturing plants, the time period of knowledge transfer, and the search cost coefficient. The disadvantage of the lead factory's search is represented by the transfer costs, which have to be incurred when the lead factory transfers (parts of) its acquired knowledge to the manufacturing plants. Through the knowledge transfer, the LFN's performance drops, where the size of this drop depends on the negative transfer cost effect and the positive knowledge effect. Both effects, in turn, depend on the depth of knowledge transfer. A transfer of more decisions from the lead factory to the other plants results in higher transfer costs (transfer cost effect) but also improves the initial performance of the other plants (knowledge effect). A large number of transferred decisions also means that the other plants can benefit from the production improvements, which have been realized in the lead factory and, therefore, can start from higher points within their landscapes.

Starting from a higher point implies that a plant will have to incur lower search costs to improve its performance in the remaining periods (search cost effect).

Based on these results, we can show how coordination mechanisms influence the performance of a LFN given the exogenous factors (parameters). More specifically, the timing and depth of knowledge transfer is analyzed and contrasted to different exogenous factors. Suppose that search and transfer costs are sufficiently low. In the case of heterogeneous plants, the best strategy for LFN to maximize its long-run performance is to transfer all decisions. In the case of homogeneous plants, however, it is preferable not to transfer all decisions due to the sticking point effect. These counterintuitive results are caused by the sticking point effect, which allows manufacturing plants to leave lead factory sticking points. In the case of heterogeneous plants and sufficiently high search costs, the optimal depth of knowledge transfer depends on the transfer costs. Given a certain transfer cost coefficient, it can be optimal to fully transfer knowledge in the short run but to transfer nothing in the long run because of the relative decreasing importance of the knowledge effect from period to period. Our model further shows that a late knowledge transfer from the lead factory to the plants increases the pre-transfer performance but results in a larger performance drop. As consequence, the performance of LFN is lower in the short run but it can obtain a higher performance in the long run.

The optimal configuration choice (i.e., LFN or AN) is determined by the exogenous factors, which include the complexity of the production process, the heterogeneity between the manufacturing plants, the number of plants in the network, and the magnitude of the search and transfer costs. We find that higher complexity of the production process deteriorates the relative performance of LFN compared to AN in both the long and short run because it decreases the marginal benefit through the knowledge transfer and, thus, increases the resulting performance drop. Similarly, higher plant heterogeneity is disadvantageous for LFN in both the short and long run except for the case of a full knowledge transfer and sufficiently low search and transfer costs. In this case, a higher plant heterogeneity can be beneficial for LFN due to the sticking point effect. Moreover, a higher number of plants improves the relative performance of LFN compared to AN in the long run due to search cost savings. But also in the short run, LFN is able to outperform AN earlier even though a larger number of plants induce a higher performance drop through the knowledge transfer. Finally, higher search costs decrease the overall performance of both manufacturing networks. Even though higher search costs slow down the performance increase in LFN after the knowledge transfer, they reduce the time period at which LFN outperforms AN and therefore are beneficial for LFN in the short run. In the long run, high search costs are also advantageous for LFN because they increase the relative performance of LFN compared to AN. Figure 11 summarizes our findings.

Figure 11: Summary of Results

Configuration	**Short Term**	**Long Term**
Exogenous parameters	Choice of AN vs LFN	
High complexity *K*	AN	AN
High plant heterogeneity *T*	AN	AN
High number of plants *E*	LFN	LFN
High search costs *y*	LFN	LFN
High transfer costs *p*	AN	AN
Coordination	**Short Term**	**Long Term**
Endogeneous parameters	Higher performance of LFN, if…	
Timing of knowledge transfer *R*	… early knowledge transfer	…late knowledge transfer
Depth of knowledge transfer *S*	… full knowledge transfer	… no knowledge transfer

5.2 Implications, Limitations, and Further Research

Our analysis combines configuration and coordination mechanisms and therefore adds to the scant literature base of the combined analysis of configuration and coordination. Specifically, the analysis shows how to coordinate knowledge transfer mechanisms to optimize performance of LFN. We agree with Rudberg and Olhager (2003) that coordination depends on the chosen configuration. In addition, we have expanded existing knowledge on lead factories by showing which factors render the lead factory more or less efficient. Besides the literature on network configuration and coordination, we also contribute to the literature on NK models. First, we have applied the NK model to the manufacturing environment by explicitly simulating the performance of two distinct network configurations. Second, we have integrated search costs into our model, which have been neglected in NK models until now.

From a practitioner perspective, we show which factors managers should consider while analyzing the optimal choice of network configuration. Some of the endogenous factors may be changed with major investments (e.g., number of plants). Therefore, the optimal choice of the network configuration may change over time. The coordination of the knowledge transfer within a lead factory yields counterintuitive results. First, the knowledge transfer paradox implies that managers of a network with homogenous plants can increase its long-run performance by not fully transferring its decisions from the lead factory to the plants. An incomplete transfer of decisions may allow the plants to improve the production process without being stuck in the same local maxima (sticking point) than the lead factory. Second, if full knowledge is transferred from the lead factory to the plants, networks with heterogeneous plants can outperform a network with homogenous plants. In this case, besides receiving full knowledge, each plant has to adapt the transferred receipt to their own circumstances in order to improve its performance. This helps to avoid the sticking points in which the lead factory may got stuck. We summarize that in order to increase performance of the network, each plant should be given enough “freedom” to improve and therefore given the possibility to influence the network performance.

Our results have shown that different endogenous and exogenous factors influence the choice and performance of a specific network configuration. However, because these factors vary between industries, it remains to be shown which industries are better suited for implementing LFN. An empirical investigation of these factors would allow us to further concretize our results. Another promising avenue for further research could be the extension of our model to take into account differences in the absorptive capacity of the receiving plants since we have shown that plant heterogeneity influences the configuration choice and performance.

A Technical Appendix

A.1 Bounce Methode

In this appendix, we introduce the bounce method whose purpose is to develop a mathematical method to transform an existing landscape V to a perturbed version $\bar{V}$ by adding some noise to its pay-off values. This transformation must satisfy the following assumptions:

A1. The pay-off values of the new landscape $\bar{V}$ are in the unit interval $[0; 1]$,

A2. The perturbations are local and unbiased, i.e., a perturbed pay-off value $\bar{v}_i$ stays in a symmetrical finite interval around the initial pay-off value v_i,

A3. The uniform distribution in the unit interval of all pay-off values that define the landscape is preserved after the transformation.

As a first step, a pay-off value v_i of the initial landscape V is altered by adding a random amount of noise to derive the new value v_i' :

$$v_i' = v_i + 2 \cdot (u - 0.5) \cdot T$$

where u is a random variable uniformly distributed on the unit interval, i.e., $u \sim [0; 1]$ and $T \in [0; 1]$. Hence, the random value added to v_i is uniformly distributed in the interval $[-T; +T]$. The parameter T enables to control the amount of noise that modifies the initial landscape, i.e., $T = 0$ does not change the initial landscape such that $\bar{V} = V$, while $T = 1$ leads to a completely new landscape $\bar{V}$, which is uncorrelated to the initial landscape.

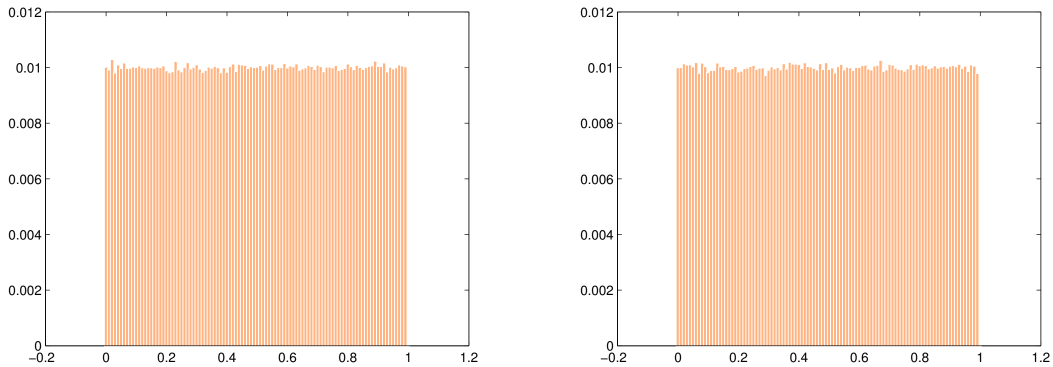
As the values v_i' are in the interval $[-T; 1+T]$ and hence are not confined to the unit interval, a second transformation is applied to v_i' to obtain the final pay-off values $\bar{v}_i$:

$$\bar{v}_i = \begin{cases} |v_i'| & \text{if } v_i' < 0 \\ v_i' & \text{if } 0 < v_i' < 1 \\ 2 - v_i' & \text{if } v_i' > 1 \end{cases}$$

This second transformation confines the values v_i' to the unit interval in which the values 0 and 1 are like walls on which the transformed values v_i' "bounce". To observe the result of the bounce method, the pay-off values of $10'000$ landscapes are represented in two normalized histograms in Figure 12. Panel (a) depicts the initial pay-off values and Panel (b) the final perturbed values. The figure shows that the transformation preserves the uniformity of the distribution.

Proof: To formally prove that the bounce method does not change the distribution, we proceed as follows. Lets Σ be a set of N-real values v_i belonging to the unit interval

Figure 12: Distribution of pay-off values



(a) Initial pay-off values (b) Transformed pay-off values

$U = [0; 1]$, i.e., $v_i \in U$, $i = 1, 2, \ldots, N$. Suppose that η is the homogeneous density of the values v_i on U. That is, the number of values of Σ in the interval $[u - \frac{\Delta u}{2}; u + \frac{\Delta u}{2}] \subset U$ is then given by $\eta \Delta u$. The bounce method transforms any value $v_i \in U$ into an image $\bar{v}_i \in U$. We further define an interval μ of width $\Delta u < T$ around some value $u \in U$: $\mu = [u - \frac{\Delta u}{2}; u + \frac{\Delta u}{2}] \subset U$. Moreover, we define N_{out} and N_{in} as

$$N_{\text{out}} = E\,[\ \#\{\ v_i \mid \forall v_i \ \text{ such that } \ v_i \in \mu \ \text{ and } \ \bar{v}_i \notin \mu\ \}\ ]$$
$$N_{\text{in}} = E\,[\ \#\{\ v_i \mid \forall v_i \ \text{ such that } \ v_i \notin \mu \ \text{ and } \ \bar{v}_i \in \mu\ \}\ ]$$

where E is the expectation operator. Hence, N_{out} is the number of values v_i that are initially inside the interval μ and leave this interval due to the bounce method transformation. Correspondingly, N_{in} is the number of values v_i that are initially outside μ, entering this interval.

We will show that for any u and an arbitrarily small $\Delta u < T$ such that $\mu \in U$, the number N_{out} equals N_{in}. This would prove that an uniform distribution is asymptotically invariant under the bounce method transformation. To formally prove this claim, we have to distinguish several cases depending on the values of T and u.

Case 0: $T = 0$. This is the trivial case as $v_i \ \rightarrow\ \bar{v}_i = v_i$. There are neither values leaving μ nor coming in for all intervals μ. Hence, $N_{\text{out}} = N_{\text{in}} = 0$. The distribution of Σ remains thus uniform in the interval U.

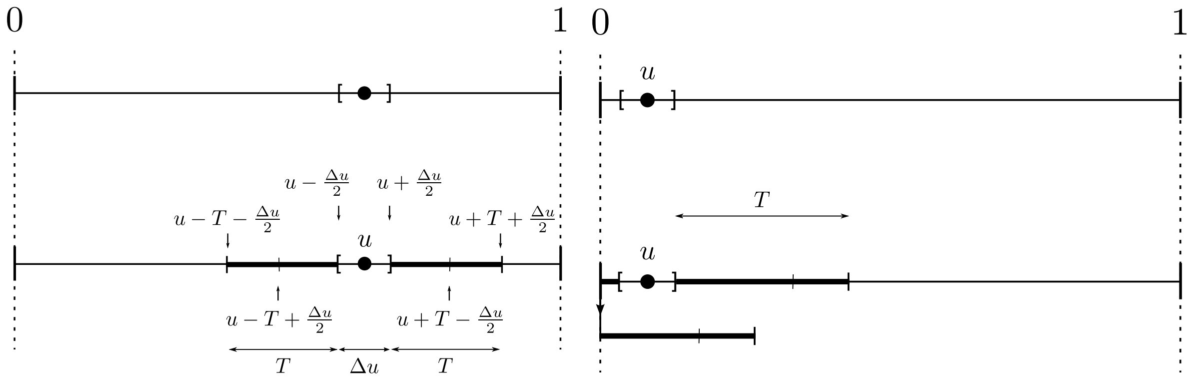
Case 1: $\{\ u, T \mid [u - T; u + T] \subset U,\ T \neq 0, T \leq 1\ \}$. This case is illustrated in

Figure 13a. In Case 1, we derive N_{out} and N_{in} as

$$N_{\text{out}} = \eta \Delta u \left(1 - \frac{\Delta u}{2T}\right) = \eta \Delta u - \eta \frac{\Delta u^2}{2T},$$

$$N_{\text{in}} = \eta \frac{\Delta u}{2T} (T - \Delta u) \cdot 2 + 2 \int_{u-T-\frac{\Delta u}{2}}^{u-T+\frac{\Delta u}{2}} \eta \left(t - \left(u - T - \frac{\Delta u}{2}\right)\right) \cdot \frac{1}{2T} \mathrm{d}t.$$

Figure 13: Illustration of Cases 1 and 2



(a) Case 1

(b) Case 2

We define the integral α as

$$\alpha = \int_{u-T-\frac{\Delta u}{2}}^{u-T+\frac{\Delta u}{2}} \eta \left(t - \left(u - T - \frac{\Delta u}{2}\right)\right) \cdot \frac{1}{2T} \mathrm{d}t = \eta \frac{\Delta u^2}{4T}.$$

It follows that,

$$N_{\text{in}} = \eta \frac{\Delta u}{T} (T - \Delta u) + 2\alpha = \eta \Delta u - \eta \frac{\Delta u^2}{2T}.$$

We conclude that $N_{\text{out}} = N_{\text{in}} = \eta \Delta u - \eta \frac{\Delta u^2}{2T}$ and hence the distribution of Σ remains uniform in the interval U.

Case 2: $\{ \; u, T \mid T > 2u + \Delta u \;$ or $\; T > 2(1-u) + \Delta u \; T \neq 0, \, T \leq 1 \; \}$. This case is illustrated in Figure 13b. In Case 2, we derive N_{out} and N_{in} as

$$N_{\text{out}} = \eta \Delta u \left(1 - \frac{2\Delta u}{2T}\right) = \eta \Delta u - \eta \frac{\Delta u^2}{T},$$

$$\begin{aligned} N_{\text{in}} &= \alpha + \eta (T - \Delta u) \frac{\Delta u}{2T} + \alpha + \eta (T - 2u - \Delta u) \frac{\Delta u}{2T} + \eta \left(u - \frac{\Delta u}{2}\right) \frac{2\Delta u}{2T} \\ &= \eta \frac{\Delta u^2}{2T} + \eta (2T - 3\Delta u) \frac{\Delta u}{2T} = \eta \Delta u - \eta \frac{\Delta u^2}{T}, \end{aligned}$$

where α is defined similarly as above. We conclude that $N_{\text{out}} = N_{\text{in}} = \eta \Delta u - \eta \frac{\Delta u^2}{T}$, and hence the distribution of Σ remains uniform in the interval U.

Case 3: $\{\ u, T \mid u < T < 2u - \Delta u \ \text{ or } \ (1-u) < T < 2(1-u) - \Delta u)\ T \neq 0,\ T \leq 1\ \}$. By choosing Δu adequately, it is possible to reduce this case and all the remaining cases to one of the cases analyzed above.

We conclude that an uniform distribution is asymptotically invariant under the bounce method transformation.

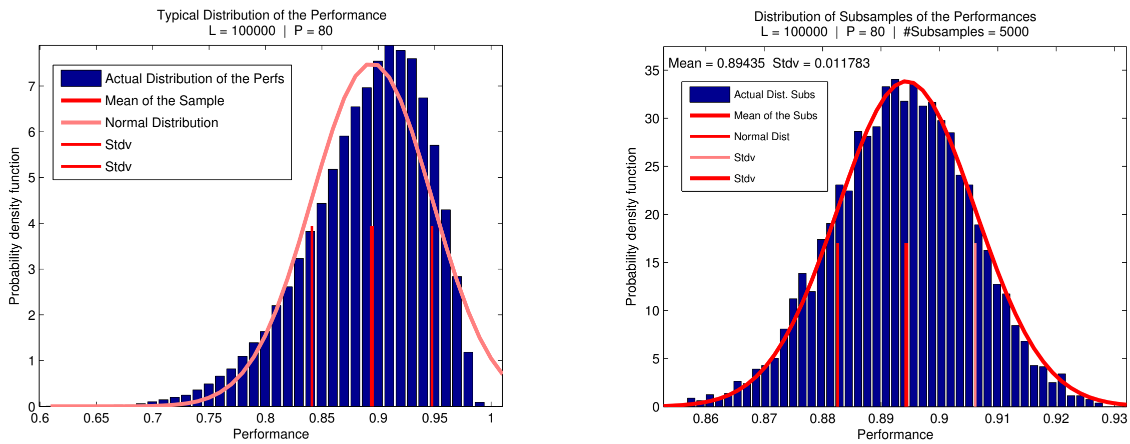
A.2 Accuracy of the Results

In this appendix, we estimate a lower bound for the accuracy of the results because all mean performances reported in the results are stochastic variables. The idea is to give a criteria that ensures, up to a certain confidence level, that the difference in mean performances is statistically significant and not due to some stochastic process.

The standard deviation of the mean performances depends on the set of parameters that are chosen in a simulation and on the number of periods involved. The aim is to estimate the worst scenario case, i.e., the largest standard deviation (stdv) from period to period.

Figure 14a shows the distribution of the average performances of LFN evaluated after 80 periods with 100'000 landscapes, i.e., $L = 100'000$, and $P = 80$. As expected, the distribution is non-normal and skewed. Due to the integration of costs, i.e., $\gamma > 0$ and $\rho > 0$, none of the performances reaches the maximum of 1.

Figure 14: Difference in distributions



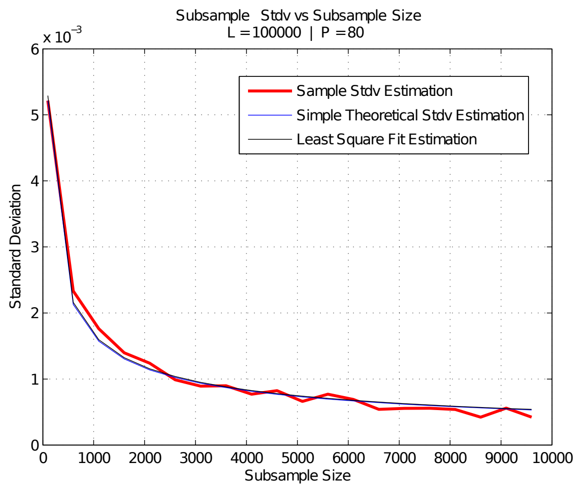
(a) Distribution of average performance

(b) Distribution of means

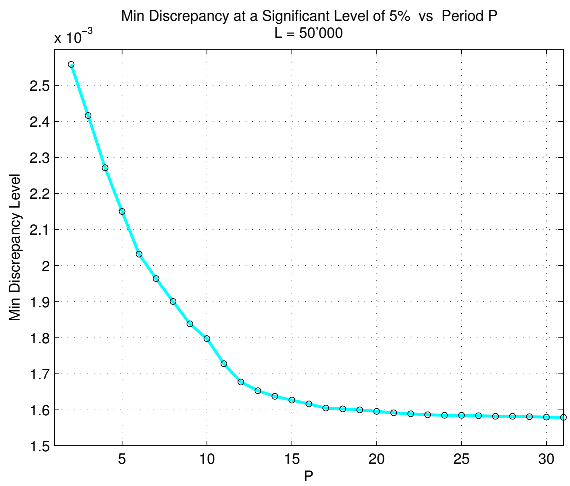
For example, the sample is now divided into $5'000$ juxtaposed subsamples composed of $n = 20$ data each. The means of the subsamples are random variables that are independent and identically distributed. Their distribution converges to a normal distribution when $n \to \infty$ due to the central limit theorem. This result is illustrated in Figure 14b, in which the distribution of the means of the subsamples is plotted in a histogram. The figure shows that it closely resembles a normal distribution.

In a next step, we create $100'000/n$ subsamples with a stdv given $\tilde{\sigma} = \frac{\sigma}{\sqrt{n}}$, where σ is the stdv of the individual performances of the whole sample (i.e., the $100'000$ data sample). This estimated stdv $\tilde{\sigma}$ is plotted in Figure 15a as a function of the size n of the subsample. The figure shows that the function $\tilde{\sigma}(\sigma, n)$ fits quite well the theoretically derived stdv estimation.

Figure 15: Standard Deviation and Minimum Discrepancy



(a) Subsample stdv $\tilde{\sigma}$



(b) Minimum discrepancy $\Delta(P)$

Finally, we consider all 648 simulations indexed by $i = \{1, 2, \dots, 648\}$, which cover the whole range of simulations used in our paper. Each of these simulations has a different set of parameter values. For each period $P = \{1, 2, \dots, 30\}$, we estimate the standard deviation $\tilde{\sigma}_i$ of each simulation $i = \{1, 2, \dots, 648\}$ and illustrate them in Figure 16. To obtain a lower bound, we calculate for each period the maximum value of $\tilde{\sigma}_i$, i.e.,

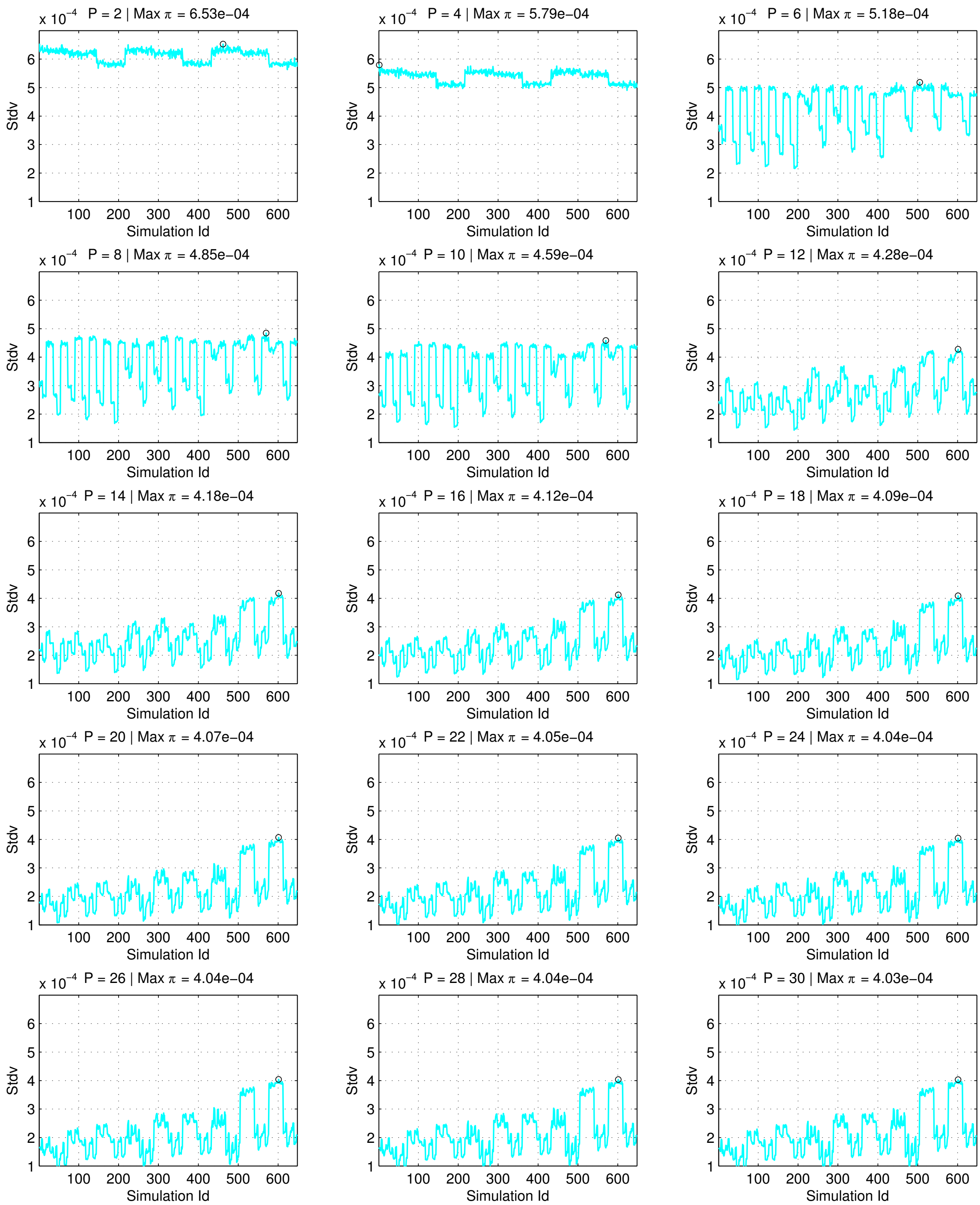
$$\hat{\sigma}(P) = \max_{i=1,\dots,648} \tilde{\sigma}_i(P). \tag{1}$$

A confidence interval $[\varphi - \Delta(P); \varphi + \Delta(P)$ at the level 95% is calculated around a simulation result φ (i.e., a performance) by assuming that the true distribution is normal with, in the worst case, a variance of $\hat{\sigma}(P)$, i.e.,

$$\Delta(P) = \Phi^{-1}(0.025) \cdot \hat{\sigma}(P),$$

where Φ is the normal cumulative distribution function. The function $\Delta(P)$ is plotted in Figure 15b for $L = 50'000$ landscapes. The figure shows that a confidence interval with range of $1.25 \cdot 10^{-3}$ at the 95% level is guaranteed in the short run (i.e., $P \leq 20$). In the long run ($P = 80$), the range of the interval at the 95% level falls below $0.5 \cdot 10^{-3}$.

Figure 16: Estimated Standard Deviations $\tilde{\sigma}_i$



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