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Preparation of Papers for IFAC Conferences & Symposia: Migration Planning for Global Production Networks using Markovian Decision Processes

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Modern globalization leads companies into a changing environment with a highly uncertain future development of key drivers of change. Especially, global production networks are affected by uncertainty and dynamic changes. Reactiveness becomes of crucial importance, as the adaptation to environmental conditions is the key to maintain competitive advantages. This article presents an approach for flexible migration planning in global production networks. The focus is on the formulation of a Markovian Decision Process (MDP) that enables the identification of optimal reactions to stochastic changes of key drivers of change. The formulation includes the description of a multi-level modelling approach for global production networks. Furthermore the valuation model of the reward function of the MDP is discussed in detail. Finally, the paper provides a brief description of exemplary optimization results solving the MDP by backward induction.

Keywords: production network, migration planning, markovian decision process

1. INTRODUCTION

The global expansion of the manufacturing sector is caused by the transfer of sales markets from industrial nations to developing economies. The possibility of using regional advantages as well as the concentration on core competencies forced the development and expansion of global production networks (Wiendahl et. al 2002). These networks have often grown historically or opportunistically and they include a variety of heterogeneous locations (Schmidt 2011). Complex network structures frequently result from relocations, acquisitions and disposals (Friedli et al. 2013). But ever since the world financial crisis happened in 2009, the challenges of globalization have been obvious. The business environment is increasingly dynamic and uncertain (McKinsey et al. 2009, Koren 2010, Váncza et al. 2011). Global production networks in particular are affected by these changes. Furthermore, modern globalization is leading manufacturing companies into a global competitive environment with increased competition, shortened product life cycles, increasing variety and a volatile demand (Wiendahl et. al 2002). The above-described dynamics and the global competitive environment put growing pressure on production networks and force them to adapt. (Váncza et al. 2011, Lanza et al. 2014). Therefore, reactiveness is a critical element of competitiveness (Wiendahl et. al 2002). Companies are trying to adapt their networks effectively to the volatile influencing factors (Schuh et al. 2014, Lanza et al. 2014). Often, investments in structural adaptions and investments in production resources are needed (Schmidt, 2011). Reducing the costs is not as much of a concern to decision-makers as it is the risk of misinvestment (Schmidt 2011). An effective and efficient adaption of the network is therefore a complex challenge for manufacturing companies.

In simplified terms, two essential questions for the decision-makers can be distinguished:

(1) What must be adapted depending on future developments of crucial influencing factors?

(2) What can be adapted proactively and independent of possible future developments?

The complexity of such decisions exceeds the cognitive skills of decision-makers. Decisions cannot be made intuitively. Hence, planning approaches which support decision making in production networks are necessary.

2. LITERATURE REVIEW

Existing research approaches provide significant contribution to the strategic planning of production networks. A majority of them are optimization approaches. But these approaches often neglect a continuous adaptation of the network configuration and the associated efforts (cf. Jacob 2006, Friese 2008, Kohler 2008, Kauder 2008). Those who integrate efforts for adaptation are mostly base on deterministic optimization models (cf. (Kohler 2008, Melo 2009, Lanza et al. 2014). Although they consider multiple future developments of key drivers of change comparing different scenarios, stochastic changes of key drivers of change are not considered adequately (Abele 2008). A few approaches take stochastic effects into account. But they only consider customer demand as stochastically (cf. (Stephan et al. 2010, Lanza et al. 2012, Lin et al. 2014)) and do not provide the possibility of modelling multiple key drivers of change stochastically. Furthermore, approaches that include in particular the planning of measures for the adaptation of network configurations, the so called migration planning, barely exist. And if so (cf. (Schuh et al.

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2014,, Lanza et al. 2014) they are still subject to the above restrictions.

3. OBJECTIVE

The objective of this paper is to present a mathematical optimization model for migration planning for globally distributed production networks. Formulating a Markovian Decision Process (MDP) in a random environment, a dynamic optimization of the production network can be realized while taking into account stochastic effects of multiple key drivers of change. The MDP identifies robust migration paths as a reaction to stochastic changes of key drivers of change taking into account costs due to the adaption of the network as well as the expected follow-up costs. The model prevents misinvestments of the decision makers considering multiple future development of key drivers of change.

4. APPROACH

The optimization model presented below is the main part of a flexible planning approach that supports migration planning for production networks and that is focused on brownfield scenarios. In this approach, the transformation is realized by gradual adaptations over a defined planning horizon depending on the condition of crucial influencing factors. An adaptation of the production network can affect both, the structure of the network but also the capacity of resources. Hence, the planning approach integrates top-level planning and base-level planning. The underlying decision problem can be described as a multi-stage decision process and is defined by the planning horizon, the discrete (finite) point in time, possible adaptation measures, and possible conditions of the key drivers of change.

The focus of the following sections will be on the comprehensive description of the developed optimization model.

4.1 Mathematical formulation of the optimization model

A stochastic, dynamic optimization model is formulated to identify robust migration paths of a production network by taking into account multi-dimensional uncertainty. The model is formulated as a (finite horizon) Markovian Decision Process (MDP) in a random environment (Lange, 2013). Below, the MDP is formally described using the standard mathematical formulation. The formulation is partially similar to (Lanza et al., 2012):

Planning horizon $t = 1, \ldots, T$: The planning horizon T represents the planning horizon of migration planning and is finite. Dividing the planning horizon into adequate time slices, a finite number of equidistant decision points is specified. For each point in time, decisions about the adaption of the network configuration must be made.

State Space S_t: For each point in time t , a finite, non-empty set of states S_t is defined. A state $s_t = (k_t, \vec{n}_t) \in S_t$ defines the initial network configuration at the beginning of t $k_t \in K_t$ and the demand situation $\vec{n}_t \in N_t$. The demand for individual products is summarized in a vector $\vec{n}_t$. Thus, it follows: $S_t = K_t \times N_t$. Since the decision model focusses on brownfield scenarios, the model is initialized with the current network configuration.

State Space W_t: For each point in time t , a finite, non-empty set of states W_t is defined. A state $\vec{w}_t = \left(w_t^1, \ldots, w_t^n\right) \in W_\tau$ determines the condition of the key drivers of change. Since several key drivers of change must be respected, a pre-analysis is executed to define consistent clusters for each point in time. Then, clusters are summarized in a vector $\vec{w}_t \in W_t$.

Action space A_t: For each single state $s_t \in S_t$, a finite, admissible set of actions $A_t(s_t)$ exists. An action $a_t(s_t) \in A_t(s_t)$ can include both, structural and capacitive adaptations of the network configuration. By choosing an action $a_t(s_t) \in A_t(s_t)$, the initial configuration migrates to configuration k_{t+1}. It is assumed that the time for reconfiguration can be neglected. Hence, the demand at t is produced with configuration k_{t+1}. The admissible action space $A_t(s_t)$ is defined implicitly by equality and inequality constraints. In total, there are two constraints considered in this model:

- Capacity restrictions of sites, suppliers and outsourcing partners
- Optional strategic inputs (here: volume flexibility)

Transition law p: The transition law p defines the probability to reach s_{t+1} being in s_t and choosing action a_t at t. Only the demand $\vec{n}_t$ in period t is stochastic while the action a_t is deterministic. Furthermore, it is assumed that the demand holds a so-called Markov property, which means the demand in $t+1$ only depends on the current demand in t. Thus, it follows: $P\left(S_{\tau+1} = s_{t+1} \,|S_\tau = s_t \wedge A_t = a_t\right) = \left(N_{\tau+1} = \vec{n}_{t+1} |\, N_\tau = \vec{n}_t\right)$

Transition law q: The transition law q defines the probability to reach W_{t+1} being in W_t in t. To hold a Markov property, future developments of the clustered key drivers of change are modelled as a homogenous markov chain. Thus, it follows that $q(t) = \left(W_{\tau+1} = \vec{w}_{t+1} |\, W_\tau = \vec{w}_t\right) = \left(W_{\tau+1} = \vec{w}_{t+1} |\, W_\tau = \vec{w}_t, W_{t-1} = \vec{w}_{t-1}, \ldots, W_0 = \vec{w}_0\right)$. Again, since the decision model focusses on brownfield scenarios, the model is initialized with the current condition of the key drivers of change $\vec{w}_o$.

One-stage reward function r_t: The one-stage reward function $\mathrm{r}(k_t, \vec{n}_t, \vec{w}_t, a_t)$ includes the period costs $tlc(k_t, \vec{n}_t, \vec{w}_t, a_t)$ and the cost for adapting the network configuration $mc(k_t, a_t)$. Since the reconfiguration time is neglected, it follows:

$$tlc(k_t, \vec{n}_t, \vec{w}_t, a_t) = tlc(k_{t+1}, \vec{n}_t, \vec{w}_t) \tag{1}$$

Migration costs are identified by comparing the configuration parameters of $k_t \in s_t$ and $k_{t+1} \in s_{t+1}$:

$$mc(k_t, a_t) = mc(k_t, k_{t+1}) \tag{2}$$