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Integration of Knowledge Graph and MILP Model for Optimizing a Reconfigurable Supply Chain

Riheb Sioud[1*], Meryem Bamoumen[1], Nadia Hamani[1]

[1]*Laboratoire des technologies Innovantes, UPJV Amiens, France*
** riheb.sioud@etud.u-picardie.fr*

Abstract:
In a global economic issue marked by constant instability, demand fluctuations, and escalating environmental troubles, conventional supply chains, characterized by rigidity, encounter significant challenges in maintaining competitiveness. Reconfigurable supply chains (RSCs) have emerged as a modern and a strategic solution, enabling dynamic adaptation to perturbation through flexible processes and infrastructure [1]. This paper puts forth a pioneering strategy for enhancing the efficacy of an RSC by integrating a Mixed Integer Linear Programming (MILP) model with a Knowledge Graph (KG) implemented in Neo4j. The proposed methodology aims to concurrently minimize operational costs (transportation, production, distribution) and CO2 emissions, while addressing variable demand in a multi-echelon network comprising suppliers, production sites, distribution centers, and retailers [2].
The approach is founded on two primary pillars: the KG and the MILP model. The KG, modeled using Neo4j, represents logistic entities (nodes) and their relationships (edges), facilitating the dynamic management of complex and heterogeneous data [3]. This configuration facilitates real-time updates and intuitive visualization of flows, thereby enhancing traceability and resilience against disruptions [4]. The MILP model optimizes reconfiguration decisions by minimizing an objective function that combines economic costs and environmental impact. This function is subject to operational (capacity, flow) and regulatory (traceability) constraints. A pivotal innovation resides in the specialization of transporters, with each transporter assigned to a particular raw material throughout the supply chain. This specialization enhances traceability and optimizes resources [5].
The model involves sets (suppliers, sites, centers, retailers, transporters, raw materials, machines), decision variables (binary, continuous, integer), and parameters (costs, emissions, capacities). It minimizes total supply chain costs while ensuring flow conservation, capacity respect, and demand satisfaction. The Knowledge Graph (KG) enriches the model with real-time data, enabling rapid adaptation to demand variations [6].
To validate the approach, a case study from the literature [7] was conducted in the electronics sector. This case study involved three suppliers, three production sites, three transporters, three distribution centers, and seven retailers, with three raw materials and three machine types. The demand was simulated over 1000 time units with a range of 100 to 1,500 units over 75-time units. The distribution of demand was modeled as cyclic, triangular, and Gaussian. The model, implemented in Python using the PuLP library and connected to a Neo4j database, was compared to the approach of Saidi et al. (2025) [7], which uses a KG without MILP. The findings indicate that the proposed model surpasses the established benchmark, achieving reduced average total costs and enhanced sensitivity to the weighting of criteria (cost and emissions).
From a managerial perspective, this methodology provides managers with a real-time decision-making tool to optimize logistic configurations, reducing costs and emissions while enhancing resilience to disruptions. The proposed user interface facilitates adoption by non-technical teams, aligning with Supply Chain 5.0 principles [8]. Academically, this work addresses a gap in the literature by combining dynamic optimization with KGs, paving the way for future research, particularly in integrating machine learning for disruption prediction [9].
Despite its strengths, the approach has limitations, including a qualitative evaluation of environmental criteria and sensitivity to input data variations. Future research directions include integrating predictive models to anticipate disruptions, enriching the KG with detailed environmental data, and extending the methodology to other industrial sectors for more comprehensive optimization [10]

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