# A Reference Architecture for IoT-enabled dynamic planning in Smart Logistics

Martijn Koot[1 [0000−0001−9143−8531]], Maria-Eugenia Iacob[1 [0000−0002−4004−0117]], and Martijn R.K. Mes[1 [0000−0001−9676−5259]]

Department of Industrial Engineering & Business Information Systems (IEBIS), University of Twente, Enschede, The Netherlands
{m.koot,m.r.k.mes,m.e.iacob}@utwente.nl
https://www.utwente.nl/en/bms/iebis/

**Abstract.** Increasing customer demands and variability in today's logistics networks force fleet operators to become more reliable and flexible in their operations. As modern-day fleets are well equipped with wireless sensing, processing, and communication devices, fleet operators could proactively respond to dynamic events. However, the use of real-time sensor data to achieve re-optimization is scarce. This observation raises the question of how logistics operators should incorporate the emerging track-and-trace services into their dynamic planning activities. In this paper, we propose a reference architecture that relies on both the Internet of Things and the Smart Logistics paradigms, and aims at enhancing the resilience of logistics networks. Since the decision of when to reschedule the network's configurations remains nontrivial, we propose a hierarchical set of disruption handling systems to facilitate the trade-off between decision quality and response time. In our design, autonomous logistics agents can quickly anticipate on minor changes in their surroundings, while more severe disruptions require both more data and computational power in higher-level processing nodes (e.g., fog/cloud computing, machine learning, optimization algorithms). We illustrate the need of our architecture in the context of the dynamic vehicle routing problem.

**Keywords:** Internet of Things · IoT · Smart Logistics · Enterprise Architecture · Disruption Handling.

## 1 Introduction

In modern-day supply chains, it is getting more challenging to deliver all goods in the most efficient and reliable way possible. Customer requirements become more variable over time due to the increasing volumes of e-commerce [1], which enables customers to instantaneously demand for more transparency, affordability, and speed in their deliveries [2]. Logistics operators try to gain competitive advantage by including those preferences into their network designs, resulting into an increased individualization of product flows and more direct-to-customer deliveries [3]. The trend towards logistics customization should be performed in an environment characterized by more complex constraints (e.g., just-in-time deliveries, congestion, safety regulations, environmental footprint, etc). Luckily, logistics planners can rely on multiple decision support tools to create an initial schedule that fulfills both customer requirements and environmental constraints, but it seems almost impossible to fully maintain reliable outcomes during execution due to the dynamic and stochastic nature of real-world logistics networks [4]. Therefore, successful supply chains are characterized by reliable and flexible operations [3, 5], which indicates the need for a more active approach towards dynamic events once observed or predicted [6].

Recent IT advancements have enabled logistics companies to manage their fleet in (near) real-time [3, 5]. Most vehicles are constantly transmitting a wide variety of data regarding the transportation system's state towards a central planning authority [7]. For example, a modern-day fleet is well-equipped with Geographic Information Systems (GIS), Global Positioning Systems (GPS), Electronic Data Interchanges (EDI), auto-identification technologies and mobile devices [2]. Logistics operators use these sensing devices to monitor their fleet remotely [8], but more advanced data processing is required to learn from the perceived disruptions and re-optimize the supply chain's resource allocations accordingly. The rise of the Internet of Things (IoT) may bridge this gap by empowering physical objects with sensory, communication, and information processing technologies, resulting into an interconnected network of context-aware devices [7, 9]. Therefore, the IoT paradigm stimulates logistics operations to progress from remote monitoring towards ambient intelligence and autonomous control [10], a key feature which is also envisioned by the Smart Logistics paradigm [11].

Both logistics researchers and business practitioners are highly interested into IoT and Smart Logistics developments to build a more resilient logistics system. Therefore, a rising number of conceptual models is found in today's scientific literature that define all technological building blocks to anticipate on logistics disturbances (e.g., [12–14]). Other authors focus more on the integration of IoT devices, communication networks, and software required for the detection and/or prediction of dynamic events [9, 10, 15]. The increasing variety of modelling approaches used in Smart Logistics indicates the need for a uniform IoT-based architecture that explains how real-time data should be processed to proactively respond towards dynamic events. We only found one publication proposing an Enterprise Architecture (EA) for situation-aware Smart Logistics, where the IoT infrastructure facilitates the perception and handling of logistics exceptions [16]. To our knowledge, no other architecture is proposed to align IoT devices, learning mechanisms, and logistics processes together. This is why the main contribution of this paper is the design of a reference architecture that links all necessary components in between the perception layer and final decision making, as reflected by the question we address in the remainder of this study.

**Research question:** How to design an enterprise system that uses IoT technology for enhancing the resilience of logistics processes in (near) real-time on the basis of dynamic events data?

We will answer the research question by following the design science methodology for information system research [17]. The remainder of this paper is structured as follows. Section 2 includes a literature review. The system's requirements are introduced in Section 3, while the IoT-based architecture is proposed in Section 4. In Section 5, we will elaborate on how the proposed architecture can be improved, while the conclusions and further research directions are given in Section 6.

## 2 Literature review

The *smartness* in the term "Smart Logistics" refers to the intelligent management of logistics operations by the use of the latest technological advancements [13]. Most logistics operators try to obtain intelligence by the development of a solid IT infrastructure, including recent data-driven processing techniques like the Internet of Things (IoT), Cyber-Physical Systems (CPS), Big Data Analytics (BDA), cloud computing, and Artificial Intelligence (AI) [14]. Real-time access towards the system's conditions enables decision makers to efficiently reallocate resources in case a dynamic event is observed. A more proactive and resilient approach is possible when the real-time data is analyzed to predict disturbances in advance already [18]. Therefore, the main aim of these technological implementations is to obtain a more flexible and scalable system in which the decision making of logistics entities is decentralized [13], a vision that is strongly associated with the Industry 4.0 concept developments of the past decade [11]. The implementation of the six design principles originating from Industry 4. 0 could be helpful to obtain a logistics network that is more intelligent than traditional systems [19]:

1. **Real-time capability:** the ability to collect and analyze data and immediately provide the derived insights.
2. **Interoperability:** the ability of logistics objects to connect and communicate with each other.
3. **Virtualization:** the ability to create a digital/virtual copy of the physical world by linking sensor data with virtual models and simulation techniques.
4. **Decentralization:** the ability of logistics objects to make decisions on their own and to perform their tasks as autonomous as possible, including exceptions, interferences, and/or conflicting goals' handling.
5. **Modularity:** the flexible adoption of logistics networks to the changing requirements by replacing or expanding individual modules.
6. **Service orientation:** the ability to offer the services with other logistics objects or decision entities.

IoT technologies are essential building blocks for many applications related to Industry 4.0 [14]. The IoT network forms a global infrastructure of interconnected physical objects empowered with electronic devices that rely on sensors, communication, and information processing technologies [9]. The dynamic behavior of IoT networks would require a flexible layered architecture, allowing all electronic components to deliver their services [20]. Multiple alternative IoT architectures have been developed over the years [20], but a Service-Oriented Architecture (SOA) is most commonly applied to decompose the IoT network into smaller, re-usable, and well-defined components [8, 10]. The number of layers may differ for each application, but all IoT architectures are composed of a perception layer (e.g., identification and sensing devices installed on physical objects), a network layer (e.g., middleware technologies that allow the sensing objects to connect, coordinate, and share information), and an application layer in which the system's functionalities are exposed to the end-users.

The layered configuration of IoT architectures explains how logistics objects can extend their real-time monitoring functionalities with more intelligent and autonomous decision making [10], aiming for a more resilient logistics system [11]. Many IoT-based reference architectures highlight the need to integrate more IoT devices, cloud-based computing, and data-driven processing techniques for better decision making (e.g., [12–14]), while other researchers focus more on the detection and/or prediction of dynamic events [9,10,15]. However, the majority of IoT architectures do not explain how the real-time data should be processed to pro-actively respond towards dynamic events. The reference models proposed by [12] and [16] also highlight the need for new disruption handling systems, but the decision logic encapsulated in those applications remains unknown. Therefore, we need a comprehensive model to better align dynamic planning with the supporting IT infrastructures in logistics domains, allowing decision makers to gain more insights into the added value of their own IoT implementations. We argue that an EA approach enables us to improve the business-IT alignment for logistics execution [21]. We will use the enterprise modelling language "*ArchiMate*" for the development of an online disruption handling system, inspired by [5], where solutions are computed as soon as a dynamic event occurs during the operational process. All our EA models are based on the ArchiMate 3.1 Specification (`https://pubs.opengroup.org/architecture/archimate3-doc/`).

## 3 Requirement analysis

Today's supply chains are more vulnerable towards both internal and external disruptions due to globalization, lean operations, and customization trends [6]. The presence of dynamic events will cause deviations from the planned operations, which in turn may dissatisfy customers when the Service Level Agreements (SLAs) are not met [16]. A more proactive approach towards dynamic events enables logistics operators to reduce operational risks by re-configuring their resource allocations. However, re-optimization is scarcely done in the logistics domain [12], and if rescheduling happens, than purely reactive by relying on human intuition only. Therefore, the main driver behind this research is to design a logistics disruption handling system with flexible and automated operations to satisfy customer requirements in the most reliable way [3, 5].

The next step is to derive the system's stakeholders and their requirements. We base our assessment on the stakeholder analysis made by [12] and [16], both researches derived the requirements from interviews with company representatives of the associated case studies. We limit our design to the most important stakeholders involved in logistics operations only:

1. **Customers:** persons, departments, or organizations who can either send or receive goods. In case a dynamic event disrupts the logistics operations, customers still demand reliable outcomes:
   (a) On-time pick-up and/or delivery of goods according to the SLA;
   (b) Immediate incident notification (including order tracking);
   (c) The ability to alter the decision and/or SLAs in case conflicts among stakeholders emerge.
2. **Logistics operators:** entities who coordinate the physical flow of goods (e.g., order picking, transportation, storage, etc.). Logistics operators are responsible to handle disruptions effectively by re-configuring the network's configurations in a flexible matter:
   (a) Increase responsiveness to disruptions;
   (b) Reduce operational risks;
   (c) Guarantee SLAs to customers.

Our vision is to design a resilient system similar to [6] that incorporates event readiness, autonomous re-optimization procedures, and recovering capabilities. In this system, logistics objects should perform their tasks autonomously under "standard" operational conditions, while decisions are delegated to a central planning authority in case of a severe incident, interference, or conflicting goal is observed [22]. The ability to interchange local and global optimization procedures for different severity levels requires a solid IT foundation, consisting of remote sensing capabilities, wireless communication networks, and distributed processing nodes. Even better performances are expected when the system is able to predict the occurrences of dynamic events by re-examining the decisions previously made, resulting into a positive feedback loop. We will use the six design principles originating from the Industry 4.0 paradigm to define the general properties of our logistics disruption handling system [19].

The *"motivation strategy view"* in Figure 1 visualizes how the stakeholders, requirements, system outcomes, design principles, and course of actions are interrelated with each other. The implementation of our vision requires three main courses of action:

1. **Logistics IoT architecture:** event readiness is achieved by empowering physical resources with context-aware measuring systems. A regular IoT device extends its sensing function with communication, data (pre-) processing, and remote management capabilities due to the integration of sensors, actuators, micro-controllers, storage devices, data interfaces, and power sources into one device [8, 20]. The installation of those IoT devices allows logistics objects to sense and control the physical world [9], while the use of locations receivers and identification tags stimulates accurate monitoring of the objects' business operations in real-time [8, 23]. The use of wireless communication networks would improve the system's interoperability (e.g., RFID,

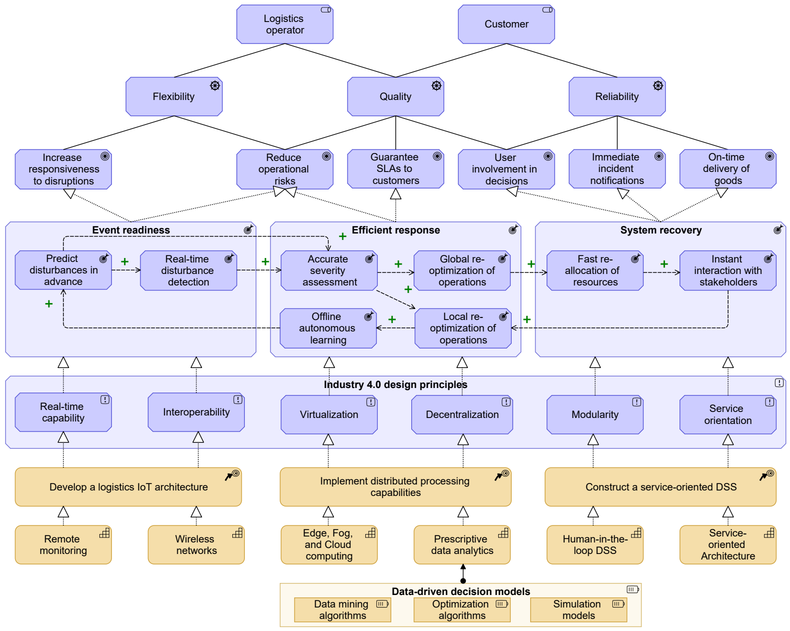


**Fig. 1.** Motivation strategy view.

NFC, W-LAN, LP-WAN, etc.), because logistics objects are characterized by their dynamic behaviour.

2. **Distributed processing capabilities:** a distributed network of processing nodes has to be equipped with prescriptive data analytical tools to autonomously re-optimize the objects' individual interests. The logistics objects already include some intelligence to handle minor disturbances due to the IoT devices installed, but re-optimization of a large logistics network demands both data and computational time. Therefore, cloud computing is used to create a centralized and powerful pool of computing resources to be shared and accessed when severe incidents emerge [23]. Both data-intensive techniques and centralized data warehouses can run on the core's servers to virtualize logistics networks and accurately assess the severity of incidents without intervening into the actual operations. We make use of IoT gateways to speed up the data interchange and local decision making [20, 24]. Therefore, the IoT gateway's purpose is twofold: 1) facilitating the communication of heterogeneous IoT devices over the internet, and; 2) leveraging its network knowledge by executing optimization algorithms for a minor part of the logistics network [9].
3. **Service-oriented Decision support system (DSS):** The IoT's hardware layer will bridge the gap between the physical and virtual world by installing a modular design of interoperable measuring devices [10]. A service-oriented

Architecture is required to ensure a fast-reallocation of the heterogeneous logistics objects once a potential disturbance has emerged [9]. The main aim of our system design is to automate the dynamic planning activities, but dynamic events may also change the stakeholders' preferences during the actual execution of the initial plan. Therefore, our system should include a symbiotic relationship where intelligent agents focus on task execution, while human stakeholders can modify objectives, constraints and decision parameters [25].

## 4 System design

In this section, we gradually develop an IoT-based architecture to better coordinate dynamic events in logistics networks. First, we develop a baseline EA that represents how logistics operators embrace IoT techniques nowadays. The baseline EA in Section 4.1 is founded on three major sources:

1. a systematic literature review of state-of-the-art IoT developments in today's supply chain and logistics research [26];
2. the business logic modeled by [12] and [16], and;
3. multiple informal interviews with Dutch logistics stakeholders regarding the IT support for their decision making; The results from these interviews coincide with those reported in [27, 28].

Second, we will design our target EA by referring to the "*motivation strategy view*" given earlier in Figure 1. We explicitly motivate how our reference architecture meets the system requirements in Section 3 by *highlighting* the corresponding Industry 4.0 design principles in italic. Finally, we will conduct a gap analysis by evaluating the discrepancies in between the baseline and target EAs in Section 4.3, and demonstrate the need for our system design by referring to the Dynamic Vehicle Routing Problem (DVRP) in Section 4.4.

### 4.1 Baseline architecture

Logistics operators commonly empower their fleet with flexible track-and-trace devices for some decades already to monitor the dynamic behaviour of their logistics networks [8, 9, 23]. Therefore, modern-day fleets are characterized by a sophisticated IT infrastructure that continuously gathers enormous amounts of real-time data regarding the system's state, while wireless communication technologies rapidly transmit those heterogeneous data streams towards a central fleet operator [2, 7, 29]. Human fleet operators can monitor, control, and plan their logistics activities by using the fleet management system's graphical user interface [30], a central application that is fed with data from the vehicles' onboard systems, the organization's legacy systems, and other external applications (e.g., traffic, weather, and news institutions). Cloud computing has become the standard for data processing, mainly due to the internet-based computing platform where configurable resources can be shared and accessed on demand [23].

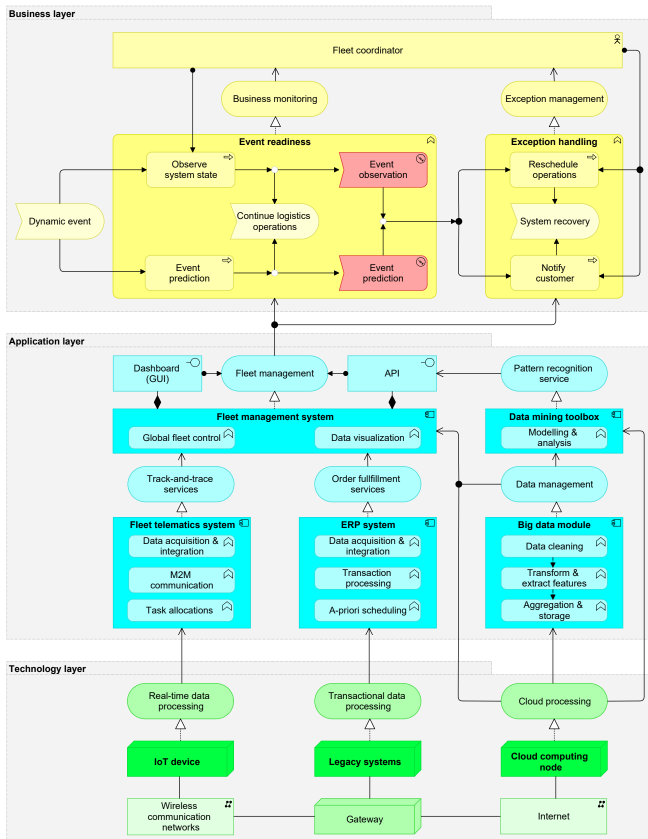


**Fig. 2.** Baseline EA - layered view

The predictive power of pattern searching algorithms (e.g., big data analytics, data mining, machine learning, etc.) enables logistics operators to adopt a proactive approach in response to potential disturbances in advance as well [18]. We have summarized the baseline EA in Figure 2, which indicates that two out of six Industry 4.0 design principles (*real-time capability*, and *interoparability*) are commonly implemented already, mainly to incorporate event readiness into today's logistics networks.

### 4.2 Target architecture

As stated earlier in Section 3, our vision is to design a resilient system where logistics objects should perform their tasks autonomously under "standard" operational conditions, while decisions are delegated to a central planning authority in case of a severe incident, interference, or conflicting goal is observed [22]. Both

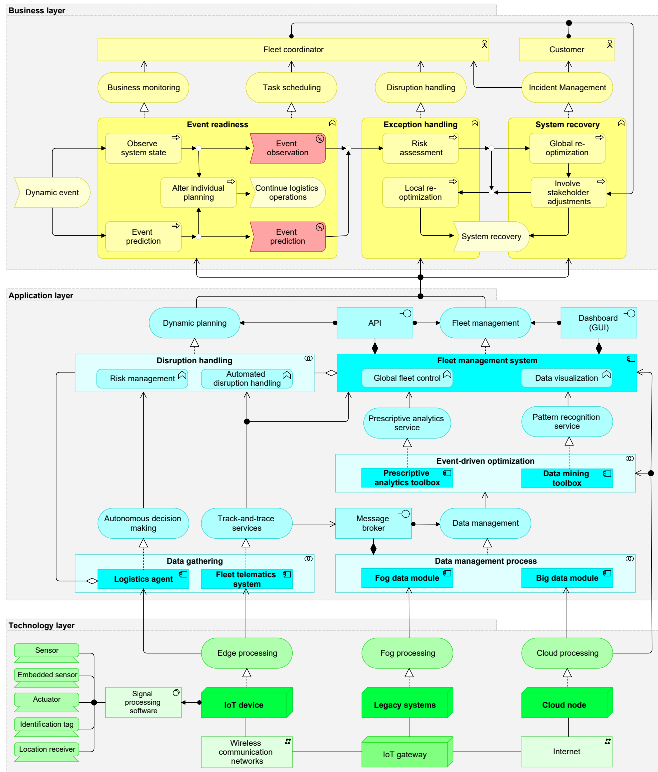


**Fig. 3.** Target EA - layered view

the *remote sensing capabilities*, and the *interoperability* offered by IoT devices, enables self-operating agents to anticipate on dynamic events in a *decentralized* way. However, more severe incidents require heavier support in terms of data management and computational resources. Therefore, we use self-organizing agents to ensure a *modular*, and *service-oriented* design of the logistics network, while the collaboration with a central fleet management system mitigates the trade-off between decision quality and response time (as visualized in our target EA in Figure 3). The disruption handling collaboration will automatically *virtualize* the logistics network, and initiate a risk assessment once a dynamic event emerges. The risk management module will decide which logistics activities need to be rescheduled to maintain reliable outcomes, without the intervention of any human operator. Only highly severe incidents require additional input from the fleet coordinator and/or customer, since the stakeholders' preferences may change due to the incident's impact.

The success of our dynamic disruption handling collaboration in Figure 3 strongly depends on the availability of accurate data sources and fast computational resources. Therefore, we advocate to diversify the logistics objects with a variety of sensors and/or actuator systems (e.g., embedded sensors, location receivers, identification tags, etc.). We also propose a cloud-based architecture for an efficient and process-oriented utilization of the computational resources [31], while fog computing resources are installed nearby the IoT devices in a distributed way to provide "quick-and-dirty" computing responses on sites [24]. The cooperation among edge-, fog-, and cloud computational resources supports both the prescriptive analytics and data mining toolboxes in terms of data (pre-) processing, networking, and storage activities. The prescriptive analytics toolbox will re-optimize the network's configurations by virtualizing the stakeholders' objectives, environmental conditions, and system constraints. We also need a data mining toolbox consisting of various pattern searching algorithms (e.g., classification, association, clustering, rule induction, etc.). The predictive power of classification and regression techniques can be used to predict the system's state at a future state, while decisions are better customized when continuous learning gives us a more accurate description of the problem context (e.g., input parameters, objective functions, constraints, and recovery policies).

### 4.3 Gap analysis

The baseline EA in Figure 2 shows that most logistics operators use their IoT architecture to monitor their fleet, while a cloud-based configuration is implemented to efficiently process incoming data streams. However, all those technological innovations are mainly hardware-driven, while the development of more intelligent software is relatively neglected [2]. Most logistics organizations lack the capacity to mine through the increasing data volumes and transform the observed patterns into valuable knowledge [18], which obstructs fleet operators to efficiently respond towards dynamic events. As a result, data-driven re-optimization is scarcely done in the logistics domain [12]. The central role of the fleet management system enforces fleet coordinators to manually reschedule logistics once disturbances emerge. This means that large volumes of IoT data are still being processed and acted upon by human operators with little decision support [2], a time-consuming operation which reduces the system's responsiveness towards dynamic events. Therefore, techniques for data acquisition, pattern recognition and mathematical optimization have to be merged into the application layer to adequately anticipate on dynamic events as soon as they emerge.

The main aim of our target EA in Figure 3 is to automate the dynamic planning activities in case a disruption is either observed or predicted. Logistics objects have to quickly reschedule their tasks to become more responsive towards dynamic events, but a (near) optimal reconfiguration of the logistics network requires both data and computational time. Consequently, the dynamic reallocation of resources depends on the disruption's severity, area of impact, and the available planning horizon. We propose an hierarchical disruption handling architecture to compromise the trade-off among the decision's quality and response time, consisting of five main applications (as visualized in Figure 4):

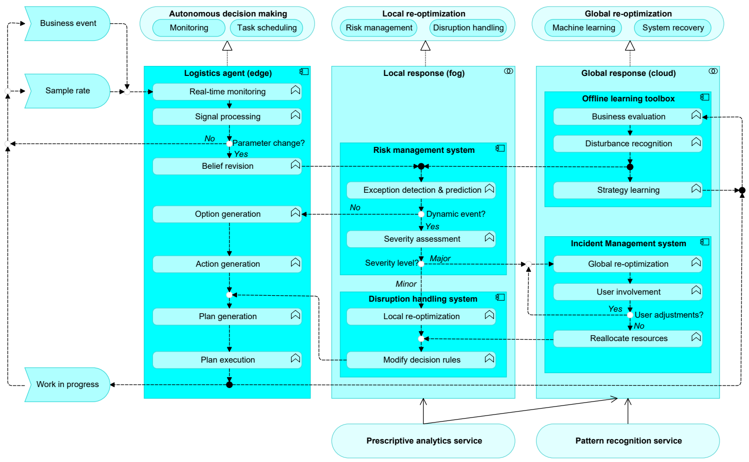


**Fig. 4.** Application behaviour view - a hierarchical disruption handling architecture

1. **Logistics agent:** the logistics agent represents the virtual twin of the logistics object on which the corresponding IoT device is installed. The agent's main responsibility is to monitor the object's status and environmental conditions in real-time, while the perceived knowledge can be shared with nearby agents to speed up data acquisition. Logistics agents autonomously act on the gathered data by a fixed set of decision rules stored on the IoT devices' local memory (=edge computing). The agents' behaviour is designed according to the individual Belief-Desire-Intention (BDI) architecture proposed by [32].
2. **Risk management system:** logistics agents can quickly anticipate on minor changes in their surroundings already, but an effective response towards severe disruptions require both more data and computational power in higher-level processing nodes (=fog computing). First, the risk management system aggregates the real-time data gathered by a cluster of IoT devices to detect any harmful exceptions in the network's conditions. Second, the risk management system assigns a severity level to the dynamic events observed, which is used to allocate the recovery tasks more effectively.
3. **Disruption handling system:** less severe incidents (e.g., little impact, minor impact radius, and/or quick resolution) are easily solved by relying on "quick-and-dirty" solution mechanisms. Therefore, the disruption handling system is equipped with optimization heuristics that require limited data and computational time. The disruption handling will anticipate on the network's configurations assessed by the risk management system, and re-optimize the network locally by updating the decisions' rules of all IoT devices affected.
4. **Incident management system:** serious and prolonged events require a more radical re-optimization approach. Therefore, we accept a longer response time to centralize all the network's real-time data gathered (=cloud

computing). The incident management system has access to simulation and optimization techniques to automatically reconfigure resource allocations, while data mining tools can either transform dynamic events into parameters for improved decision making, or reduce the available solution space. There is also a high probability that customer preferences are not met in case the incident causes delays (e.g., delivering in the desired time windows, or delivering the right quantity). Therefore, the incident management system keeps customers up-to-date of the network's conditions, and receives new customer input if preferences change over time.

5. **Offline learning toolbox:** the logistics agents, disruption handling system, and incident management system are developed to immediately anticipate on the disturbances observed. However, an additional toolbox evaluates all online responses and performances afterwards. The risk management system can better recognize severe incidents by extracting features from historical events with a variety of data mining techniques, while offline simulations enable the system to prescribe a suitable recovery strategy in advance already.

### 4.4 Demonstration

We will demonstrate the need for our target EA (Figure 3) and the corresponding disruption handling systems (Figure 4) using the Dynamic Vehicle Routing Problem (DVRP). In the VRP, vehicles are assigned to a sequence of geographically scattered customer locations with the aim to minimize overall routing costs, subject to a set of constraints [4]. In the DVRP, not all information is known in advance, but will be revealed during logistics execution [5]. This implies that all stochastic elements gradually change into static parameters due to the vehicles' remote monitoring capabilities (see technology layer in Figure 3).We would expect that logistics operators incorporate the fleet's tracking data into their route planning, since there is plenty of evidence supporting the need to reschedule the DVRP when the uncertainty in the network's conditions increases (e.g., [29,33]). However, data-driven re-optimization is often not the case [26–28]. Consequently, the question is not how to detect disturbances, nor to find a suitable recovery strategy, but how to automate rescheduling of the DVRP by assessing the fleet's real-time data. For example, attended home delivery services, such as online grocers and parcel deliveries, can become more flexible if a vehicle autonomously monitors its surroundings, and alters its route to avoid problems beforehand. The deliveries' reliability is likely to be enhanced as well when centralized algorithms search for disruptions that negatively influence customer SLAs, and immediately reallocate the fleet without human delays (e.g., vehicles may interchange orders, dispatch additional vehicles, complete overhaul, etc.).

## 5 Discussion

The reference architecture in Figure 3 is designed to obtain more reliable and flexible logistics operations by anticipating on the dynamic events observed in the IoT's perception layer. The hierarchical disruption handling architecture in Figure 4 autonomously initiates the dynamic planning activities once a severe disturbance emerges, while our edge-, fog- and cloud-based architecture design compromises the trade-off in between response time and decision quality [5]. Therefore, the central role of fleet management systems and human decision making, as depicted in Figure 2, is replaced by a fully automated collaboration of decentralized logistics agents, "quick-and-dirty" solution heuristics, and data-intensive re-optimization algorithms. However, our initial design is still open for discussion, since other technical approaches may fulfill the stakeholder requirements even better. For example, microprocessors are becoming more powerful, which makes it possible to empower edge devices with deep neural networks [34]. We can also modify the BDI architecture proposed by [32] to alter how logistics agent interact with each other, maybe process mining could be helpful to implement a more context-aware set of agent decision rules [35]. Our claim to speed up dynamic planning with fog computing resources, as inspired by [24], becomes doubtful if we take into account that most logistics operations require minutes, hours, or even days, but not seconds. The decisions when to reschedule, how to classify dynamic events, and how much time to reserve for computations are also far from trivial and require further investigation [1]. The wide variety of design alternatives indicates that validation of our reference architecture should be prioritized before proceeding further. We especially pursue the implementation of real-life demonstrations to evaluate if our reference architecture enhances the reliability and flexibility of logistics networks. Real-life demonstrations also provide the opportunity to reflect on non-technical implementation issues as well (e.g., city regulations, customer habits, and sustainability).

## 6 Conclusion & further research

In this paper, we proposed an IoT-based reference architecture to face the increasing variability of today's digitized logistics networks. Our design improves the system's responsiveness towards dynamic events by replacing the fleet operator's manual rescheduling tasks with a fully automated disruption handling system. The Industry 4.0 design principles inspired us to develop a hierarchical disruption handling architecture that compromises the trade-off among decision quality and response time. Minor events are resolved by logistics agents, while more severe disruptions are processed in higher-level processing nodes (e.g., fog and/or cloud computing). Future research is required to investigate when to initiate the risk assessment module, how to classify dynamic events, and how much time to reserve for dynamic planning. Real-life demonstrations are required to validate the system's benefits as well.

## References

1. M. G. Speranza, "Trends in transportation and logistics," *European Journal of Operational Research*, vol. 264, no. 3, pp. 830–836, 2018.

2. T. G. Crainic, M. Gendreau, and J.-Y. Potvin, “Intelligent freight-transportation systems: Assessment and the contribution of operations research,” *Transportation Research Part C: Emerging Technologies*, vol. 17, no. 6, pp. 541–557, 2009.
3. P. Dallasega, M. Woschank, H. Zsifkovits, K. Tippayawong, and C. A. Brown, “Requirement analysis for the design of smart logistics in smes,” *Industry 4.0 for SMEs*, p. 147, 2020.
4. V. Pillac, M. Gendreau, C. Guéret, and A. L. Medaglia, “A review of dynamic vehicle routing problems,” *European Journal of Operational Research*, vol. 225, no. 1, pp. 1–11, 2013.
5. U. Ritzinger, J. Puchinger, and R. F. Hartl, “A survey on dynamic and stochastic vehicle routing problems,” *International Journal of Production Research*, vol. 54, no. 1, pp. 215–231, 2016.
6. S. Y. Ponomarov and M. C. Holcomb, “Understanding the concept of supply chain resilience,” *The international journal of logistics management*, 2009.
7. H. Billhardt, A. Fernández, L. Lemus, M. Lujak, N. Osman, S. Ossowski, and C. Sierra, “Dynamic coordination in fleet management systems: Toward smart cyber fleets,” *IEEE Intelligent Systems*, vol. 29, no. 3, pp. 70–76, 2014.
8. L. Atzori, A. Iera, and G. Morabito, “The internet of things: A survey,” *Computer networks*, vol. 54, no. 15, pp. 2787–2805, 2010.
9. L. Xu, W. He, and S. Li, “Internet of things in industries: A survey,” *IEEE Transactions on industrial informatics*, vol. 10, no. 4, pp. 2233–2243, 2014.
10. S. Li, L. Da Xu, and S. Zhao, “The internet of things: a survey,” *Information Systems Frontiers*, vol. 17, no. 2, pp. 243–259, 2015.
11. Y. Issaoui, A. Khiat, A. Bahnasse, and H. Ouajji, “Toward smart logistics: Engineering insights and emerging trends,” *Archives of Computational Methods in Engineering*, pp. 1–28, 2020.
12. P. Singh, M. van Sinderen, and R. Wieringa, “Smart logistics: an enterprise architecture perspective,” in *CEUR Workshop Proceedings*, 2017, pp. 9–16.
13. Y. Ding, M. Jin, S. Li, and D. Feng, “Smart logistics based on the internet of things technology: an overview,” *International Journal of Logistics Research and Applications*, pp. 1–23, 2020.
14. S. Winkelhaus and E. H. Grosse, “Logistics 4.0: a systematic review towards a new logistics system,” *International Journal of Production Research*, vol. 58, no. 1, pp. 18–43, 2020.
15. D. J. Bijwaard, W. A. Van Kleunen, P. J. Havinga, L. Kleiboer, and M. J. Bijl, “Industry: Using dynamic wsns in smart logistics for fruits and pharmacy,” in *Proceedings of the 9th ACM Conference on Embedded Networked Sensor Systems*, 2011, pp. 218–231.
16. M.-E. Iacob, G. Charismadiptya, M. van Sinderen, and J. P. S. Piest, “An architecture for situation-aware smart logistics,” in *2019 IEEE 23rd International Enterprise Distributed Object Computing Workshop (EDOCW)*. IEEE, 2019, pp. 108–117.
17. K. Peffers, T. Tuunanen, M. A. Rothenberger, and S. Chatterjee, “A design science research methodology for information systems research,” *Journal of management information systems*, vol. 24, no. 3, pp. 45–77, 2007.
18. S. Tiwari, H.-M. Wee, and Y. Daryanto, “Big data analytics in supply chain management between 2010 and 2016: Insights to industries,” *Computers & Industrial Engineering*, vol. 115, pp. 319–330, 2018.
19. S. Mittal, M. A. Khan, D. Romero, and T. Wuest, “Smart manufacturing: characteristics, technologies and enabling factors,” *Proceedings of the Institution of Me-*

*chanical Engineers, Part B: Journal of Engineering Manufacture*, vol. 233, no. 5, pp. 1342–1361, 2019.
20. A. Al-Fuqaha, M. Guizani, M. Mohammadi, M. Aledhari, and M. Ayyash, "Internet of things: A survey on enabling technologies, protocols, and applications," *IEEE communications surveys & tutorials*, vol. 17, no. 4, pp. 2347–2376, 2015.
21. M. Lankhorst *et al.*, *Enterprise architecture at work*. Springer, 2009, vol. 352.
22. M. Hermann, T. Pentek, and B. Otto, "Design principles for industrie 4.0 scenarios," in *2016 49th Hawaii international conference on system sciences (HICSS)*. IEEE, 2016, pp. 3928–3937.
23. M. Ben-Daya, E. Hassini, and Z. Bahroun, "Internet of things and supply chain management: a literature review," *International Journal of Production Research*, vol. 57, no. 15-16, pp. 4719–4742, 2019.
24. C.-C. Lin and J.-W. Yang, "Cost-efficient deployment of fog computing systems at logistics centers in industry 4.0," *IEEE Transactions on Industrial Informatics*, vol. 14, no. 10, pp. 4603–4611, 2018.
25. A. Dobrkovic, L. Liu, M.-E. Iacob, and J. van Hillegersberg, "Intelligence amplification framework for enhancing scheduling processes," in *Ibero-American Conference on Artificial Intelligence*. Springer, 2016, pp. 89–100.
26. M. Koot, M. Mes, and M.-E. Iacob, "A systematic literature review of supply chain decision making supported by the internet of things and big data analytics," *Computers & Industrial Engineering*, p. 107076, 2020.
27. P. Vermeulen, "Internet of things survey: Nederland 2016," https://www.logistiekprofs.nl/uploads/content/logistiekprofs/file/Onderzoek-Hoe-ver-is-Nederland-met-IoT-2016.pdf, Pb7 Research, Tech. Rep., 2016.
28. TLN, evofenedex, and Beurtvaartadres, "Nationaal onderzoek data en digitalisering in de logistiek," https://www.tln.nl/app/uploads/2019/11/Rapport-data-en-digitalisering.pdf, TLN, Tech. Rep., 2019.
29. V. Zeimpekis, I. Minis, K. Mamassis, and G. Giaglis, "Dynamic management of a delayed delivery vehicle in a city logistics environment," in *Dynamic Fleet Management*. Springer, 2007, pp. 197–217.
30. A. Goel, *Fleet Telematics: Real-time management and planning of commercial vehicle operations*. Springer Science & Business Media, 2007, vol. 40.
31. A. Jede and F. Teuteberg, "Towards cloud-based supply chain processes," *The International Journal of Logistics Management*, 2016.
32. N. Jabeur, T. Al-Belushi, M. Mbarki, and H. Gharrad, "Toward leveraging smart logistics collaboration with a multi-agent system based solution," *Procedia Computer Science*, vol. 109, pp. 672–679, 2017.
33. A. Haghani and S. Jung, "A dynamic vehicle routing problem with time-dependent travel times," *Computers & operations research*, vol. 32, no. 11, pp. 2959–2986, 2005.
34. H. Li, K. Ota, and M. Dong, "Learning iot in edge: Deep learning for the internet of things with edge computing," *IEEE network*, vol. 32, no. 1, pp. 96–101, 2018.
35. R. H. Bemthuis, M. Koot, M. R. Mes, F. A. Bukhsh, M.-E. Iacob, and N. Meratnia, "An agent-based process mining architecture for emergent behavior analysis," in *2019 IEEE 23rd International Enterprise Distributed Object Computing Workshop (EDOCW)*. IEEE, 2019, pp. 54–64.