From Conventional to IoT-Enhanced: Simulated Object-Centric Event Logs for Real-Life Logistics Processes

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Abstract

With the growth of Internet-of-Things (IoT) applications, integrating IoT data into business processes has received increasing attention. IoT data, typically low-level, is unsuitable to be directly integrated with event logs that capture high-level process information. Compared to XES event log representation, Object-Centric Event Log (OCEL) 2.0 is better suited for integration as it captures intricate object-event relationships in processes. We present two OCEL 2.0 logs simulating the cargo pickup process at a Chinese port: one for the traditional process and the other incorporating IoT technology. These logs advance event log representations and research on integrating IoT data into business processes.

Keywords

Object-Centric Event Log, Simulated Event Log, Logistics Process, Internet of Things

1. Introduction

As the number of IoT applications increases, more research focuses on integrating IoT data into business processes. De Luzi et al. [1] conduct a systematic literature review of existing approaches to IoT-aware business process management (BPM). Janiesch et al. [2] highlight the benefits and 16 challenges of integrating IoT and BPM. Our work aims to address one of these challenges—"bridging the gap between sensor data and event logs for process mining". Since IoT data is usually low-level, and event logs contain relatively high-level process execution information, it is often not suitable to integrate IoT data directly into event logs.

In process mining, there are two types of event log representations: XES [3] and OCEL [4]. XES logs are formatted as tables, each row representing an event related to a single object (*a.k.a.* case) and each column specifying an event attribute. OCEL, on the other hand, is represented as a relational database that captures the objects involved in a process and their interactions with events. The recently proposed Object-Centric Event Data (OCED) meta-model [5] further extends OCEL by introducing dynamic object attributes and relationships between objects.

Some existing IoT-enriched event logs [6, 7] integrate low-level IoT data into processes following the XES standard. However, the XES format is limited to a single-object perspective, making it unsuitable for capturing processes that involve multiple interacting objects, such as business entities and IoT devices. Mangler et al. [8] propose an IoT-enriched event log converted from XES to OCEL 1.0. However, this log fails to capture the relationships between business objects and their interactions with events. Moreover, it is unclear how the interactions between IoT devices and business processes are represented in such an event log.

In our work, we incorporate process-related information captured by IoT devices into event logs. We adopt the OCEL 2.0 schema which is better suited for the integration as it captures object interrelation-

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ships and their interactions with process events. Existing IoT-enriched event logs [6, 7, 8] record IoT data into event logs following the XES standard or OCEL 1.0. Unlike their work, our work generates event logs that not only conform to the OCEL 2.0 schema but also introduce extensions to integrate IoT data into event logs.

In this paper, we present two OCEL 2.0 logs, both generated through simulations using CPN, that aim to capture the cargo pickup process in one of the major ports in China. The two logs and the CPN models used to generate them are available at https://github.com/JennyJiaW/OCELs_CargoPickup. The first log aims to represent the conventional cargo pickup process, encompassing multiple object types such as cargo, pickup plans, trucks, and silos. It also aims to capture the static and dynamic relationships between objects as well as their interactions with process events. The second log builds upon the first with the aim to integrate IoT data to capture relationships between IoT objects and business objects, as well as between IoT device entities and process events.

By simulating a real-life process, the two OCEL logs produced from this work serve as valuable public data resources for the BPM research community. These logs can provide the community with insights to enhance OCEL log representations, and contribute to future research on integrating IoT data with process event logs.

2. Description of Resources

We present the two aforementioned OCEL logs for the conventional cargo pickup process at a Chinese port and its IoT-enhanced process, respectively. Table 1 lists the object types and their corresponding attributes in both logs. Table 2 lists IoT device types used in the cargo pickup process.

Table 1
Object types and corresponding attributes involved in the cargo pickup process

Object Type	Attribute Name
Pickup Plan	PickupPlanID, CargoID, Num of trucks, Total Pickup Weight
Truck	TruckID, LPT(LicensePlateNo), Axles, PickupPlanID, CargoID, Scheduled Pickup Weight, Truck Status, ***Truck Weight****, ***RFID No*****, ***Is_normal*****
Cargo	CargoID, Cargo Type, Cargo Stock Weight (scheduled), SiloID
Silo	SiloID, Silo Status, ***Temperature*****, ***Humidity*****, ***Silo Temperature*****, ***Grain Temperature*****

* Attribute value can be captured manually or by IoT devices.
** Attribute value is captured only by IoT devices.

Table 2
IoT device types and corresponding attributes involved in the IoT-enhanced cargo pickup process

IoT Device Type	Attribute Name
Weight Sensor	IoTDeviceID, Location, Type
Temperature Sensor	IoTDeviceID, timestamp, Location, Value, (Measurement)Unit
Humidity Sensor	
IndoorTemperature Sensor	
GrainTemperature Sensor	

2.1. The conventional cargo pickup process

Figure 1 depicts an overview of the conventional cargo pickup process. The process begins when the customer lodges a pickup plan to arrange trucks for cargo pickup. On the scheduled date, each truck arrives at the port and is weighed to record its empty weight. The truck proceeds to the designated silo to load the cargo. After loading, the truck is weighed again to record its loaded weight. The port then issues a weighing ticket and a tally sheet, and the truck departs.

In this simulated OCEL log, we include four types of relational tables:

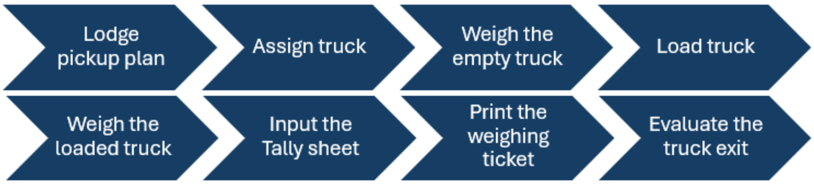

Figure 1: A value chain modelling an overview of the conventional cargo pickup process

- **Event** tables: Capture the temporal order of events and record event information, including ***Event_id***, ***Activity***, ***Timestamp***, and event attributes (if any).
- **Object** tables: Document static and dynamic attributes of each object, including ***Object_id***, ***Timestamp***, ***Ocel_changed_field*** (indicating which attribute, if any, changed), and attributes. The pickup plan object table is an exception, omitting the ***Ocel_changed_field*** since all attribute values are generated at the start of the process.
- **Event-to-Object relation** (E2O) table: Records relationships between objects and events during process execution, including ***Event_id***, ***Object_id***, and an ***E20_qualifier*** specifying the semantics of each E2O relationship.
- **Object-to-Object relation** (O2O) table: Records relationships between objects, including ***Source_object_id***, ***Target_object_id***, an ***O2O_qualifier*** specifying the semantics of each O2O relationship, and a ***Timestamp***, as these relationships may change during process execution.

2.2. The IoT-enhanced cargo pickup process

As shown in Figure 2, the cargo pickup process in this real-world scenario has evolved with the adoption of IoT technologies. Activities in italics relate to the IoT devices listed in Table 2. These activities could be new process activities arising from the use of IoT devices or existing process activities enhanced by incorporating IoT devices. For example, the "weigh the empty truck" and "weigh the loaded truck" activities utilise real-time data from weight sensors. In addition, two new activities, "Check empty truck weight abnormality" and "Determine the continuance of the pickup", have been introduced due to IoT integration.

When a truck enters the weighbridge, an RFID tag on its windshield is read, recording past empty truck weights and manufactured weight. By comparing the current empty weight with the historical average, weight anomalies can be detected in real-time, preventing fraudulent deliveries at ports. Furthermore, because of the inclusion of real-time data from temperature and humidity sensors in silos, an activity is introduced to determine if the current pickup meets the continuation criteria. For instance, if a truck is picking up rice, silo staff will verify if the rice meets discharge criteria by ensuring the grain's temperature is higher than the dew-point temperature, which is calculated from atmospheric temperature and humidity.

As a result, in addition to the four types of tables in the previous log, this simulated OCEL log contains two new relational tables:

- **IoTDevice-to-Object relation** (IoT2O) table: Records the relationship between IoT devices and business objects, and consists of columns: ***IoT_object_id***, ***Object_id***, an ***IoT2O_qualifier*** specifying the semantics of each IoT2O relationship and a ***Timestamp***, as IoT2O relationships may change during execution of the process.
- **IoTDevice-to-Event relation** (IoT2E) table: Records the relationship between IoT devices and events in the process and is comprised of columns: ***Event_id***, ***IoT_object_id*** and ***IoT2E_qualifier*** to specify the meaning of their relationship.

Moreover, in the IoT-enhanced cargo pickup process, there are two types of interactions between IoT devices and business processes: push and pull interactions [9].

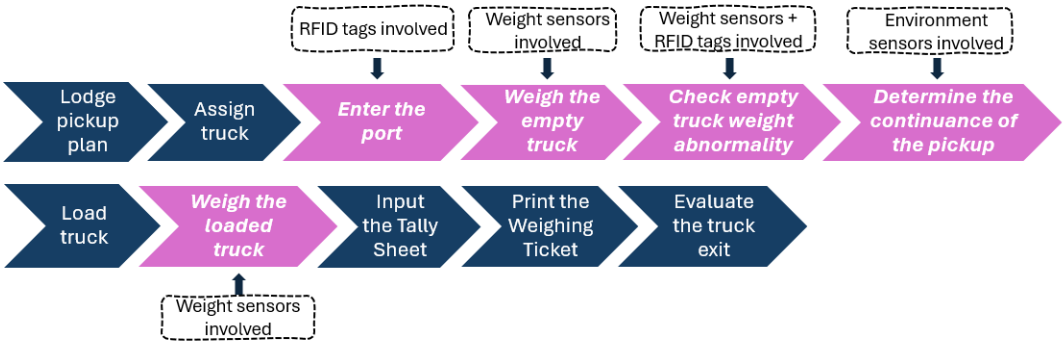

Figure 2: A value chain, annotated with involvement of IoT devices, modelling an overview of the IoT-enhanced cargo pickup process

- **Push Interaction**: IoT devices automatically send data to the business process. For instance, when a truck arrives at the platform of the weighbridge, a weight sensor makes the real-time weight of the truck available to the process.
- **Pull Interaction**: Data collected by IoT devices are requested on demand. That is, interactions are triggered by the business processes. For instance, environmental sensors continuously measure the temperature or humidity of the environment; only when the activity "Determine the continuance of the pickup" is executed are the aggregated temperature and humidity data made available to the process.

3. Preliminary Analysis

3.1. Generation of Simulated Event Logs using CPN

A simulation approach to generate the two event logs was used as though the cargo pickup process originates from a real-world scenario, obtaining real data directly from the port system is challenging. For each business process, two CPN models were created using CPN Tools[1], one concerned with object initialisation and definition of static and dynamic attributes (referred to as CPN^{i} and CPN^{i}_{IoT} resp.) and one modelling the business process (referred to as CPN^{bp} and CPN^{bp}_{IoT} resp.). These four CPN models were then used to generate the two simulated event logs correspondingly.

The simulated values for all static and dynamic attributes follow a normal distribution with parameters informed by domain knowledge. Dynamic attributes were initially set to 0.0 or null, depending on their data type. In addition, the time frame and frequency of truck arrivals at the port are designed according to domain knowledge, with truck arrival following an exponential distribution. The "process" CPN models (CPN^{bp} and CPN^{bp}_{IoT}) capture dynamic attribute changes and when these occur. For CPN^{bp}_{IoT}, the IoT device types and their attributes (see Table 2) serve as inputs for certain process activities (see Figure 2), simulating the interactions between the business processes and the IoT devices.

The two logs, the CPN models used to generate them, and the documentation on how to generate these simulated logs are available at https://github.com/JennyJiaW/OCELs_CargoPickup.

3.2. Basic Statistical Analysis

In this subsection, we compare some basic statistics of the two simulated OCEL logs as shown in Table 3. These statistics were obtained from tables generated from the CPN simulation, stored in an SQLite database, and analysed using the pm4py package[2].

Cargo theft may be enabled by modified trucks. In the conventional process, truck weights are recorded manually, while IoT technology (weight sensor and RFID tag for each truck) allows their

[1] https://cpntools.org/
[2] https://pm4py.fit.fraunhofer.de/

Table 3
Some basis statistics of the simulated OCEL Logs for the conventional cargo pickup process and its IoT-enhanced version

Description	IoT-enhanced	Conventional	Event occurrences	IoT-enhanced	Conventional
Number of events	3611	3447	Lodge Pickup Plan	10	10
Number of objects	80	70	Assign Truck	491	491
Number of activities	13	8	Enter the port	491	N/A
Number of object types	4	3	Weigh the Empty Truck	491	491
E2O relations	3621	3457	Check the Empty Truck Weight Abnormality	491	N/A
O2O relations	883	992	***Fail to Weigh***	***300***	N/A
IoT2E relations	2619	N/A	Arrive at the Silo	191	N/A
IoT2O relations	1637	N/A	Determine the Continuance of the Pickup	191	N/A
Objects occurrences (number of objects)			Load Truck	191	491
Truck	50	50	***Weigh the Loaded Truck***	***191***	491
Cargo	10	10	Evaluate the Truck Exit	191	491
Pickup Plan	10	10	Input the Tally Sheet	191	491
Silo	10	N/A	Print the Weighing Ticket	191	491

automatic capture and comparison with their historical weights to detect whether there is a significant deviation from the past. If so, the weighbridge alerts the port and the truck is prevented from picking up the cargo. Table 3 shows that “Fail to Weigh” and “Weigh the Loaded Truck” occurred 300 resp. 191 times, hence around 39% of pickups were successfully completed.

4. Conclusion

We present two OCEL logs generated to simulate the cargo pickup process in a Chinese port as an example of real-life logistics processes. Unlike existing process event logs incorporating IoT data, we focus on generating logs that conform to the OCEL 2.0 schema as well as integrating process-related information captured by the IoT data. The two OCEL logs produced from this work serve as valuable public data resources for the BPM research community. In future work, we plan to extend these IoT-enriched event logs by incorporating additional IoT data and analysing the resulting logs to understand how IoT data impacts process performance. We aim to use the insights from this study to inspire the community to advance event log representation for real-life processes and to further research on the integration of IoT data with process event logs.

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