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MOBILITY DATA WAREHOUSE FOR TRANSPORTATION OF OIL PALM FRESH FRUIT BUNCHES

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Abstract. *The palm oil industry contributes significantly to Indonesia's social economy because it provides USD 21 billion income and involves nearly 20 million people working on it. One crucial factor related to fruit quality is the oil palm Fresh Fruit Bunches (FFB) to Palm Oil Mill (POM) transportation system. By now, the FFB transportation system still has a high cost at around 15%-20% of the FFB price, which should be reduced to only 8%-10%. Transportation problems in the palm oil industry are the ineffectiveness of the loading process at Fruit Collection Point (FCP), the long queue time of trucks to be processed at the POM, and low road quality. Existing mobility monitoring and managing the shipping of FFB to the POM systems have significantly reduced transportation costs. However, these systems only manage the transactional process of FFB transportation. Due to the limitation, it is hard for managers to rely on transactional data in making decisions. This paper presents a mobility data warehouse using a new data model and representation of measure with spatiotemporal data type for transportation, FFB loading/unloading, and plantation productivity analysis. The implementation results reveal the descriptive, diagnostic, and predictive analysis effectiveness to reduce cost and maximize FFB quality.*

Keywords: Mobility data warehouse, Transportation, Transportation analysis, Oil palm, Fresh fruit bunches

1. **Introduction.** The palm oil commodity is one of the significant economic contributors for Indonesia. Crude Palm Oil (CPO) could produce cooking oil, margarine, salad oil, creamer, lipstick, soap, and biofuel. This commodity's best product could be achieved from the raw materials' maximum quality called the palm Fresh Fruit Bunch (FFB). The ultimate quality of oil palm FFB is the fruit that has the proper maturity and minimum Free Fatty Acid (FFA) content level. FFA content could be minimized by avoiding fruit bruises in cutting or transporting to the Palm Oil Mill (POM). Bruises of the oil fruit will increase the FFA rate. The average FFA levels in oil fruit before harvested are around 0.2%-0.7% when falling to the ground, which will increase by 0.1% every 24 hours. Due to bruising, soft cell walls will immediately lead to enzymatic processes, autocatalysis, or

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hydrolysis, which will increase FFA significantly. The higher FFA brings the lower palm oil quality [1].

The transportation process contributed quite a lot of damage or bruising to FFB. It was increasing the FFA rate when it arrived at the loading ramp for processing. The process of transporting FFB using wood trucks or dump trucks also potentially causes bruises and degrading FFA levels because of two factors: a) the throwing process of FFB into the tub and b) vehicle vibration shaking the FFB during the trip. Krisdiarto and Wisnubhadra have developed the *logtransawit* software to prevent the increasing FFA level in FFB, which is used to minimize queuing time using location-based mobile technology, SMS gateway, and web-based applications [2] (*Logtransawit* available at http://logtransawit.online). However, more complex and intuitive analysis is needed to analyze some issues related to transportation analysis, loading/unloading analysis, and production analysis, which could be carried out using mobility data as a data source captured using the *logtransawit* application. Mobility DW is the answer to the complex analysis of FFB transportation for describing, diagnosing, and predicting information.

This paper contributes to i) a new representation for measures and dimensions that define Moving Object (MO) data as measures in DW, ii) an evaluation of query execution performance, and iii) the design of queries on descriptive, diagnostic, and predictive analytics on FFB transportation. This study implements the mobility DW for oil palm FFB transportation analysis. This approach gives plantation managers a useful tool for supporting decision making with impressive performance. The usage of MOs as measures and dimensions makes data modeling more natural and straightforward. This paper is the first implementation of mobility DW in the palm oil industry to the best of our knowledge.

The remainder of this paper is structured as follows. Section 2 describes related works. Section 3 describes the methodology of this research. Section 4 describes the discussions and results, while Section 5 concludes the paper and future work challenges.

2. Related Works.

2.1. Fresh Fruit Bunch (FFB) logistic system. The palm oil production process is a supply chain system. The process starts from the palm plantation block, the FFB mills in the Palm Oil Mill (POM), the palm oil stores in the storage tank, processed in the refinery, and distributed to the customer [3,4]. One of the important factors to maximize the quality of the products is the quality control in the inbound logistics system of oil palm plantations, the quality of FFB. The higher the Free Fatty Acid (FFA) content of the FFB, the lower the quality of the oil palm fruit. Since the minimal transportation time from the plantation to the mills is crucial, this indicator will be the objective function of some optimization techniques. Gao et al. proposed an approach to improve the delivery efficiency of kiwi fresh fruit with a theoretical basis for decision making. Their approach utilizes sensitivity analysis to observe fruit and the regional transportation network [5].

2.2. Mobility analytics. Mobility analytics is an approach for mobility pattern analysis to support decision making. Mobility analytics is based on Moving Objects (MOs) data that have been captured by sensors, GPS, wireless network sensors, etc. MOs are objects (e.g., moving clouds, bird migrations, cars, and pedestrians) that change continuously in time [6,7]. MOs create a massive amount of data captured by ubiquitous sensors, GPS, smartphones, and IoT technologies stored in the Moving Object Database (MOD).

MOD is a transactional database that stores the positions of MOs at any point in time. Although these databases are appropriate for querying, they do not support complex analytical queries such as "Display the total number of trucks with a load more than 10 tons passing alfa block at speed higher than 40 km per hour". Moving objects data could be collected, integrated, stored, and analyzed in many ways, such as discovering mobility patterns in related fields like traffic management, transportation, telecommunication, tourism, and smart cities called mobility data analysis [8].

To support efficient collection, integration, store, and analysis of the mobility pattern, data warehousing technologies are needed, yielding the notion of mobility Data Warehouse (DW) [7]. Mobility DW is the heart of mobility analytics as an extension of Business Intelligence (BI) that supports collecting, analyzing, and presenting information over mobility data. A mobility DW deploys BI by taking advantage of the operations associated with spatiotemporal data types to allow complex queries [7]. Mobility analytics utilizes the Online Analytical Processing (OLAP) technique, which collects operations that manipulate the data cube. The popular OLAP operations are **roll-up**, **drill-down**, **slice**, and **dice** [9].

MOs produce data in the form of coordinate sequences that vary according to time, denoted as $< x, y, t >$, usually grouped in the form of trajectories. The mobility DW uses this mobility data as a data source to be extracted, transformed, and integrated into the mobility DW, which will then be manipulated using an analytical tool for decision making. Vaisman and Zimányi represent MOs in mobility DW using temporal types. Temporal types define a collection of data types that captures the evolution over time of base types and spatial types [9]. The temporal type has subtypes like Boolean, integer, float, text, and geometric. An example of a temporal float is the temperature of the human body, and an example of temporal geometric (point) is a truck's location read by a GPS device. Temporal types as MOs can be implemented in the MO databases using MobilityDB. Figure 1 depicts the architecture of mobility DW used in this implementation.

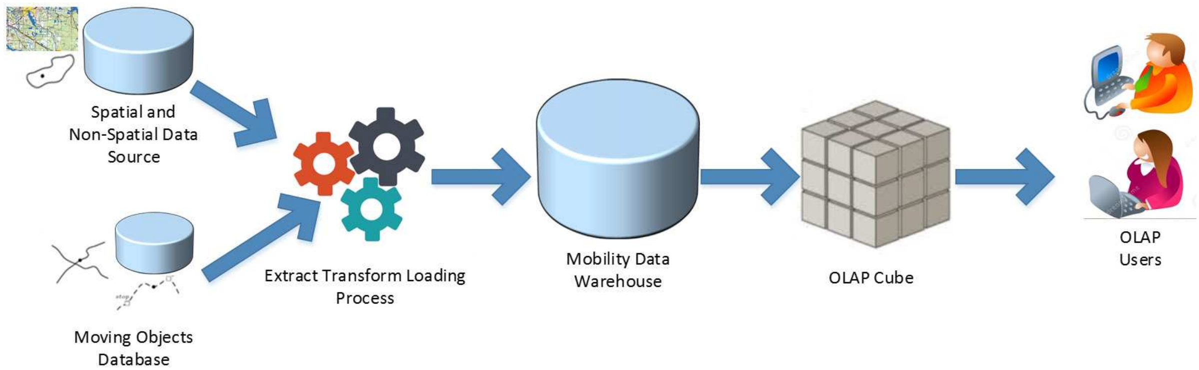


Figure 1. The architecture of mobility DW

Vaisman and Zimányi defined the notion of spatiotemporal queries with aggregation extended with spatial and moving types [10]. Based on this, they determined spatiotemporal DWs with spatiotemporal query support. Plenty of works and prototypes have been published using the trajectory data warehouses approach. This research proposed spatiotemporal DW for storing aggregate measures using base types in fact tables, spatial types, and trajectories with additional semantic information. Table 1 shows the comparison of mobility DW with the diverse subject of analysis.

3. Methodology.

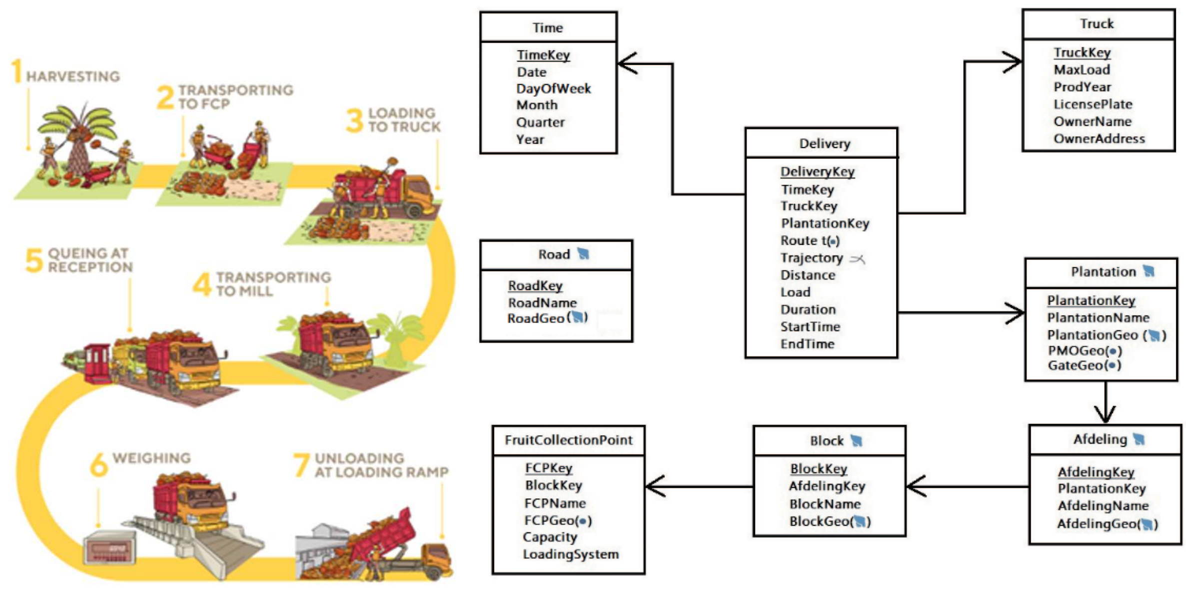
The mobility DW implementation consists of the following steps.

3.1. Business process analysis.

This implementation is deployed for the transportation of the oil palm industry in Indonesia. This palm plantation has two primary fresh fruit providers. The first provider is the factory plantation itself, and the other is the independent farmer outside the factory plantation. The factory and farmer cooperation want to minimize transportation time, cost, and loading/unloading time to increase competitiveness. Figure 2(a) depicts the FFB transportation process from harvesting until POM. Fruit harvesting is the first step of the crucial phase in the FFB transportation process.

TABLE 1. Mobility analytics comparison

Authors	Measures	Subject of analysis	Measure data types
Leonardi et al. [11]	Visits, distance, speed	Road traffic, vessel sailing	Base types
Wang et al. [12]	The best location of billboard placement	Advertisement	Base types, spatial types
Cho and Kang [13]	Visitor locations	People movement	Spatial types
Nardini et al. [14]	Sample representation of points, duration, distance	Tourist recommendation	Base types, spatial types, semantic info
Garani and Adam [15]	Duration, satisfaction	Nursing productivity	Base types, semantic info
Georgiou et al. [16]	Location	Predictive analytics of MOs	Base types, semantic info
Mello et al. [17]	Trajectory	Tourism	Base type, spatial types, semantic info
This paper	Maximum load, trajectory, speed, duration	Plantation transportation and productivity	Base types, spatial types, temporal types, spatio-temporal types



(a) (b)

FIGURE 2. (a) The business process of FFB transportation; (b) logical model of mobility DW

The fruit is then collected into the Fruit Collection Point (FCP) using technology like the net system, grabber system, or collected manually. After being collected, the Fresh Fruit Bunch (FFB) will be transported to the POM with the following steps: loading to the truck, thrilling to the POM, entering and queueing in the factory gate, weighing, and unloading into the loading ramp, and finally, the FFB will be processed in the POM. This cycle takes time and significantly affected the quality of palm oil, especially when the fruit has bruised.

3.2. **Requirements analysis.** The requirements analysis is the analysis of stakeholders' needs for mobility analytics that is captured with the following steps: a) identifying the stakeholders, b) defining the stakeholders' needs, c) refining, d) prioritizing goals, and e) operationalizing the goals [9] – some of the stakeholders, including executive, management, and professional users. Specification captures the information and functional requirement, which defines the query and operations for descriptive and diagnostic questions for mobility analytics. The requirement specification must be aligned with the business goals.

The group of users of the system and the requirements:

a) Factory Executive: Transportation, Loading/Unloading, Productivity Analysis.

b) Farmer's Cooperation: Transportation Analysis

The goal of Transportation Analysis:

a) Reduce transportation costs by reducing the duration of truck operations.

b) Reduce the FFB transportation time to the POM to minimize the FFB quality loss.

c) Maximize the road support for effective FFB transportation.

The goal of Loading/Unloading Analysis: Reduce the FFB loading/unloading time to minimize the FFB quality loss.

The goal of Plantation Productivity: Maximize plantation productivity.

3.3. **Mobility DW modeling.** The modeling process started with the conceptual and logical design of the data warehouse. The design process discovers the fact table, measures, dimensions, and hierarchies. Figure 2(b) shows an extended MultiDim model that supports spatiotemporal logical modeling. This model has a natural and straightforward approach. The information has been represented in the fact and dimension table by rich types, including spatiotemporal types that naturally resemble reality. Route t(•) is a measure as a trajectory of truck positions at any point in time, load t() as temporal integer types changing over time, and trajectory as spatial types represented by a line with the symbol ( ). The other measures are Distance, Load, and Duration as numeric types. The Route t(•) measure as a temporal point type allows deliveries to be aggregated along the dimensions. For example, a similar route could be merged into a single owner, and the route could be union, intersect, etc.

The Delivery fact has a relationship with seven dimensions: Truck, Time, Plantation, Road, Afdeling, Block, and FruitCollectionPoint. The Truck, Time, and Plantation dimensions related to the fact through one-to-many relationships. The Road, FruitCollectionPoint, Block, Afdeling, and Pantatiton dimensions are spatial dimensions indicated by the symbol ( ) and have a topographical relationship with the fact table. These dimensions share a geography hierarchy where geometry is associated with each level in both dimensions.

The FruitCollectionPoint dimension has topological constraints that indicate an FCP in Plantation Block and Plantation Block is contained in Plantation Afdeling and creates a parent-child relationship. This dimension creates hierarchies.

3.4. **Extract, Transform, and Loading (ETL) process.** ETL process loads the data from the transactional system from the *logtransawit* database as the data source to the mobility DW. The data source for this data warehouse is the datasets derived from MOs data of FFB transport trucks stored in *logtransawit* mobile apps. Spatial data in road networks derived from GoogleMaps and other spatial and non-spatial data have been captured from Instiper university's educational plantation in Bawen, Central Java, Indonesia. The raw trajectory data has a temporal geometric point and temporal integer types, which are the extension of temporal types introduced in MobilityDB. Each row has a data point/location (long, lat), time, and truckload. Currently, MobilityDB provides types and operations function and temporal types to accommodate the mobility database.

The raw trajectory data captured, then extracted, transformed, summarized, and inserted into the staging database and DW in MobilityDB by an ad-hoc PL/SQL code.

4. **Discussions and Results.** The discussion and results consist of query design, visualization, and the experimental results of query execution.

4.1. **Query and visualization.** The query and visualization are run to gather descriptive, diagnostic, and predictive information from the DW. The temporal types and associated operations have been used to express DW mobility queries for some prioritized goals. As a result, the queries combine typical OLAP operations, such as roll-up, slice, spatial slice, temporal slice, dice, with spatial and temporal operations on MOs. The sample queries for analysis are explained and depicted in Figure 3.

Transportation Analysis:

Query#1: Give the average distance traveled by each truck per month this year. The query involves some operations that are **roll-up** along the Time and Truck dimensions. Then, the computation of the **distance** and **slicing** operations are performed to the Time dimension.

```
SELECT t.Month, tr.TruckKey, AVG(length(Route))
FROM Delivery d, Truck tr, Time t
WHERE d.TruckKey = tr.TruckKey AND t.TimeKey = d.TimeKey
AND t.Quarter = 3
GROUP BY t.Month, tr.TruckKey
```

Query#2: Determine the total loading time of the truck per month in 2017-2019 owned by Farmer Cooperation. The query involves **roll-up** operations along the Time and Truck dimensions, **computation** of the transit time, and **slicing** operations performed to the Truck dimension. Loading time is defined as a stopping period of more than 2 minutes and the location is within 100 m of the FCP.

```
SELECT OwnerName,Year,Month,SUM(timespan(r)) FROM Time t,
(SELECT tr.OwnerName, d.TimeKey,
unnest(periods(getTime(atValue(round(speed(d.Route),5),0)))) as r
FROM Delivery d, FruitCollectionPoint g, Truck tr
WHERE tr.OwnerName <> 'Factory'
st_intersects(d.Trajectory,g.FCPGeo))TableX
WHERE timespan(r) > interval '2 min'
AND t.TimeKey = TableX.TimeKey AND t.Year in (2017,2018,2019)
group by OwnerName,Year,Month
```

Query#3: Give the cumulative truckload per road segment for each month in the year 2019. This query involves **roll-up** operations along the Road and the Time dimensions and **computation of cumulative** truckload per road segment.

```
SELECT Month, RoadSegment, SUM(Avg)
FROM  (SELECT t.Month as Month,j.RoadKey as RoadSegment,
        twAvg(atPeriod(load,unnest(periods(getTime(atGeometry(Route,j.RoadGeo)))))) as Avg
        FROM Delivery d, Road j, Time t
        WHERE d.Trajectory && j.RoadGeo
        AND t.TimeKey = d.TimeKey AND t.Year = 2019)X
GROUP BY Month,RoadSegment
```

Loading/Unloading Analysis:

Query#4: Give the average timespan unloading/loading time by the loading system used in FCP per month, quarter, and year for the factory's truck. The query performs **roll-up** on time dimension hierarchy and the FCP dimension to compute the unloading/loading time. The query also performs **slice** operation on truck dimension.

```
SELECT t.Year,t.Quarter,t.Month, fcp.LoadingSystem,
AVG(timespan(getTime(atValue(speed(Route),0))))
FROM Delivery d, Time t, Truck tr, FruitCollectionPoint fcp
WHERE d.TimeKey = t.TimeKey AND tr.ownerName = 'Factory'
AND st_intersects(d.Trajectory,fcp.FCPGeo)
```

```
GROUP BY t.year, t.quarter, t.month, fcp.LoadingSystem, d.Trajectory
```

Plantation Productivity:

Query#5: Compute the total palm FFB harvest of each block per quarter in the year between 2017 and 2019 in Afdeling Alfa. This query involves some roll-up operations along the afdeling and block dimensions, and **slicing** operations performed for periods.

```
SELECT a.AfdelingName, b.BlockName, SUM(getValue(atTimeStamp(Load,
    EndTimeStamp(getTime(atGeometry(d.Route,b.BlockGeo)))) -
    getValue(atTimeStamp(Load,
    StartTimeStamp(getTime(atGeometry(d.Route,b.BlockGeo))))))
    FROM Delivery d, Afdeling a, Time t, Block b
    WHERE t.TimeKey = d.TimeKey
    AND ST_WITHIN(b.BlockGeo,a.AfdelingGeo)
    AND t.Year BETWEEN 2017 AND 2019
    AND a.AfdelingName = 'Afdeling Alfa'
    GROUP BY g2.AfdelingName, g.BlockName
```

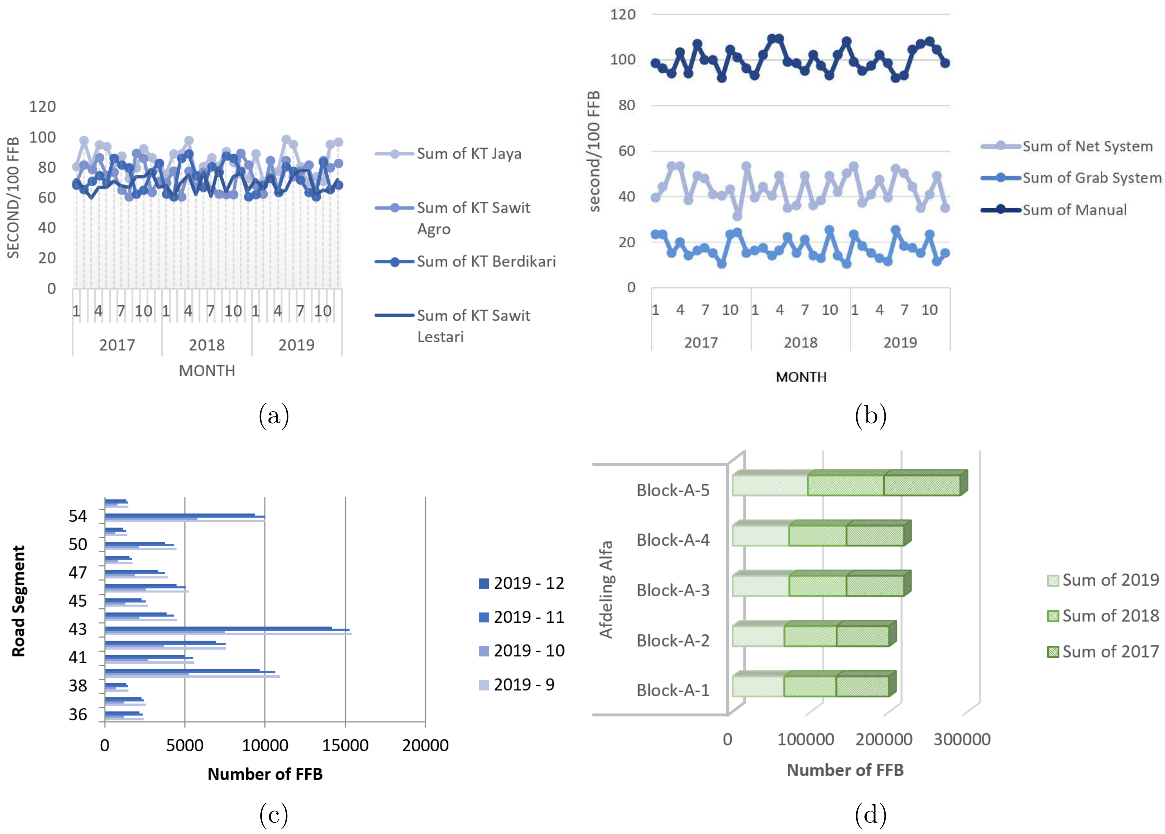


FIGURE 3. Query visualization: (a) Query#2, (b) Query#3, (c) Query#4, and (d) Query#5

4.2. **Query performance.** The paper focuses on implementing mobility analytics for FFB delivery using a new data model, representation, and methods offered by MobilityDB [7]. Nevertheless, the performance issues could not be ignored as we use this technology to support decision making. The mobility DW depicted in Figure 1 was implemented using a PostgreSQL object-relational database with PostGIS and MobilityDB extension. The DW fact table contains 1536 tuples with approximately 1000 temporal point data for each tuple, 25 tuples of geometry data as road segments, and ten rows of geometry data as geolocation of FCP, Afdeling, Factory Gate, and PMO. The DW time dimension contains 365 tuples representing a date in 2019. These five queries were executed on Pentium Core i5 8th generation with a 12 GB RAM computer. Table 2 shows five test times of the queries.

Table 2. Query execution test

Query	**OLAP features**	**Analysis category**	**Execution time (s)**				
			1	**2**	**3**	**4**	**5**
Q1	roll-up, slice, distance	descriptive	0.15	0.22	0.18	0.18	0.16
Q2	roll-up, slice, duration, drill-down	descriptive, diagnostic	0.36	0.46	0.45	0.43	0.44
Q3	roll-up, duration, spatial slice, slice, drill-down	descriptive, diagnostic, predictive	15.85	22.27	21.98	21.83	21.90
Q4	roll-up, cumulative computation, subquery, spatial slice, temporal slice, drill-down	descriptive, diagnostic, predictive	3027	3051	3038	3054	3037
Q5	roll-up, spatial slice, temporal slice, dice, drill-down	descriptive, diagnostic, predictive	43.60	33.28	33.24	33.29	32.86

The experiments proved that the mobility DW implementation has a convenient, simple model, and expressive performance (below 1 s, for regular OLAP query, and below 1 minute for OLAP query with spatial and temporal slice) for supporting the executive to make an analysis based on spatiotemporal data, and then make the best decision.

5. **Conclusion and Future Works.** The implementation of the mobility analytics for FFB transportation was developed with a new mobility data warehouse concept using the MobilityDB (which is an extension of PostgreSQL). This approach can answer critical questions for transportation, road, loading/unloading, and productivity analysis using mobility queries. These queries include a roll-up, drill-down, slice, dice, spatial function, and temporal function with an impressive execution time. The query report is beneficial for descriptive, diagnostic, and predictive analysis for transportation and productivity of the palm plantation. The implementation shows that mobility analytics has a natural, straightforward, simple model and is impressive for supporting managers to analyze MOs data before decisions can be made.

In the future, the challenge is how to extend the mobility DW with the data source in the format of Linked Open Data (LOD) Semantic Web. Integration with existing vocabulary and another LOD will enhance the capability with a bigger catalog and standardization. Using this LOD as a data source, the data warehouse also could be enriched with the new semantic and mechanism to provide further knowledge to DW [18].

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