# Mobile Data Collection in Smart City Applications: The Impact of Precedence-based Route Planning on Data Latency

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**Abstract**

Data collection is one of the key building blocks of smart city applications. Sheer number of sensors deployed across the city generate huge amount of data continuously. Due to their limited transmission range, sensors form a sensor network with a base station. The base station acts as a gateway between the network and the remote user and the generated data is collected by the base station. However, due to sensor locations and the transmission range the network may consist of several partitions. A typical solution is employing one or more mobile element(s) to collect data from partitions periodically. Mobile data collection enables intermittent connectivity between sensors and the base station. The major drawback of mobile data collection is increased data latency depending on the velocity of the mobiles. Another challenge is specifying importance for individual sensors in a smart city application. This study evaluates the impact of precedence-based routing of mobiles on data latency in a realistic manner through employing spatial data obtained from a geographic information system. Precedence levels for sensors are determined based on the amenity type of the building they monitor. Mobility of the mobiles is restricted with the drivable road network. The impact of the precedence-based routing according to total path length, maximum data collection delay, and the maximum data latency is evaluated. Obtained results indicate an increase in total path length up to 14% when precedence-based routing is applied. The results also suggest that precedence-based routing increases maximum data collection delay unless the amenity type has fewer points of interest to monitor.

*Keywords:* Smart City, Wireless Sensor Network, Data Collection, Route Planning, Data Latency.

# 1. Introduction

The rapid population growth of the world requires efficient use of the limited resources [1]. To address this challenge, the "smart city" phenomenon presents a data driven citizen-centric approach in order to improve efficiency of city operations. Exploiting information and communication technologies in managing city operations improves the decision making process of several essential services including transportation, security, garbage collection, and tourism [2]. According to a recent study, smart cities can reduce daily water consumption up to 25-80 liters per person and crime rate up to %30-%40 [3]. Another study suggests the potential of saving back up to 125 hours in a year per person thanks to improved efficiency in transportation, safety and health services [4].

To ensure sustained efficiency, smart city applications require continuous data flow generated from data sources across the city [5]. Two common approaches exist for data collection regarding ambient conditions. The first approach employs dedicated hardware such as sensors and cameras. Typically, the city owns the hardware in this model. The other approach is known as crowdsensing and follows a volunteered data collection model where the participants collect data using their smart devices [6]. While the first model requires deploying several sensors across the city and collecting data preferably using wireless communication means, the second model avoids the cost of ownership and maintenance. Furthermore, the participants cover the cost of data collection in the second model. Despite its opportunities, crowdsensing has its own complications. First of all, this model is participant centric and the performance of the system depends on the participants. In terms of coverage, this model requires availability of a certain number of participants at desired locations whenever needed. Also, data quality depends on the employed hardware (e.g. accuracy, calibration, etc.) and its location (e.g. pocket, hand, bag, etc.). In the worst case, malicious participants may send incorrect data deliberately [7]. This study assumes deployment of dedicated sensors owned by the municipality considering recent regulations on data protection [8] and the lack of essential sensors (e.g. air and water quality sensors) on typical smart devices.

To monitor the ambient information several sensors are deployed across the city and sensors form a wireless sensor network (WSN). To determine the locations for sensor deployment, this study suggests Points of Interest (POIs) in given cities. POI is an abstract concept used in geographical information systems (GIS) to represent geographic entities that might be of interest to visitors [9]. Some examples include libraries, restaurants, touristic facilities, etc. Without the loss of generality, this study considers three amenity types as POIs to monitor; hospitals, schools, and police stations. Note that the selection of considered POIs does not impose any restriction on the applied methods and other POIs can also be included as well. In a realistic smart city application, it is likely to have different sensors with different data generation rates based on the importance of the monitored region. To be able to demonstrate different importance levels for sensor data, this paper defines prominence of sensors based on the monitored POI and follows a precedence-based data collection scheme. Precedence-based data collection is detailed in Section 3.

OpenStreetMap (OSM) [10], one of the volunteered geographic information systems (VGIS), is employed to obtain POIs and their respective coordinates. OSM is open data unlike its competitors Google Maps [11] and ArcGIS [12]. Data is generated by volunteers in OSM. Therefore, data quality and reliability is variable [13]. This paper employs OSM to collect geographic data. However, collected data is modeled as a graph and presented approaches are

independent from the employed GIS. OSM employs three basic components to model the physical world, namely node, way, and relation. Node is a specific coordinate on the surface of the world. Way is an ordered list of nodes to define road segments or outlines of buildings. A POI can be represented as a node or way in OSM. If the building footprint is available, POI is defined as a way. To determine the sensor deployment locations, available POIs are retrieved for considered cities. According to the representation of the POI, one or more sensors are deployed to monitor the POI. If the POI is represented as a node, one sensor is deployed at the respective node location. If the POI is represented as a way, one of the nodes comprising the way is selected randomly and the sensor is placed accordingly.

The WSN topologies for given cities are generated by placing sensors at computed locations and setting the wireless communication range. This study assumes employment of one of the low-power wireless communication means (e.g. ZigBee, 6LowPAN, LPWAN, etc.). Low-power protocols extend the network lifetime by conserving the energy consumption through reduced transmission ranges. Cellular technologies offer extended transmission ranges. However, they are not preferred in this study due to the increased hardware cost and monthly subscription costs. On the other hand, approaches presented in this work are independent from the employed wireless communication methods and other technologies can also be adopted to enable wireless communication among sensors and the base station. This study assumes availability of a single base station to connect the WSN to the rest of the world.

WSNs can be modeled as a graph. In this model, the network may comprise multiple connected components (i.e. partitions) based on the sensor locations and the employed transmission range. Obtained results indicate that the resulting graphs are sparse and partitions typically consist of one sensor. The problem considered in this work can be formally expressed as follows: "Given a WSN with multiple connected components, enable connectivity between sensors and the base station in a cost effective manner". In the literature, several approaches are available to restore connectivity [14]. This study follows a mobile data collection (MDC) based approach and provides intermittent connectivity for partitions by periodically visiting them and the base station. This approach has lower hardware cost compared to other approaches. Also, the solution is reactive and it can be activated without any intervention. Unlike earlier studies, this work models the network topology by using real data obtained from a GIS. Locations of the sensors and their data generation rates are determined according to POIs. Also, the mobility of the MDCs is limited with the road segments connecting POIs. This study assumes availability of smart vehicles with wireless communication capabilities to act as MDCs. A detailed discussion on similar studies can be found in Section 2.

In a graph, the shortest path between two nodes can be determined by applying one of the shortest path algorithms including Dijkstra, Bellman Ford, etc. The problem that is evaluated in this paper, on the other hand, requires finding the shortest path which visits more than two nodes depending on the sensor count. Therefore, the current problem can be modeled as the Traveling Salesman Problem (TSP). TSP is a well-studied problem in the literature. According to this problem, a salesman visits a set of cities once and returns to the initial city by following a path with the shortest possible distance. In the considered problem, MDC represents the salesman and visits each partition once to collect data. The original location of the MDC is assumed to be next to the base station. The travel of the MDC also terminates at the base station to deliver the collected data. The mobility of the MDC is limited with the road network as mentioned earlier. Even if the POIs are not located on the road network, MDCs can stop at the closest point on the road network to collect

data remotely using wireless communication. We assume a common transmission range for MDCs and sensors which is greater than the maximum distance between POIs and the road network. A sample road network along with POIs for the city center of Ankara can be found in Figure 1.

The road network is modeled as a directed and weighted graph. In this graph, edges represent road segments. Edge weights are assigned according to the length of the road segment. In order to calculate mobility-based delay, we consider the velocity of the MDC on each road segment and the edge weights. The velocity of the MDC is assumed to be dynamically set based on the maximum speed limit defined for the corresponding road segment. Speed limits are obtained from OSM where available. If the speed limit is not defined for a road segment, the velocity is set to the default value of 50 km/h. TSP requires availability of the distances between sensors. Since the sensors are located on the road network, shortest paths are calculated between every pair of sensors using Dijkstra.

Considering the fact that different sensors deployed across the city may have different data generation rates and priorities, different precedence levels for sensors based on the POI that they monitor are defined. It should be noted that, different methods can be applied to determine sensor priorities depending on the application level requirements. The precedence-based model that is applied in this study can be easily generalized by assigning priorities based on the requirements. In this work, two different data collection schemes, namely Precedence-based Mobile Data Collection (Pb-MDC) and Neutral-Mobile Data Collection (N-MDC) are presented. Pb-MDC identifies sensor priorities according to POIs they monitor and assigns MDCs accordingly. N-MDC, on the other hand, does not consider priorities for sensors. A detailed discussion on the proposed approaches can be found in Section 3.
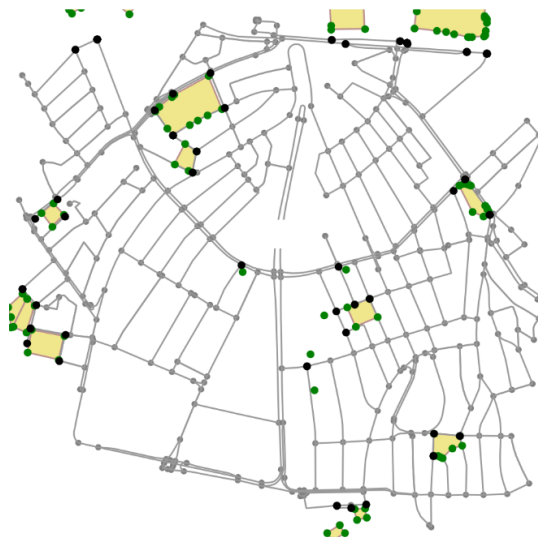


**Figure 1.** The road network and points of interest of certain amenity types for the city center of Ankara. The data is limited to a region   within the 1000 meters from the city center. Gray nodes and lines represent the road network. Yellow polylines denote POIs defined with building outlines. POIs are limited with hospitals, schools, and police stations. Green nodes indicate possible locations for sensor deployment. Black nodes are the closest points on the road network to the nearest POI.

## 2. Related Works

Smart devices equipped with a wide array of onboard sensors are becoming increasingly ubiquitous. This phenomenon leads to radical changes in the way that geographical data is collected and disseminated. OpenStreetMap [10] is one such example of a collaborative project to generate an open representation of the physical world through crowdsourcing. OpenStreetMap provides an alternative to propriety map services [11-12] by enabling free access to geospatial data under an open license. On the other hand, the participatory model of the contributors is a major concern regarding quality and reliability of the OpenStreetMap data. Thus, data quality has been one of the core research areas for crowdsourced geographic data in the literature [13]. Besides, OpenStreetMap has been used in building mapping [15], developing pervasive games [16], defining test scenarios for self-driving cars [17], etc. This study employs OpenStreetMap to obtain drivable road network for the vehicle and geographical locations of various POIs including hospitals, schools, and police stations. OSMnx [18] library is employed for data visualization.

WSNs consist of sensor nodes in large quantities. Nodes are equipped with a sensor module to collect ambient information and a radio module for wireless communication. Due to their limited physical size, nodes have limited batteries. Energy harvesting can be an option to extend the lifetime. Nevertheless, low-power wireless communication technologies are desired to conserve energy [19]. To connect the WSN to the rest of the world, one or more base stations are deployed in the network. Base stations are less resource restricted and exploit long-range wireless communication means to forward data collected in the network. Due to their limited wireless communication range, nodes typically form a multi-hop network to reach the base station. However, multi-hop routing model leads to dependency on other nodes for data delivery. The connection between a node and the base station can be broken due to initial topology or after failure of intermediate nodes. In the literature, several solutions exist which aim to restore connectivity in WSNs [14].

Some of the typical applications for WSNs are forest fire detection, glacier monitoring, landslide detection, border surveillance, etc. Therefore, WSNs are expected to sustain operations in harsh environmental conditions. However, ambient conditions can lead to node failures. Other possible reasons for node failures include battery depletion and hardware malfunction. When the network is modeled as a graph, some of the nodes act as cut-vertices. Failure of a cut-vertex node partitions the network into multiple sub-networks isolated from the rest of the network. This study assumes a partitioned network due to initial deployment. There are two common approaches for node deployment. The first approach is deterministic where nodes are deployed at pre-determined locations. In the second approach, nodes are assumed to be dropped from an unmanned aerial vehicle and placed randomly. This study follows the first approach and determines node locations according to spatial data obtained from OpenStreetMap.

Connectivity restoration solutions for WSNs can be broadly classified into two groups based on whether a proactive or reactive measure is taken. The main goal of the proactive solutions is avoiding connectivity problems in a precautionary manner. A common proactive method is exploiting node redundancy. The main idea of node redundancy is deploying redundant nodes in the network to limit the adversarial effects of mode failures. Some proactive solutions provide $k$-connectivity to the network. Such a network can tolerate up to $k$-1 node failures by providing $k$ different paths for connectivity. This group of solutions increases the initial deployment cost due to increased demand for redundant nodes.

Also, proactive solutions cannot guarantee a solution if the scope of the inflicted damage is larger than the scale of the taken measure. The main challenge for the proactive approaches is the uncertainty of damage location and scope before the failure. To address this challenge, the second group of solutions follows a reactive approach to restore network connectivity. Reactive solutions are triggered on demand after detecting a failure. Reactive solutions can also be classified based on the applied solution scheme. Relay node placement is a possible reactive solution to recover connectivity. As the name suggests, relay placement solutions deploy additional nodes to the network to link partitions. This scheme assumes the feasibility of intervening the application area. If the application area is accessible, relay nodes can be dropped from an unmanned aerial vehicle and then relay nodes move to their final positions. Different goals can be defined such as minimizing the number of relay nodes to be deployed or minimizing their travel distances. It should be noted that more than one batch of deployment may be needed if the number of relay nodes is not sufficient to ensure connectivity. Deployment of a city-scale WSN requires relay nodes in large quantities to ensure network connectivity [1]. Therefore, a relay node placement approach is not desired in this study.

Another class of reactive solutions is restructuring network topology through exploiting node mobility [20]. Connectivity of a partitioned network can be recovered by relocating some of the nodes to appropriate locations. Determining the subset of nodes to be relocated and identifying their final locations are some of the key challenges of this type of solutions. Despite the likelihood of selecting only a subset of nodes, this approach requires controlled mobility to all existing nodes in the network. This requirement is essential since the nodes that will require mobility cannot be identified in advance until the failure occurs. Attaching nodes to mobile robots enables controlled mobility. The solution is reactive in the sense that the network topology is only restructured upon needed. Some of the core goals of this type of solutions are minimizing total travel distance and minimizing the number of mobile nodes to be able to extend the network lifetime. This recovery scheme is not applied in this study due to various reasons. First, this approach relocates existing nodes. Consequently, the sensing coverage will be affected. In this study, we deploy sensors to monitor certain POIs. After relocation, it is likely to loss sensing coverage unless other sensors monitor the region. Second, enabling node mobility is expensive. We aim to minimize the hardware cost by avoiding the mobility requirement of the nodes. Third, autonomous node relocation is complicated in the urban environment. This study follows another mobility-based reactive approach to restore network connectivity. In this approach, the nodes remain stationary and a mobile data collector (MDC) is employed to carry data between partitions and the base station. The approach is reactive in the sense that the MDC is located next to the base station and not activated unless required. MDC-based approach provides intermittent connection and the data latency depends on the travel length and velocity of the MDC. In this study, the number of MDCs to assess the relationship between MDC count and latency have been varied. Different precedence levels for nodes and assigned MDCs according to node significance have also been defined.

This study presents a precedence-based data collection scheme to collect data periodically from various POIs for smart city applications. According to a recent study, the number of end devices will reach 25 billion by 2021 [21]. 6LoWPAN and LPWAN are two emerging technologies to enable low-power wireless communication between end devices in smart cities. LPWAN is a long-range low-power protocol operating in the unlicensed spectrum to lower the cost of service. 6LoWPAN, on the other hand, provides IPv6 connectivity over short-range IEEE 802.15.4 networks. LPWAN networks

are typically organized in a star topology. 6LoWPAN also supports mesh networks. Due to the lack of IPv6 support, limited bandwidth, and low duty-cycle of LPWAN, this study assumes the deployment of 6LoWPAN.

Despite the low-power characteristics of ZigBee and Bluetooth, the limited transmission range of these technologies is a challenge to provide city-scale connectivity for smart city applications [22]. Considering the typical topology of WSNs and their connectivity patterns, LTE and similar traditional cellular technologies are not suitable for IoT applications [22]. SigFox, Ingenu, and LoRa are some of the possible alternative technologies that are classified as LPWAN solutions [22]. IoT-based smart city applications constitute mass amount of sensors generating heterogeneous data in large volumes. [23] proposes a tiered architecture to model smart city applications. The bottom layer is responsible from data collection in this model and ensures quality of the collected data. Tier II is responsible from sensor communication. Tier III handles big data and performs data analytics for both real-time and historical data. [23] employs a relay node to collect data from sensors using ZigBee. In the literature, studies addressing the quality of service also exist including [24]. To reduce latency, [24] exploits a paradigm known as mobile edge computing or fog computing. According to this paradigm, the computing resources closer to the mobile network edge are employed for computing tasks. The solution proposed by [24] is viable for applications requiring real-time transfer of high definition video. Our paper also aims minimizing the latency. However, real-time video transfer is not a use-case considered in this study and we assume a delay-tolerant network.

## 3. Approach

A smart city platform, which collects data from sensors deployed across the city is assumed. The data analytics component of the smart city platform analyzes the collected data so that efficiency of various city operations can be improved. Depending on the application level requirements, different urban amenities can be identified for monitoring. This study considers schools, hospitals, and police stations, without the loss of generality, as the amenities to be monitored. Given the employment of geographical data, this approach provides the regions of interest in a realistic manner thanks to spatial data obtained from OpenStreetMap. To be able to simulate various importance levels for different sensors, we follow a amenity-based identification of sensor significance. According to this approach, the importance of sensors is determined based on the amenity they monitor. Again, without the loss of generality, three different importance levels have been defined. For demonstration purposes the highest priority have been given to schools and the lowest priority to police stations. It should be noted that the number of importance levels can be changed according to application requirements. To be able to assess the relationship between sensor priority and data latency, two different approaches for data collection are presented as follows:

- **Precedence-based Mobile Data Collection (Pb-MDC):** This approach assigns MDCs to sensors according to amenity types when multiple MDCs are available. For example, if two MDCs are available, one of the MDCs will be assigned to amenities with the highest priority while the other is assigned to the rest of the amenities. If three MDCs are available, each MDC will be assigned to a separate amenity type. If four MDCs are available, amenity type with the highest priority will be served by two MDCs while rest of the amenities are served by a single MDC.
- **Neutral Mobile Data Collection (N-MDC):** This approach does not consider precedence levels for sensors and assigns MDCs to sensors according to their locations.

The road network obtained from OSM is modeled on a weighted directed graph. On this graph, edges represent road segments while nodes represent end points of road segments. Road segments can be one-way or two-way. The direction of the traffic flow for a particular road segment determines the direction of the corresponding edge. Edge weights are set according to the length of the corresponding road segment. Maximum speed limits for road segments are also obtained from OSM to determine to velocity of the MDC during its movement. The maximum speed is set to 50 km/h unless the speed limit for a particular road segment is available on OSM.

For each POI of considered amenity types, geographical coordinates are obtained from OSM. OSM represents POIs as a node or as a way. Way is a polyline representing the building footprint and defined as an ordered list of nodes. If the POI is represented with a way, one of the nodes defining the building footprint is selected for sensor deployment location. If the POI is represented with a node, the sensor is deployed at the geographical coordinate of this node. The network topology is finalized once the sensor locations are identified. The first sensor is selected to act as the base station in simulations. To provide connectivity between sensors and the base station, one or mode MDCs are employed. An MDC can be assigned to visit multiple sensors. Determining the optimal path following the road network is modeled as the Traveling Salesman Problem (TSP). TSP is solved using OR-Tools library [26]. TSP requires the distances between sensors. Since mobility between sensors is limited with the road network, the shortest paths between sensors are computed using Dijkstra and the distances between sensors are set accordingly.

Pb-MDC and N-MDC provide the same result when the number of MDCs is set to one. When $m>1$ MDCs are available, N-MDC solves TSP for $m$ salesmen. When $m=2$, Pb-MDC assigns one MDC to sensors with the highest priority and one MDC to the rest of the network. For $m=3$, Pb-MDC assigns an exclusive MDC to each amenity type. When the number of MDCs is set to 4, Pb-MDC assigns two MDCs to the amenity type with the highest priority while other amenity types are served exclusively by a single MDC.

## 4. Experimental Results

### 4.1. Performance Metrics

The performance of the presented approaches according to three performance metrics was evaluated as explained below.

- **Total path length:** The total path length of MDCs available in the network.
- **Maximum data collection delay:** Data generated by sensors are stored in the sensor cache until collected by an MDC. This metric reports the highest waiting time for generated data to be collected by an MDC. We report results for each POI separately. Extended waiting time implies cache overflow depending on the available cache size.
- **Maximum data latency:** The tour of each MDC originates and terminates at the BS. This metric reports the highest amount of time for an MDC to complete its tour. The duration of the MDC's tour depends on the total path length and the variable velocity of the MDC. The maximum speed limit for each road segment defines the velocity of the MDC on the corresponding part of its tour. This metric denotes the freshness of the collected data.

## 4.2. Results

### 4.2.1. Total Path Length

The performance results of the presented approaches in terms of the total path length can be found in Figure 2. The number of MDCs is varied between 1 and 4. According to obtained results, increased MDC count elevates the total path length for both approaches. The total path length increases 39% and 57% for N-MDC and Pb-MDC respectively when the number of MDCs is increased from 1 to 4. When the number of MDCs is set to 1, both approaches provide the same result. For multiple MDCs, Pb-MDC increases the total path length between 12% and 14%. N-MDC performs better than Pb-MDC since Pb-MDC determines MDC tours according to amenity types. However, N-MDC does not consider amenity types and designates tours according to geographical coordinates of the sensors only. Pb-MDC cannot optimize the MDC tours due to focusing on the amenity types while selecting sensors to be visited by each MDC. Consequently, Pb-MDC is outperformed by the N-MDC.
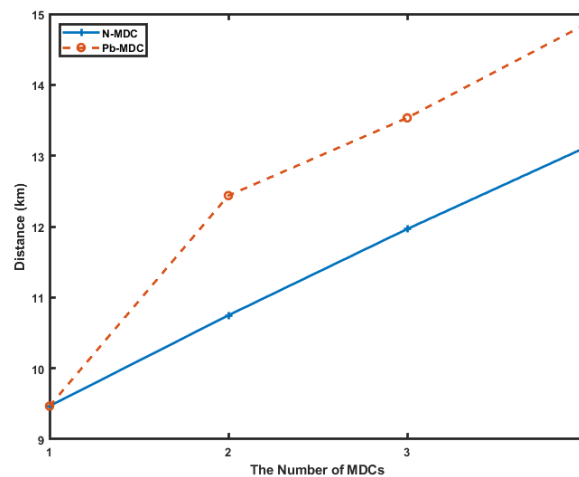


**Figure 2.** Total path length with respect to MDC count.

### 4.2.2. Maximum Data Collection Delay

Figure 3 presents the maximum data collection delay for each amenity type when the presented approaches are applied. It can be observed from Figure 3 that the maximum data collection delay declines when the number of MDCs is increased no matter which data collection scheme is employed. The decline in the maximum data collection delay can be attributed to the simultaneous data collection by MDCs in higher numbers. When the number of MDCs is increased from 1 to 4, the maximum data collection delay of hospitals decreases 55% and 61% for Pb-MDC and N-MDC respectively. For schools, increased MDC count alleviates the maximum data collection delay by 44% and 60% respectively when Pb-MDC and N-MDC are applied. For police stations, increased MDC count reduces the cost by 66% and 65% respectively for Pb-MDC and N-MDC. Within the considered amenity types, police stations have the least number of POIs in cities. Obtained results suggest that Pb-MDC performs better than N-MDC for amenity types with fewer POIs. Compared to N-MDC, Pb-MDC decreases the maximum data collection delay by 4% and 24% for 2 and 3 MDCs respectively.
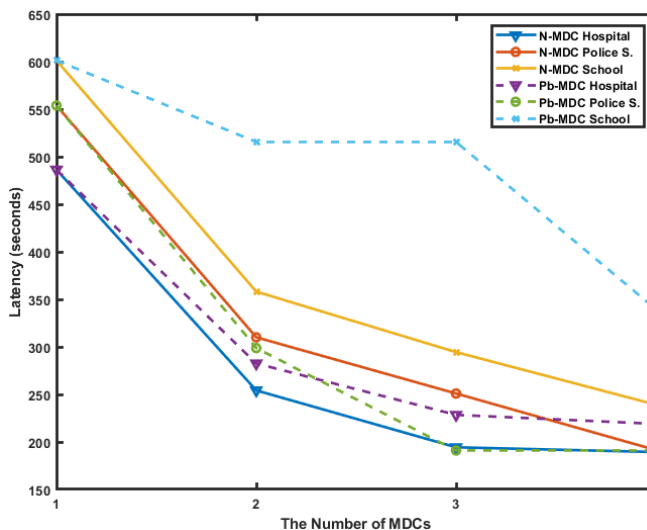
**Figure 3.** Maximum data collection delay with respect to MDC count.

### 4.2.3.    Maximum Data Latency

Figure 4 presents the maximum data latency with respect to MDC count for the presented approaches. It can be noticed from Figure 4 that the maximum data latency declines with the increased MDC count for both approaches. When the number of MDCs is increased from 1 to 4, the maximum data latency declines 48% and 34% for N-MDC and Pb-MDC respectively. The decline in the maximum data latency is expected due to simultaneous data collection by additional MDCs. N-MDC outperforms Pb-MDC by alleviating the maximum data latency by 23%, 35%, and 21% for 2, 3, and 4 MDCs respectively. As discussed earlier, N-MDC does not consider priorities and assigns MDCs to sensors based on their locations. On the other hand, Pb-MDC focuses on amenity types when designating MDC tours.
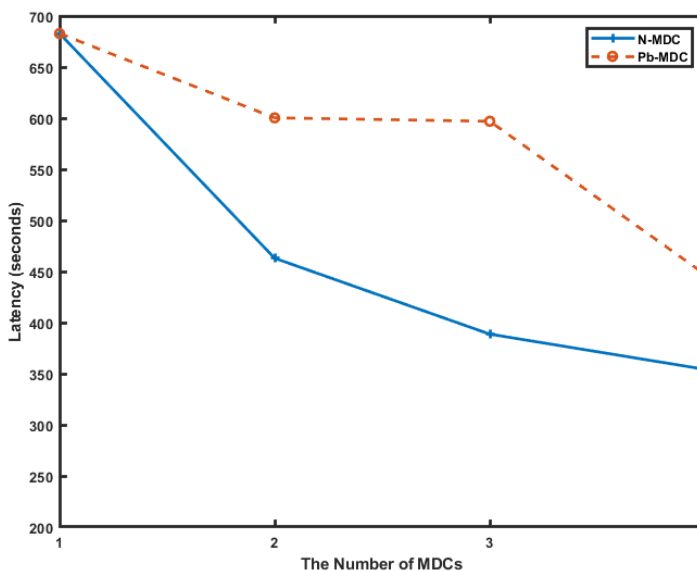


**Figure 4.** Maximum data latency with respect to MDC count.

## 5. Conclusion

Smart cities improve the efficiency of various city operations including transportation, security, tourism, etc. through a data-driven decision making process. This phenomenon requires continuous data collection from sensors deployed across the given city. However, sensors are typically equipped with limited batteries and employ low-power low-range wireless communication technologies to deliver their data. To ensure data collection from sensors spread across the city, this paper presents two mobile data collection schemes. The approaches employ a mobile entity to visit sensors to collect data and then forward to a base station for further processing. The first approach assumes various precedence levels for sensors and assigns the mobiles according to significance of the sensors. The second approach regards equal importance to all sensors. To be able to simulate importance levels in a realistic manner, this study classifies sensors according to amenity type of the POIs they monitor. Geographical data is obtained from a open geographical information system. Without the loss of generality, schools, hospitals, and police stations are selected as the POIs to be monitored and precedence levels are identified according to these amenity types. Mobility of the MDCs is limited with the drivable road network for the given city. In the experiments, the city centers of 30 metropolitan municipalities in Turkey are used. Presented approaches are evaluated in terms of total tour length, data collection delay, and data latency. Obtained results indicate that precedence-based mobile data collection increases the overhead compared to non-precedence-based mobile data collection. Precedence-based mobile data collection is only desirable for amenity types with fewer POIs.

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