Data Collection in Advanced Metering Infrastructure Using UAVs

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***Abstract*— The use of unmanned aerial vehicles (UAVs) in the collection of data from wireless devices, sensor nodes, and Internet of Things (IoT) devices has recently received significant attention. In this paper, we study the data collection process from a set of smart electric meters enabled by UAVs. Our objective is to minimize the total annual cost of the electric utility by jointly optimizing the number of UAVs, their power source sizing (represented by the UAVs' batteries), the selected starting point of each UAV as well as the data collection trip planning. The problem is formulated as a mixed-integer nonlinear programming (MINLP) problem, which is generally difficult to be optimally solved. In order to find a solution, the problem has been decoupled into two sub-problems where a candidate UAV and a number of buildings are first grouped into trips via genetic algorithms (GA), and then the optimum trip path is found using a travelling salesman problem (TSP) branch and bound algorithm in the second.**

***Keywords*— advanced metering infrastructure, unmanned aerial vehicles, power source sizing, trip planning.**

I. Introduction

Advanced metering infrastructure (AMI) is considered a vital part of integrated power management solutions that are based on the SCADA system. AMI incorporates electrical hardware devices such as smart meters, smart sensors, circuit breakers, switchboards, uninterruptible power supply (UPS) systems and communication gateways [1].

Smart meters play an important role in AMI systems, where data can be manually collected, this is prone to errors and consumes more time and cost. Smart meters can be connected also through a power line communication (PLC) system, which has limitations [2]. In [3], the authors investigated the software details of the communication gateway in an AMI system using PLC where smart meters are connected to the gateway through a LonWorks-type industrial bus and the collected data is then transmitted from the gateway to a central computer through GSM. Similarly, the work in [4] proposed an approach for data collection and transmission from the energy meter to the utility through the GSM network.

A different approach based on master-slave architecture was investigated in [5] to collect data wirelessly from the smart meters by using the low power wireless mesh network standard 6LoWPAN and then sending it to the server using GPRS technology. A similar proposal was given in [6] where an energy and cost-efficient solution was achieved using an IEEE 802.15.4-compliant wireless network. But wireless communication has its own limitations including causing congestion.

On a different but related front, the work in [7] explored joint ant colony optimization (ACO) with guided local search (GLS) for optimizing data collection from smart meters using drones to overcome collisions while sending the collected data wirelessly. However, the focus was to minimize the packet transmission time without taking into account the other factors such as the available energy of the drone's battery or the cost of the data collection.

When using UAVs for data collection, there exists two options for the UAV selection. The first is a UAV with a small-capacity low-mass battery which means more data collection trips are expected and thus more frequent recharging of the battery, which leads to a reduction in its lifetime [8]. In this case, the UAV can fly for a short time and short distance, therefore one UAV may be unable to cover all the smart meters in a specific vicinity. The second is a UAV with a high capacity but heavier battery is used, which means that the UAV is capable of flying for a longer time, and can cover longer-distance trips but at the same time, the big mass leads to more power consumption [9]. According to these two options, one needs to choose the proper number of UAVs and their proper batteries, choose the proper starting point of each UAV and to manage the trips properly as well.

Based on the previous discussion, in this paper, we suggest a new optimization framework to achieve a joint optimal selection of the number of needed UAVs and their proper batteries, the selection of each UAV's starting point, and trip planning. Specifically, the objective is to meet the utility requirement of data collection within a limited period at a minimum cost.

II. System Model

We consider a system with $k \in \mathcal{D} = \{1, 2, \dots, D\}$ UAVs, where D is the maximum number of available UAVs. Each UAV is assumed to use only one battery from a set of batteries $\mathcal{B} = \{1, 2, \dots, B\}$ to collect data from the smart meters installed on a number of randomly distributed buildings in a city where the meters belong to the set $\mathcal{N} = \{1, 2, \dots, N\}$ as shown in Fig. 1. The horizontal coordinates of the n^{th} meter are denoted by $\boldsymbol{q}_n \in R^{2\times 1}$. In addition, it is assumed that each UAV flies at a fixed altitude H above the ground and it collects data from the meters in a total of T trips, where $T \leq N$. Also, let the starting point of the k^{th} UAV be denoted by s_k, which is assumed to have coordinates $\boldsymbol{q}_{s_k} \in R^{2\times 1}$. Finally, we define the subset of meters allocated to UAV k as $\mathcal{N}_k = \mathcal{N} \cup \{s_k\}$.

As shown in Fig. 1, a UAV collects data from a subset of buildings in each trip. We assume that the UAV could collect data from each building weekly or monthly and the smart meters can send the data to the UAV using one of the various wireless communication technologies mentioned in [10]. Finally, assuming that the amount of target data that must be collected from each smart meter is the same and is denoted by bits, the UAV hovering time T^{HOV} during data collection from each smart meter in each building is simply given by

$$T^{HOV} = \frac{D}{R}. \tag{1}$$

where $R = BW \times \log_2(1 + \text{SINR}_n)$, is the achievable rate between the UAV and the smart meter in each building measured in bits per second (bps), BW is the allocated channel bandwidth in Hz, $\text{SINR}_n = \frac{p_n}{10^{\frac{PL_{nd}}{10}}\sigma^2}$ is the signal-to-interference-plus-noise ratio (SINR) at the UAV when communicating with the smart meter of the nth building, and $PL_n = 10\alpha \log_{10}\left(\frac{4\pi f d_n}{c}\right) + L^{los}$ is the LOS path loss (in dB)[11], where α is the free space path loss exponent, f is the carrier frequency, c is the speed of light and L^{los} is a fixed attenuation term that is added to the LOS environment.

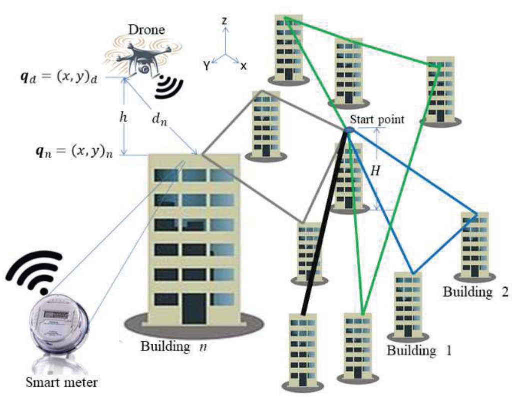

Fig. 1. UAV collecting data from smart meters.

III. Problem Formulation

As mentioned earlier, we aim to minimize the total annual cost of using UAVs for data collection. This includes both the capital cost of the chosen set of UAVs and their associated batteries in addition to the operating cost of all the trips per year due to the UAVs' batteries recharging. This is achieved via proper choice of the number of UAVs, their batteries as well as proper choice of the UAVs' starting points and trip planning. The proposed optimization problem can thus be expressed as

$$\left.\begin{aligned}\min_{\mathcal{X},\mathcal{Y},\mathcal{Z},\mathcal{S}} \sum_{k\in\mathcal{D}} X_k \left(cost_k + \sum_{b\in\mathcal{B}} Y_{b,k}\left(cost_b + C_{b,k}^{tot}\right)\right) \\ \text{subject to } (6-22)\end{aligned}\right\}, \tag{2}$$

where $\mathcal{X} = \{X_1, X_1, \dots, X_D\}$ and X_k represents a binary decision variable that indicates whether or not UAV k is selected. Also, $\mathcal{Y} = \{Y_{1,k}, Y_{2,k}, \dots, Y_{B,D}\}$ and $Y_{b,k}$, $b \in \mathcal{B}$, represents a binary decision variable that indicates whether battery b is associated with UAV k. Moreover, $\mathcal{Z} = \{Z_{u,w,t,k}\}$ where $u, w \in \mathcal{N}_k, t \in \mathcal{T} = \{1, 2, \dots, T\}$, with $Z_{u,w,t,k} \in \{0,1\}$ being another binary decision variable, which indicates that the k^{th} UAV travels from point u to w as part of trip t. Finally, $\mathcal{S}$ represents the set of all possible points in the city, which could act as starting points for any UAV.

In (5), $cost_k$ and $cost_b$ are the annualized capital cost of the UAV with its wireless charging pad and the battery, respectively. The former is calculated as follows:

$$cost_k = CRF_k \times p_k, \tag{3}$$

where p_k is the price and $CRF_k = \frac{i(1+i)^{L_k^{year}}}{(1+i)^{L_k^{year}} - 1}$, is the capital recovery factor (CRF), both of UAV k [12]. i represents the interest rate and L_k^{year} is the lifetime of UAV k in years. The annualized capital cost of the battery can be calculated using the same equations in (3) but using p_b and $CRF_{b,k}$ instead. In addition, the lifetime of battery b when associated with UAV k in years is $L_{b,k}^{year}$, which can be calculated as:

$$L_{b,k}^{year} = \min\left(\frac{L_b^{cycle}}{C_{b,k}^{cycle}}, L_{max}\right), \tag{4}$$

where L_{max} is the chemical lifetime of any battery in years. Also, L_b^{cycle} represents the maximum number of recharging cycles of battery b . Finally, $C_{b,k}^{cycle} = \frac{E_{b,k}^{year}}{E_b^{useful}}$ is the number of recharging cycles of the battery when associated with UAV k per year, where $E_{b,k}^{year}$ is the energy consumed in one year (in Wh. In particular, $E_{b,k}^{year} = \mu \times E_{b,k}^{collection}$ with μ being the factor that captures the frequency of the data collection trips and $E_{b,k}^{collection}$ is the energy consumed for one charging cycle by UAV k assuming battery b is installed. Also, E_b^{useful} is the actual useful energy of a battery. Specifically, $E_b^{useful} = \epsilon \times E_b^{max}$ where ϵ is max depth of discharge and E_b^{max} is the battery capacity (in Wh). Looking back at (2), $C_{b,k}^{tot}$ is the operating cost of all trips per year assuming battery b is used with UAV k and can now be calculated as follows:

$$C_{b,k}^{tot} = \varrho \times \frac{E_{b,k}^{year}}{\varphi}, \tag{5}$$

where $\frac{E_{b,k}^{year}}{\varphi}$ is the consumed charging energy, ϱ is the price per Wh in dollars and φ is the discharging/charging efficiency.

A. Trip planning constraints

For any UAV k and for any point u that is visited in trip t, the total number of all outgoing trips to any other point needs to be equal to 1. In addition, for any point w, the total number of incoming trips from any other point needs to be equal to 1. Noting that these constraints do not hold for the starting point s_k, they can be formulated, respectively, as

$$\sum_{w \in \mathcal{N}_k} Z_{u,w,t,k} = 1, \forall u \neq s_k, \forall t, \forall k, \tag{6}$$

$$\sum_{u \in \mathcal{N}_k} Z_{u,w,t,k} = 1, \forall w \neq s_k, \forall t, \forall k. \tag{7}$$

In addition, to ensure that the starting point s_k for the k^{th} UAV has only one outgoing connection and only one ingoing connection in each trip t, the following two constraints are needed:

$$\sum_{u \in \mathcal{N}}^{N} Z_{u,s_k,t,k} = 1, \forall t, \forall k, \tag{8}$$

$$\sum_{w \in \mathcal{N}}^{N} Z_{s_k,w,t,k} = 1, \forall t, \forall k. \tag{9}$$

Now, based on the above definitions, the total UAV flying time during trip t is equal to

$$T_{t,k}^{fwd} = \frac{\sum_{u=1}^{N} \sum_{w=1}^{N} d_{u,w} Z_{u,w,t,k}}{V_k^{fwd}}, \forall u, w \in \mathcal{N}_k, \tag{10}$$

where V_k^{fwd} is the speed of UAV k in the horizontal motion between any two points in km/h and $d_{u,w}$ is the distance between points u and w in km, which is simply calculated as $d_{u,w} = \|\boldsymbol{q}_u - \boldsymbol{q}_w\|$. Moreover, the total hovering time of UAV k during trip t is calculated as

$$T_{t,k}^{hov} = T^{HOV} \left(\sum_{u \in \mathcal{N}_k} \sum_{w \in \mathcal{N}_k} Z_{u,w,t,k} \right), \forall t, \forall k, \tag{11}$$

where the quantity inside the parentheses represents the total number of buildings visited in trip t by UAV k.

Finally, observing that UAVs do not work all day One needs to add the following constraint:

$$T_{t,k}^{fwd} + T_{t,k}^{hov} \leq \tau_k, \forall k, \forall t, \tag{12}$$

where τ is the maximum number of working hours per UAV.

B. Number of UAVs and UAV power source sizing constraints

We first observe that a specific battery cannot be assigned to a certain UAV unless this UAV is already selected to execute trips. Also, this selected battery must have a large enough capacity to cover the distance between the starting point of the selected UAV and the furthest building in the city. This clearly leads to the following constraint, respectively, as

$$\sum_{b \in \mathcal{B}} Y_{b,k} = X_k, \forall k. \tag{13}$$

$$\sum_{b \in \mathcal{B}} Y_{b,k} d_b^k \geq 2 d_{s_k,n}, \forall n \in \mathcal{N}, \forall k, \tag{14}$$

where d_b^k is the maximum distance covered by the battery of UAV k and $d_{s,n}^k$ is the distance between the start point of UAV k and any building n that needs to be visited.

Next, it is clear that the discharge power limit of the UAV's battery should be greater than the maximum consumed power of the battery during either hovering and data collection or forward motion, which translates into the following constraint:

$$\sum_{b \in \mathcal{B}} Y_{b,k} P_b^{\max} \geq \max\left(P_{b,k}^{hov}, P_{b,k}^{fwd}\right), \forall k, \tag{15}$$

where $P_b^{\max} = E_b^{max} \cdot C_b^{rate}$, is the maximum discharge of battery b, $E_b^{max} = C_b \cdot V_b$, where C_b^{rate} is the C-rate of battery b in h^{-1}[13], V_b is its voltage rating and C_b is its capacity in Ah., $P_{b,k}^{hov}$ is the power consumed during the hovering of UAV k when powered by battery b, and $P_{b,k}^{fwd}$ is the power consumed

$$P_{b,k}^{hov} = m_{b,k}^{tot} g v_{air} = m_{b,k}^{tot} g \sqrt{\frac{2 m_k^{tot}}{n_k A_k \rho}}, \tag{16}$$

during the forward movement of the UAV k. Now, the maximum discharge battery b is calculated as

where $m_{b,k}^{tot} = m_{0,k} + \sum_b Y_{b,k} m_b$, where $m_{0,k}$ is the dead mass of the UAV k, m_b is the mass of battery b, g is the gravitational acceleration, ρ is the density of air, n_k is the number of the UAV rotorsand v_{air} is the velocity of air. In (16), A_k is the area of the cylindrical mass of air. Finally, $P_k^{fwd}$is constant for the UAV k and can be calculated as:

$$P_k^{fwd} = \frac{1}{2} \rho n_k A_k v_{air} \left(v_{air}^2 - v_{f,k}^2 \sin \theta_k^2\right), \tag{17}$$

where $v_{f,k}$ is the UAV velocity of forward movement and θ is its tilt angle.

Next, the useful energy of the battery must be enough to cover each trip assuming the battery is recharged between trips. Hence,

$$\sum_b Y_{b,k} E_b^{useful} \geq E_{t,b,k}, \forall t, \tag{18}$$

where $E_{t,b,k}$ is the consumed energy during trip t by using UAV k when installing battery b, which is calculated as:

$$E_{t,b,k} = E_{t,k}^{fwd} + E_{t,b,k}^{hov}, \tag{19}$$

where $E_{t,k}^{fwd}$ and $E_{t,b,k}^{hov}$ are the consumed energies by UAV k during the forward motion and while hovering in trip t, respectively and are calculated as:

$$E_{t,k}^{fwd} = P_k^{fwd} \times T_{t,k}^{fwd}, \forall t, \forall k, \tag{20}$$

$$E_{t,b,k}^{hov} = P_{b,k}^{hov} \times T_{t,k}^{hov}, \forall t, \forall k, \forall b. \quad (21)$$

Finally, the total consumed energy for UAV k during all trips is given by

$$E_{b,k}^{collection} = \sum_{t} E_{t,k}^{fwd} + \sum_{t} E_{t,b,k}^{hov}. \quad (22)$$

IV. Proposed Solution approach

As explained earlier, the optimization problem we proposed in (5) tries to jointly find the optimal number of UAVs, their associated batteries, the optimal starting point of each UAV as well as the optimal trip plan to be followed in order to minimize the total annual cost of the data collection process for the utility. This problem is a mixed-integer nonlinear program (MINLP), which is generally complicated to find an optimal solution for. In order to solve the previously introduced MINLP optimization problem, it is decoupled into two sub problems. The outer sub problem is solved using GA and inside the fitness function of the GA, we use branch-and-bound as a solution for the internal TSP sub problem. The two sub problems are solved in the following steps: The outer sub problem GA selects the optimal number of UAVs, their corresponding battery sizes, the optimal starting point for each UAV, and the assigned buildings to each UAV. Moreover, the GA assigned these buildings to trips. The GA then passes the selection to the internal branch-and-bound problem. The latter solves the TSP and calculates the optimal path for each trip. After path calculation, the GA uses the specifications of the selected battery and the selected path to check the constraints for each trip, as in (15) and (18), respectively. If the constraints are not satisfied, a high penalty is assigned to the fitness function and the GA generates anew population. Finally, if the stopping criterion is met, the process terminates.

TABLE I
Simulation Parameters

Parameters	Value	Parameters	Value
BW	2.4 GHZ	A_k	0.045216 m^2
H	100 m	n_k	4 rotors
V	20 km/hr	L_b^{cycle}	400
σ^2	−110 dBm	μ	12 monthly/52 weekly
L^{los}	2 dB	φ	90%
β_0	−60 dB	L_{max}	5 years
d_i	5 m	α	2.5 [14]
p_n	0.1 W	$cost_k$	526.7 $
$\mathcal{E}$	80 %	L_k^{year}	5 years
ϱ	10^{-4} $	f	910 MHZ
τ	110 monthly/25 weekly	Number of smart meters/building	50
$m_{0,k}$	0.94 kg	D/smart meter	1115 kbits weekly /4950 kbits monthly

TABLE II
Candidate Batteries Specifications

Battery	V	C	C^{rate}	m_b	Price ($)
1	11.1	350	70	0.11	8.12
2	11.1	450	70	0.12	12.18
3	11.1	1000	70	0.32	14.77
4	11.1	2200	25	0.18	15.12
5	11.1	1500	100	0.14	17.03
6	11.1	2200	25	0.41	18.62
7	11.1	2700	30	0.23	20.45
8	11.1	2200	25	0.29	20.82
9	7.4	6000	40	0.21	24.76
10	7.4	5000	50	0.2	36.50
11	11.1	7000	40	0.41	40.90
12	22.2	3200	60	0.51	48.6
13	11.1	3000	30	0.28	53.73
14	14.8	6000	50	0.59	56.7
15	22.2	5000	75	0.88	61.02
16	22.2	8000	60	1.24	85.59
17	22.2	10000	25	1.37	109.08
18	22.2	20000	25	1.5	148.64
19	22.2	22000	25	1.77	198.18

V. Simulation results and Discussions

In this section, some selected simulation results are provided to illustrate the effectiveness of the proposed approach. We implemented the solution approach proposed using MATLAB and the different simulation parameters are summarized in Table I. Moreover, we used the specifications of the commercial smart meter in [15]. We also assumed that each building has a number of smart meters and that all the meters in the building will send their data to a central server from which the UAV will be responsible for collecting the total sum of data using Wi-Fi technology. Furthermore, we assume that the distance between the UAV and the central server during data collection is equal for all buildings and is equal to or less than 10 meters. For simplicity, we assumed a set of 19 identical UAVs whose specifications are summarized in Table I. In addition, a set of 19 battery whose specifications are summarized in Table II are used.

In addition, each UAV is assumed to work 5 hours per day maximum and 22 days per month or 5 days per week. The resulting solutions for the optimization problem in the different considered cases are presented in Table III. In the following subsections, we comment on the impact of the buildings' density, the area of the city as well as the data collection frequency on the obtained solution.

A. Impact of buildings' density

Assuming the same city area and data collection frequency. As shown in Table III, for the case of 10 buildings/km^2 and a 1 km × 1 km city, the optimal number of trips is found to be three trips per month to collect all the required data from all smart meters, and the total annual cost is about 125.2$. When the density is increased to 50 buildings/km^2 for the same city area, the number of trips is found to increase to 21 trips per month and the cost increases to 127.7$.

On the other hand, increase the density of buildings leads to increase the number of UAVs as shown in Table III.

B. Impact of the coverage area

For the same buildings' density and data collection frequency, increasing the city area leads to an increase in the distances the UAV needs to take in order to collect the target data from buildings. Consequently, the number of trips increases, the UAV consumes more energy and an increase in the total annual cost is expected. Compared to the results where the city area was 1 km × 1 km, when the city area is increased to 3 km × 3 km while keeping the same buildings' density, the number of trips increases to 20 trips per month, a UAV with larger battery is chosen by the algorithm. Also, the total annual cost increases to 172$ as shown in Table III. Also increasing the area of the city leads to increase the number of UAVs as shown in Table III.

C. *Impact of data collection frequency*

Assuming an area of 1 km × 1 km and a density of 30 buildings/km^2, if the collection frequency is monthly, the number of trips is found to be 12 as shown in Tables III. Clearly, the algorithm selects a UAV with a small battery and the cost is 125.3$. If the collection frequency increases to become weekly, the number of trips changes to 12 trips per week, the algorithm selects a large battery and the cost becomes 133.5$. This means that collecting data on a weekly basis leads to a threefold increase in the cost when compared to monthly collection. On the other hand, collection frequency affects the number of UAVs as shown in Table III.

VI. CONCLUSIONS

In this paper, we have studied UAV-enabled data collection from smart meters. We have formulated and solved an optimization problem where the total annual cost is minimized by jointly determining the optimal path for a trip as well as selecting the optimal number of UAVs, their associated batteries and the optimal starting point for each UAV. The resulting MINLP optimization problem has been solved using an iterative algorithm alternating between a GA algorithm and a branch-and-bound. Simulation results have shown the impact of the city area, density and collection frequency on the selection of optimal battery and the selection of an optimal path for each trip.

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TABLE III
SIMULATION RESULTS

City Area	Buildings' Density	**10 buildings/km^2**		**30 buildings/km^2**		**50 buildings/km^2**		**100 buildings/km^2**	
	Data collection frequency	monthly	weekly	monthly	weekly	Monthly	weekly	monthly	weekly
1 km × 1 km	Total annual cost ($)	125.2	125.3	125.3	133.5	127.7	143.3	133.1	168.1
	Battery used	2200mAh @ 11.1 V	2200mAh @ 11.1 V	2200mAh @ 11.1 V	6000 mAh @ 7.4 V	6000 mAh @7.4 V	6000 mAh @ 7.4 V	6000 mAh @ 7.4 V	20,000 mAh @ 22.22 V
	Number of trips	3	2	12	12	21	21	43	2
	Starting point(s)	(542.6, 533)	(520.5, 440.1)	(500, 500)	(500, 500)	(500, 500)	(500, 500)	(481.9, 501.8)	(481.9, 495.3)
2 km × 2 km	Total annual cost ($)	133.1	170.1	164.5	299	192.2	416.1	269.3	791.3
	Battery used	6000 mAh @ 7.4 V	6000 mAh @ 7.4 V	7000 mAh @ 11.1 V	7000 mAh @ 11.1 V	7000 mAh @ 11.1 V	7000 mAh @ 11.1 V	7000 mAh @ 11.1 V	20,000 mAh @ 22.22 V
	Number of trips	24	24	66	70	118	121	254	44
	Starting point(s)	(879, 1251.3)	(572.5, 1147)	(1000, 1000)	(964.1, 1001.3)	(924.4, 983.1)	(1080, 1009.7)	(1000, 1000)	(1000, 1000)
3 km × 3 km	Total annual cost ($)	172	388.8	333.7	985.7	489.2	1,957	1,071.7	4,189.5
	Battery used	20,000 mAh @ 22.2 V	20,000 mAh @ 22.2 V	20,000 mAh @ 22.2 V	20,000 mAh @ 22.2 V	20,000 mAh @ 22.2 V	Two identical 20,000 mAh @ 22.2 V	Two identical 20,000 mAh @ 22.2 V	Three identical 22,000 mAh @ 22.2 V
	Number of trips	20	19	73	71	123	U_1=67, U_2=71	U_1=146, U_2=141	U_1=99, U_2=87 U_3=87
	Starting point(s)	(902, 919.6)	(902.2, 919.5)	(1410, 1590)	(1349.1, 1650.9)	(1511, 1499.8)	(1429, 1805) (1489, 1620)	(1982, 1562) (1905, 1906)	(1773, 1295.6) (1656, 1791.5) (1312.3, 1304)