

Optimising the Vehicle Routing Problem with Time Windows under Standardised Metrics

1st Krupa Prag

CSAM, University of the Witwatersrand
Johannesburg, South Africa
e-mail: Krupa.Prag@wits.ac.za

2nd Matthew Woolway

CSAM, University of the Witwatersrand
Wits Institute of Data Science
Johannesburg, South Africa
e-mail: Matthew.Woolway@wits.ac.za

3rd Byron A. Jacobs

CSAM, University of the Witwatersrand
Maths & Stats, UNSW Australia
Johannesburg, South Africa
e-mail: Byron.Jacobs@wits.ac.za

Abstract—The Vehicle Routing Problem with Time Windows (VRPTW) is an established \mathcal{NP} -hard Combinatorial Optimisation Problem (COP). While much research has been undertaken in developing solution mechanisms to the VRPTW, this work has been developed without comparative metrics. Previous work on the VRPTW has failed to provide both a comprehensive computational review comparing the performance of metaheuristics applied to finding solutions to the VRPTW under standardised experimental conditions, and the effects of the employed metric schemes. This work aims to introduce a means of comparison between leading metaheuristic methods found in the literature. Conducted experiments applied Genetic Algorithm (GA) and Particle Swarm Optimisation algorithm (PSO) under two standardised metrics on a well-known benchmark dataset. The results verify and resemble previously reported results, question the design of the applied metric schemes and record the CPU time taken to obtain solutions to the VRPTW. This computational comparative review critically analyses, compares and comments on the replicated applied techniques and employed metric schemes. Significant results include: obtaining competitive timings relative to those which have been reported if the GA is terminated when the best known solution is met; the quality of the solutions produced by the GA and the PSO algorithm; insight into the design of the metric schemes. The results obtained match the benchmark values, and the time within which the solutions are computed are competitive with the benchmark times. The solution technique and metric scheme combination which, in general, efficiently obtained solutions to the VRPTW are the PSO algorithm and Metric A.

Keywords—Vehicle routing, optimisation; genetic algorithm; particle swarm optimisation

I. INTRODUCTION

Optimising the logistics of the distribution procedure is an important topic of study in the field of Operational Research. The Vehicle Routing Problem with Time Windows (VRPTW) is a particularly well defined logistics problem. The VRPTW is classified as a \mathcal{NP} -hard problem, a Combinatorial Optimisation Problem (COP) and can be formulated as a Multi-objective Optimisation Problem (MOP). The VRPTW entails designing a set of minimum cost routes, originating and terminating at a central depot, for a fleet of vehicles which service a set of customers with known

demands. Since the VRPTW is formulated as a MOP by Solomon in [1], the goal is to minimise: the number of vehicles dispatched, the waiting time to service a customer, total travel time, and accumulated total travelled distance incurred by the fleet of dispatched vehicles.

Literature ([2]–[5]) on the VRPTW records obtaining solutions to the VRPTW using both deterministic and non-deterministic techniques. Due to the potential held by non-deterministic techniques to produce quality solutions in reasonable time, in comparison to deterministic techniques, in solving unstructured realistic size problems, the two compared non-deterministic metaheuristic solution techniques replicated and applied to the VRPTW problem instances set-up by Solomon [6] in this paper are the Genetic Algorithm (GA) [7] and the Particle Swarm Optimisation (PSO) algorithm [8].

II. BACKGROUND

In this paper, a computational comparative review is conducted of applied optimisation techniques and employed solution evaluation formulations in finding solutions to the VRPTW, which was initially proposed by Solomon in [1]. Surveying the literature on the VRPTW, it was found that both deterministic and non-deterministic optimisation techniques have been applied to find solutions to this COP. The performance of the applied solution schemes were directly compared with the obtained results recorded in the literature. Due to the different implementation styles, programming languages and hardware used in conducting the experiments, a fair comparison cannot be claimed.

A. Mathematical Model

The VRPTW is represented by a fleet of homogeneous vehicles denoted by \mathbf{V} , and a directed graph $G = (\mathbf{C}, \mathbf{A})$. In graph G , the vertex set is represented by \mathbf{C} and the arc set \mathbf{A} . In the vertex set $c_i \in \mathbf{C}$, $\{i \in [0, n] \mid i \in \mathbb{N}_0\}$, where c_0 denotes the depot and $c_i \forall i \in [1, n]$ denote the n customers which are to be served. Each customer $c_i \in \mathbf{C}$, where $i \in [1, n]$, has delivery details associated to them. These details are tabulated in Table I. Note, all these variables are assumed to be non-negative. The details corresponding to the depot, that is where $i = 0$, are given in Table II.

The authors thank the National Research Foundation (NRF) in South Africa for funding this work under the CoE-MaSS, as well as the Wits Institute of Data Science (WIDS) and BankSeta.

TABLE II: Depot Detail Variables

Customer Detail Variables	
Variable	Description
q_i	Demand.
s_i	Service time.
e_i	Earliest time to start servicing customer c_i .
l_i	Latest time to start servicing customer c_i .

TABLE I: Customer Detail Variables

Depot Detail Variables	
Variable	Description
q_0	$q_0 = 0$.
s_0	$s_0 = 0$.
e_0	Earliest time that any vehicle is allowed to be dispatched from the depot c_0 .
l_0	Latest time that any vehicle is allowed to return the depot c_0 .

In graph G , the arc set is given as $\mathbf{A} = \{\langle c_i, c_j \rangle | c_i, c_j \in \mathbf{C}, i \neq j\}$. Each arc $\langle c_i, c_j \rangle$ is associated with a Euclidean distance d_{ij} between the two vertices c_i and c_j , where $d_{ij} = d_{ji}$. Due to the condition that service routes begin and terminate at the depot, the arc set starts and ends at c_0 for each service route. The design of routes to service all the customers requires a binary decision variable a_{ij}^r . If there exists an arc between c_i and c_j which is traversed by vehicle v_r then $a_{ij}^r = 1$, otherwise $a_{ij}^r = 0$. A customer c_i , $\{i \in [1, n] | i \in \mathbb{N}\}$, begins to be serviced with their specified time window $[e_i, l_i]$, this start time is denoted by b_i . A vehicle v in \mathbf{V} is indexed by r , where $\{r \in [1, |\mathbf{V}|] | r \in \mathbb{N}\}$. A binary decision variable is used to indicate by which vehicle, r , a customer, c_i , is serviced. If customer i is serviced by vehicle r , $b_i^r = 1$, otherwise $b_i^r = 0$. For any vehicle $v_r \in \mathbf{V}$, the maximum capacity that any vehicle may be loaded with is denoted by Q , where $Q > 0$.

The goal of the VRPTW is to design a set of minimal cost routes whereby each customer is visited exactly once, and the time windows and capacity constraints are observed. The VRPTW's primary objective is to reduce the number of vehicles to be dispatched, and it's secondary objective is to reduce the total travelled distance by the dispatched vehicles. These two objectives are respectively expressed by Equations (1) and (2).

$$\min Z_1 = |\mathbf{V}|, \quad (1)$$

and

$$\min Z_2 = \sum_{i=0}^n \sum_{j=0}^n \sum_{r=1}^{|\mathbf{V}|} a_{ij}^r d_{ij}. \quad (2)$$

subject to,

$$\sum_{i=0}^n a_{ij}^r = b_j^r \quad \forall r = 1, \dots, |\mathbf{V}|, \quad \forall j = 1, \dots, n \quad (3)$$

$$\sum_{j=0}^n a_{ij}^r = b_i^r \quad \forall r = 1, \dots, |\mathbf{V}|, \quad \forall i = 1, \dots, n \quad (4)$$

$$\sum_{i=0}^n b_i^r \times q_i \leq Q, \quad \forall r \in 1, \dots, |\mathbf{V}| \quad (5)$$

$$\sum_{r=1}^{|\mathbf{V}|} b_i^r = 1, \quad \forall i = 1, \dots, n \quad (6)$$

$$\sum_{r=1}^{|\mathbf{V}|} b_0^r = |\mathbf{V}| \quad (7)$$

$$t_i + w_i + s_i + t_{ij} = t_j, \quad \forall i, j = 0, \dots, n, \quad i \neq j \quad (8)$$

$$e_j \leq t_j \leq l_j, \quad \forall j = 0, \dots, n \quad (9)$$

$$w_i = \max \{e_i - t_i, 0\} \quad \forall i = 0, \dots, n. \quad (10)$$

The constraints given in Equation (3) and Equation (4) denote that exactly one arc enters and leaves each vertex associated with a customer. The constraint given by Equation (5) states that each vehicle must not be loaded with more than its carrying capacity Q . The constraint given by Equation (6) states that each customer can only be served by one vehicle. The constraint given by Equation (7) represents that all routes start from the depot. Formula (8) defines t_j , the time at which the customer c_j starts to be serviced; t_j is the sum of: the time of arrival at customer c_i , denoted by t_i , the waiting time or idle time before starting to service customer c_i within its specified time window, the time to service customer c_i , denoted by s_i , the travel time between customer c_i and c_j , denoted by t_{ij} . The time window within which customer c_j starts to be serviced is denoted by Formula (9), where e_j is the earliest time at which customer c_j can start to be serviced and l_j is the latest time at which the customer can start to be serviced, thus the time at which customer c_j starts to be serviced is the sum of the time of arrival at customer c_j and the waiting time to service customer c_j . The waiting time is calculated using Formula (10).

III. SOLUTION TECHNIQUES

As the VRPTW problem size scales, the problem requires exponentially increasing number of enumerations. Hence, it is not feasible to obtain deterministic solutions in reasonable time. Thus, the two non-deterministic solution techniques applied are the GA and the PSO algorithm. The parameter values stipulated in Table III and Table IV are respectively obtained from the application of the GA and PSO algorithm to the VRPTW conducted by [7] and [8]. Note, the parameters referred to in the Comprehensive Learning PSO (CLPSO) are found in [9].

A. Critical Review

Critically comparing the implemented solution techniques to their references, the assumptions made must be highlighted. In replicating the GA for the VRPTW from [7], the paper does not explicitly state the numerical values used in initialising the initial candidate solution. The greedy encoding method requires the next customer to be selected within some empirical Euclidean distance. The calculation of the range within which the nearest neighbour is to be

TABLE III: Parameter Values of the Applied GA to the VRPTW

Variable	Variable Description	Value
Z	Number of chromosomes in population Γ	300
α	Weight coefficient for the number of vehicles in the fitness function Λ	100
β	Weight coefficient for the total accumulated travel distance in the fitness function Λ	0.001
μ	Percentage of initial population encoded using Random Permutation Encoding	90%
ρ	Tournament selection benchmark probability of selecting the <i>fittest</i> chromosome	0.8
K	Number of chromosomes κ selected for the tournament selection set T	4
ρ	Probability of mutation	0.1
Υ	Predefined terminating number of generations	350
θ	Crossover rate	0.8
rad	Empirical radius used in selecting the nearest neighbours in the initialisation of candidate solutions	$\frac{(max - min)}{2}$

TABLE IV: Parameter Values of the Applied PSO algorithm to the VRPTW

Variable	Variable Description	Value
N	Number of particles in population P	20
σ_1	Random weight value associated to the cognitive term	2
σ_2	Random weight value associated to the social term	2
ζ_1	Weight for cognitive term, between	(0,1)
ζ_2	Weight for social term, between	(0,1)
ϕ	Probability of greedy initialisation	0.3
ω	Inertia weight coefficient for CLPSO velocity update. Linearly decreases from:	0.9 to 0.4
P_c	Current learning probability	2
sg	Global terminating criterion (25 customers; 50 and 100 customers)	1000;10000
rg	PSO criterion	7

selected is not specified. Hence, the following calculation has been used:

$$rad = \frac{max - min}{2},$$

where the nearest neighbour is searched for within the radius rad , and max and min respectively represent the maximum and minimum distances between any two vertices in the dataset. This formulation was used as all customers had fallen within this range with respect to each other.

The PSO algorithm for VRPTW applied in [8] does not explicitly state all the parameters selected for the implementation, but refers to the parameter values selected by the CLPSO application in [9]. The selected values are given in Table IV.

Each particle's position and velocity in the PSO algorithm have been defined using a square matrix representing all the states, such that an arc from state a to b in a matrix defined as $\langle a, b \rangle$. The details of these matrices are given as follows:

- **Position:** for an arc between a and b , $\langle a, b \rangle$, is set to be a binary value. That is if the arc exists then the position value of the arc is set to 1, and 0 otherwise.
- **Velocity:** for an arc between a and b , $\langle a, b \rangle$, is set to be a probability, thus a value between 0 and 1. The arc does not have to necessarily exist in the current route design solution, however, this defines a probability

associated to the particular arc. At initialisation the probability of each of the possible arcs between any two states have been set to a value between 0 and 1 generated using an uniform distribution.

IV. METRICS

As the VRPTW is formulated as a MOP it aims to minimise the weighted sum of two objective values; the number of dispatched vehicles and their accumulated distance. Two particular metrics are considered in evaluating the solution designs, these are discussed respectively in Section IV-A and Section IV-B.

A. Metric A

Metric A, presented by [7], evaluates a solution to the VRPTW as a weighted sum as defined in Equation (11). The value of Λ sums the objective functions: the number of vehicles $|V|$ dispatched to service all the customers C and the distances D of the accumulated distance travelled by the dispatched vehicles, hence transforming the objective function of the VRPTW into a single optimisation problem. The parameters α and β weight the two aforementioned objectives.

$$\Lambda = (\alpha \cdot |V|) + (\beta \cdot D). \quad (11)$$

B. Metric B

Metric B, presented in [8], evaluates a solution to the VRPTW by summing both the number of vehicles $|V|$ used to service all the customers and the normalised value of the accumulated distance travelled D , given in Equation (13). The sum of the objective functions is represented by Θ and is defined by Equation (12).

$$\Theta = |V| + \text{normalise}(D). \quad (12)$$

$$\text{normalise}(D) = \arctan(D)/(\pi/2). \quad (13)$$

Both Metric A and Metric B's primary objective is the number of vehicles dispatched and the secondary objective is the total travelled distance. These metrics award a greater penalty to the number of dispatched vehicles in comparison to the total travelled distance. In the case of Metric B, it is noted that the normalisation of the total travelled distance value D tends to 1 when $D > 10$, since all recorded distances are greater than 10, this imposed penalty is insignificant. Furthermore, due to the sensitivity of the sigmoid function, the metric is highly sensitive to machine precision.

V. EXPERIMENTAL RESULTS

Solomon introduced the benchmarking data [6] for the VRPTW, on which all experiments were conducted. To highlight the influence of the geographical arrangements of the customers and time window positioning, the problem sets are categorised into three spatial classes: random, clustered and random-clustered; and two temporal classes: short and long time horizons.

The results recorded in Table V tabulate benchmark results alongside the experimental results. The benchmark

results record the best known results to the VRPTW problem instances and the results obtained by applying a PSO algorithm given in [8]. It must be noted that the GA applied in [7] does not record the results for the problem instances comprising of 25 customers. The experimental results recorded are obtained by applying both the GA and the PSO to the VRPTW using the two respective metric schemes, Metric A and B. For each problem instance, the first row records the result obtained when the algorithm applied is run to completion and the second row records the results obtained when the algorithm is executed with an additional condition for termination which states to terminate the algorithm if the solution's result matches either of the benchmark results. Each result records the number of dispatched vehicles (NV), the total travelled distance by the dispatched vehicles (DIST) and the CPU time in seconds (Time) taken to obtain the solution to the respective problem instances.

Analysing the solution to the problem instances with only 25 customers, it is found that the irrespective of the solution technique and metric used, there is greater variability in the solutions produced when customers have wider service time windows, and if the spatial class is random or random-clustered; that is in contrast to the customers spatially clustered with shorter time windows. Thus, highlighting the influence of the spatial and temporal characteristics of the problem. The GA is found to be more robust than the PSO algorithm as the produced solutions are indifferent irrespective of the employed metric. Solutions produced using the GA were found to dispatch fewer vehicles than the solutions produced using the PSO algorithm, whereas the PSO algorithm's solutions were compensated by lower accumulated wait time and total travelled distance. As the problem scales, the PSO algorithm with Metric A is competitive to the solutions produced using the GA with respect to CPU time.

A. Experimental Settings

The applied solution technique algorithms are coded in Python 3[®] and are run on an Intel[®] Xeon(R) CPU E5-2683 v4@2.10GHz 32-core processor machine. Each experiment was independently run 30 times. The best result obtained from the 30 experiments are recorded. The results to the VRPTW containing 25 customers are tabulated in Table V. The Python scripts and the Solomon data sets can be found at [11]. A comprehensive study of the applications to the VRPTW datasets with 50 and 100 customers can be found in [10].

VI. CONCLUSION

Conducting a comparative review under standardised experimental conditions of metaheuristic techniques applied to the VRPTW, conclusions are drawn with respect to the applied solution techniques, metric schemes and the CPU time.

Critically comparing the applied metric schemes, both Metric A and Metric B are formulated as weighted sums of the objective values; number of dispatched vehicles and total travelled distance. The design of the metrics are respective to the prioritised objectives and are selected dependent on the specifics of the problem.

A possible factor to include in the metric evaluation scheme in search of solutions with efficiently designed routes is the accumulated waiting time or the total time which dispatched vehicles are idle in order to satisfy the customer's stipulated time window.

With regard to the CPU times, the benchmark results are computed using the C programming language, whereas the recorded results are computed using the Python programming language. The CPU times obtained for when the algorithms are terminated when the benchmark solution is met can be directly compared to the benchmark recorded times. These times are also in general more competitive to that when the applied solution techniques are run to completion.

Summarising the results obtained by applying the GA and the PSO algorithm, it is found that, in general, the results obtained using either the GA or the PSO algorithm with Metric A meet the benchmark results quicker than when Metric B is used. The combination of the PSO algorithm with Metric A are found to produce the best quality solutions in general, when execution time is prioritised and the solution technique is stipulated to run to completion.

REFERENCES

- [1] Solomon MM. Algorithms for the vehicle routing and scheduling problems with time window constraints. *Operations Research*. 1987 Apr;35(2):254-65.
- [2] Bräysy O, Gendreau M. Vehicle routing problem with time windows, Part I: Route construction and local search algorithms. *Transportation Science*. 2005 Feb;39(1):104-18.
- [3] Baldacci R, Mingozzi A, Roberti R. Recent exact algorithms for solving the vehicle routing problem under capacity and time window constraints. *European Journal of Operational Research*. 2012 Apr 1;218(1):1-6.
- [4] Bräysy O, Gendreau M. Vehicle routing problem with time windows, Part II: Metaheuristics. *Transportation Science*. 2005 Feb;39(1):119-39.
- [5] Glover F. Tabu Search Part I. *ORSA Journal on computing*. 1989 Aug;1(3):190-206.
- [6] Solomon, Marius M., "Solomon Benchmarking Dataset, Online; accessed 5-March-2018" <https://www.sintef.no/projectweb/top/vrptw/solomon-benchmark/>, 1987.
- [7] Ombuki B, Ross BJ, Hanshar F. Multi-objective genetic algorithms for vehicle routing problem with time windows. *Applied Intelligence*. 2006 Feb 1;24(1):17-30.
- [8] Gong YJ, Zhang J, Liu O, Huang RZ, Chung HS, Shi YH. Optimizing the vehicle routing problem with time windows: a discrete particle swarm optimization approach. *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)*. 2011 May 27;42(2):254-67.
- [9] Liang JJ, Qin AK, Suganthan PN, Baskar S. Comprehensive learning particle swarm optimizer for global optimization of multimodal functions. *IEEE transactions on evolutionary computation*. 2006 May 30;10(3):281-95.
- [10] Prag K, "Computational Logistics of the Vehicle Routing Problem," University of the Witwatersrand, GitHub: <https://github.com/KrupaPrag/VRPTW>, 2019.
- [11] Prag K, "Vehicle Routing Problem with Time Windows," GitHub: <https://github.com/KrupaPrag/VRPTW>, 2019.

TABLE V: Results to VRPTW (25 Customers).

Dataset	Benchmark		Genetic Algorithm										Particle Swarm Optimisation												
			Reported					Metric A					Metric B					Metric A					Metric B		
	NV	DIST	NV	DIST	Time	NV	DIST	Time	NV	DIST	Time	NV	DIST	Time	NV	DIST	Time	NV	DIST	Time	NV	DIST	Time		
C101	3	191.3	3	191.81	7.8	3	191.81	378.79	3	191.81	383.25	3	191.81	32.93	3	191.81	33.76								
C102	3	190.3	3	190.74	7.8	3	191.81	11.91	3	198.6	19.39	3	191.81	32.87	3	217.57	34.53								
						3	190.74	370.95	3	190.74	430.17	3	213.03	37.06	3	225.65	42.46								
C103	3	190.3	3	190.74	8.4	3	190.74	10.9	3	192.1	9.07	3	213.03	34.67	3	217.54	32.09								
						3	190.74	317.58	3	190.74	378.07	3	207.6	39.8	3	210.68	39.35								
C104	3	186.9	3	187.45	8.4	3	190.74	10.59	3	220.98	6.88	3	200.42	40.07	3	205.56	39.76								
						3	187.45	313.41	3	187.45	346.05	3	200.91	51.04	3	206.5	54.08								
C105	3	191.3	3	191.81	7.8	3	187.45	278.68	3	194.09	5.38	3	203.11	48.1	3	207.96	52.35								
						3	191.81	406.41	3	191.81	450.01	3	191.81	34.99	3	191.81	36.3								
C106	3	191.3	3	191.81	7.8	3	191.81	19.65	3	191.81	18.02	3	191.81	35.1	3	191.81	34.21								
						3	191.81	421.51	3	191.81	386.06	3	191.81	33.2	3	191.81	35.44								
C107	3	191.3	3	191.81	7.2	3	191.81	36.09	3	191.81	15.96	3	191.81	33.79	3	191.81	34.43								
						3	191.81	383.23	3	191.81	371.71	3	191.81	34.67	3	191.81	35.04								
C108	3	191.3	3	191.81	8.4	3	191.81	17.18	3	206.06	13.26	3	191.81	35	3	191.81	40.61								
						3	191.81	369.23	3	191.81	364.8	3	191.81	41.22	3	199.88	43.21								
C109	3	191.3	3	191.81	7.8	3	191.81	30.2	3	202.33	10.16	3	193.17	40.99	3	192.18	39.15								
						3	191.81	364.4	3	191.81	360.15	3	204.82	39.88	3	205.89	38.32								
R101	8	617.1	8	618.33	9	3	191.81	9.71	7	226.1	7	3	204.82	43.21	3	204.82	38.36								
						9	689.85	711.99	9	730.32	663.3	8	619.17	40.99	8	625.19	42.49								
R102	7	547.1	7	548.11	14.4	9	689.85	590.97	10	733.91	815.09	8	619.17	41.78	8	619.17	43.19								
						7	551.93	533.22	7	548.11	546.43	7	567.3	43.23	7	567.3	41.97								
R103	5	454.6	4	473.39	8.4	7	548.95	455.29	7	646.81	8.4	7	567.3	45.29	7	577.12	47.41								
						4	459.67	420.72	4	459.67	414.03	4	514.5	45.12	5	511.03	42.87								
R104	4	416.9	4	418.3	10.8	4	480.33	16.85	5	529.57	11.32	4	536.23	46.8	5	480.41	46.53								
						4	417.77	376.06	4	417.77	383.82	4	448.13	50.75	4	468.62	47.75								
R105	6	530.5	5	556.72	8.4	4	417.77	376.73	4	518.98	6.64	4	442.48	54.6	4	529.22	23.66								
						7	638.31	817.91	7	753.23	853.49	5	556.72	39.94	5	556.72	37.39								
R106	3	465.4	5	466.48	10.2	7	667.38	602.91	8	638.68	727.09	5	556.72	41.57	5	585.45	4.78								
						5	466.48	626.93	5	466.48	638.44	5	505.67	44.75	5	515.42	48.22								
R107	4	424.3	4	425.27	12	5	466.48	460.73	5	522.53	15.24	5	505.67	47.96	5	631.63	0.21								
						4	425.27	512.16	4	425.27	519.63	4	454.59	49.1	4	476.31	50.97								
R108	4	397.3	4	405.39	12.6	4	425.27	395.31	4	474.74	9.79	4	467.78	48.3	4	493.38	5.25								
						3	413.87	455.41	3	413.87	439.79	4	439.78	53.78	4	439.38	51.98								
R109	5	441.3	4	460.52	9	3	437.18	11.5	4	472.1	6.18	4	444.77	53.06	4	561.86	3.87								
						5	442.63	614.76	5	442.63	572.04	4	468.16	45.34	4	486.55	44.5								
R110	4	444.1	4	445.8	9	5	442.63	132.53	5	518.26	17.35	4	474.04	48.3	4	523.25	18.26								
						4	469.95	499.87	4	452.22	516.55	4	446.87	45.43	4	446.87	48.88								
R111	5	428.8	4	429.7	9.6	4	469.95	431.09	4	503.57	29.82	4	445.8	48.15	4	480.2	14.05								
						4	429.7	465.63	4	429.7	475.52	4	466.66	48	4	491.69	43.95								
R112	4	393	4	394.1	10.2	4	447.38	9.08	5	487.34	9.87	4	453.79	46.92	4	504.2	18.79								
						4	394.1	419.18	4	394.1	426.26	4	407.06	60.24	4	420.26	57.43								
RC101	4	461.1	4	462.16	7.8	4	394.1	95.79	4	465.57	7.39	4	413.11	51.03	4	523.54	1.29								
						6	554.64	593.4	6	548.04	670.8	4	462.16	39.87	4	476.64	38.29								
RC102	3	351.8	3	352.74	9	6	561.38	561.64	6	557.64	683.44	4	463.85	38.33	4	501.51	2.36								
						3	352.74	458.68	3	352.74	470.68	3	355.37	38.07	3	365.49	36.71								
RC103	3	331.8	3	352.74	9	3	352.74	13.57	3	363.07	14.71	3	355.33	40.09	3	368.34	1.06								
						3	333.92	450.29	3	333.92	423.56	3	339.9	47.39	3	341.48	39.64								
RC104	3	332.8	3	333.92	9	3	333.92	10.68	3	337.45	10.99	3	335.07	43.03	3	357.97	18.93								
						3	305.95	389.01	3	305.95	318.18	3	319.59	45.18	3	322.97	50.5								
RC105	3	306.6	3	307.14	9	3	305.95	322.91	3	332.1	3.25	3	321.65	45.15	3	335.99	4.37								
						4	457.32	479.69	4	481.11	507.78	4	421.37	44.42	4	416.48	41.53								
RC106	4	411.3	4	412.38	7.8	4	466.74	455.99	5	498.78	598.1	4	419.58	44.44	4	452.53	16.19								
						4	443.87	479.51	4	442.86	487.42	3	354.76	37.16	3	355.09	39.58								
RC107	3	345.5	3	346.51	8.4	4	443.87	448.67	4	448.51	580.22	3	352.13	39.95	3	366.76	1.75								
						3	330.23	419.68	3	333.12	426.97	3	316.06	40.75	3	316.92	38.38								
RC108	3	298.3	3	298.95	8.4	3	330.23	390.83	3	351.68	16.72	3	317.68	41.26	3	357.72	2.44								
						3	306.02	345.89	3	306.02	382.78	3	308.13	43.21	3	307.47	45.3								
C201	2	214.7	2	215.54	7.2	3	306.02	345.89	3	332.09	11.37	3	308.38	44.69	3	382.77	1.58								
						1	334.12	1032.05	1	334.12	758.23	2	215.54	31.02	2	215.54	31.39								
C202	2	217.7	1	223.32	7.2	1	334.12	9.64	2	215.54	8.03	2	215.54	31.41	2	293.9	0.08								
						1	223.31	996.91	1	223.31	731.91	1	250.48	33.1	1	249.7	33.76								
C203	2	214.7	1	223.31	11.4	1	223.31	5.21	1	234.81	8.81	1	245.58	33.44	1	312.3	3.99								
						1	223.31	692.51	1	223.31	746.5	1	240.88	37.19	1	248.69	3.16								
C204	2	214.7	1	221.28	12.6	1	223.31	4.76	1	261.46	5.39	1	262.09	38.46	1	330.11	6.12								
						1	213.93	501.09	1	213.93	638.76	1	292.47	46.95	1	320.79	50.92								
C205	2	213.1	1	297.45	6.6	1	212.18	3.07	1	226.34	5.1	1	261.93	51.07	1	330.65	4.46								
						1	297.24	1092.32	1	297.24	759.85	1	297.45	30.09	1	297.45	29.62								
C206	2	214.7	1	285.39	6.6	1	297.24	5.51	2	215.54	6.59	1	297.45	30.85	1	336.8	0.91								
						1	255.54	994.03	1	255.54	695.16	1	289.36	31.77	1	303.86	28.99								
C207	2	214.7	1	274.78	6.6	1	278.05	4.3	1	340.68	4.36	1	285.39	31.56	1	347.23	0.11								
						1	274.78	1039.39	1	274.78	904.38	1	279.42	30.28	1	279.42	30.42								
C208	2	214.5	1	229.84	6.6	1	309.68	3.72	1	299.77	5.56	1	279.42	31.03	1	296.7	0.07								
						1	229.84	906.25	1	229.84	879.8	1	230.01	32.7	1	230.01	33.3								
R201	4	463.3	2	523.66	9	1	229.84	3.36	1	246.11	5.22	1	230.01	32.59	1	336.8	0.08								
						2	523.66	477.5	2	523.66	450.27	2	536.14	37.81	2	562.64	42.89								
R202	4	410.5	2	455.53	12.6	2	567.9	4.87	2	590.07	8.92	2	544.41	38.02	2	536.14	37.81								
						2	457.74	410.08	2	457.57	354.39	2	497.17	38.03	2	508.29	38.82								
R203	3	391.4	2	408.89	13.8	2	653.85	2.33	2	484.5	5.42	2	543.05	38.97	2	497.17	38.03								
						2	406.24	394.56	2	401.29	258.9	2	474.2	40.35	2	492.87	38.09								
R204	2	355	1	389.91	12.6	2	429.93	1.78	2	473.35	4.12	2	460.42	41.63	2	474.2	40.35								
						1	392.25	380.3	1	388.58	521.71	1	467.51	46.42	1	472.55	51.29								
R205	3	393	1	501.83	7.2	1	406.93	2.57	1	455.37	2.55	1	471.05	51.92	1	467.51	46.42								
						1	501.83	605.31	1	501.83	632.95	1	521.71	40.8	1	542.19	42.92								
R206	3	374.4																							