

Reto: Problema del Agente Viajero

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Instrucciones: *Resuelve completa y correctamente cada uno de los siguientes puntos.*

Se evalúa el procedimiento. Resultado sin procedimiento no tiene puntaje alguno.

1. Diseña 10 redes de 40 nodos (direcciones) de forma aleatoria a partir de la siguiente lista de direcciones. Recuerda que vamos a minimizar la distancia recorrida.

Para este paso, se llevó a cabo un script que generó dichas 10 redes, por cantidad de nodos, subsecuentemente guardándolo en 4 diferentes excels: donde en cada uno hay 10 redes de diferentes cantidad de nodos por excel. El primer excel tiene 40 nodos por red, el segundo excel tiene 100 nodos por red, el tercer excel tiene 150 nodos por red, y el cuarto excel tiene 200 nodos por red.

Se anexa una imagen de ejemplo de estos excels:

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y	Z	AA
1	166	34	107	99	240	176	227	132	97	192	232	118	219	25	122	31	72	123	108	209	14	269	278	104	144	150	
2	166	9999.99	12.13789	13.70185	6.0742	8.91392	2.18757	12.20522	8.70839	49.44739	18.75034	12.20522	15.11448	12.20522	10.57317	12.40543	9.59883	9.13349	7.13739	13.91363	12.20522	9.13349	17.37793	1	7.35038	14.94219	8.580
3	34	12.13789	9999.99	1.56518	6.99009	15.81257	10.06546	19.81038	6.10401	60.30231	29.13638	19.81038	4.12108	19.81038	8.97465	8.67797	7.94475	3.48721	5.6506	6.64687	19.81038	3.48721	8.80424	12.13789	5.32297	3.20824	8.755
4	107	13.70185	1.56518	9999.99	7.91107	17.36426	11.63033	21.13697	7.29205	61.70957	30.54274	21.13697	3.27929	21.13697	9.8463	9.24483	8.94346	4.96107	7.11672	6.74446	21.13697	4.96107	7.83314	13.70185	6.8331	2.23415	9.96
5	99	6.0742	6.99009	7.91107	9999.99	12.36018	4.33194	16.28987	3.24319	54.04494	22.90963	12.36018	9.04334	16.28987	6.34601	7.59039	5.04406	4.27531	1.6974	8.20086	16.28987	4.27531	13.2319	6.0742	3.4373	9.47192	7.604
6	240	8.91392	15.81257	17.16426	12.36018	9999.99	8.77234	4.02664	15.60294	53.61599	24.81673	4.02664	19.80598	4.02664	18.43784	19.91418	17.2256	12.36946	13.37655	20.35352	4.02664	12.36946	16.68046	8.91392	10.73733	17.38672	7.401
7	176	2.18757	10.06546	11.63033	4.33194	8.77234	9999.99	12.47449	7.33867	51.58422	20.78433	12.47449	13.24414	12.47449	9.77097	11.41003	8.63242	6.96918	5.40023	12.47753	12.47449	6.96918	15.21904	2.18757	5.16651	12.79591	6.755
8	227	12.20522	19.81038	21.13697	16.28987	4.02664	12.47449	9999.99	19.52435	53.07346	25.7503	1	23.82281	1	22.23486	23.79046	21.05996	16.38252	17.32957	24.34849	1	16.38252	20.03831	12.20522	14.76379	21.21221	11.260
9	132	8.70839	6.10401	7.29205	3.24319	15.60294	7.33867	19.52435	9999.99	54.56369	23.42766	19.52435	7.18935	19.52435	3.46178	4.3789	2.16436	5.83385	2.29471	5.20528	19.52435	5.83385	14.14843	8.70839	5.96661	9.28784	10.475
10	97	49.44739	60.30231	61.70957	54.04494	53.61599	51.58422	53.07346	54.56369	9999.99	31.16744	53.07346	61.56585	53.07346	53.02936	54.76317	53.43926	58.11742	54.66125	58.0138	53.07346	58.11742	66.79484	49.44739	56.5685	63.47565	57.722
11	192	18.75034	29.13638	30.54274	24.81673	20.78433	25.7503	23.42766	31.16744	9999.99	25.7503	30.50267	25.7503	22.21331	24.02471	22.42279	27.04338	23.49954	27.17218	25.7503	27.04338	35.85516	18.75034	25.57762	32.31464	27.293	
12	232	12.20522	19.81038	21.13697	16.28987	4.02664	12.47449	1	19.52435	53.07346	25.7503	9999.99	23.82281	1	22.23486	23.79046	21.05996	16.38252	17.32957	24.34849	1	16.38252	20.03831	12.20522	14.76379	21.21221	11.260
13	118	15.11448	4.12108	3.79239	9.04334	19.80598	13.24414	23.82281	7.18935	61.56585	30.50267	23.82281	9999.99	33.8281	8.64599	7.4407	8.13419	7.44185	8.01288	4.32082	23.82281	7.44185	10.71612	15.11448	9.11915	4.88941	12.865
14	219	12.20522	19.81038	21.13697	16.28987	4.02664	12.47449	1	19.52435	53.07346	25.7503	1	23.82281	9999.99	22.23486	23.79046	21.05996	16.38252	17.32957	24.34849	1	16.38252	20.03831	12.20522	14.76379	21.21221	11.260
15	25	10.57317	9.97465	9.8463	6.34601	18.43784	9.77097	22.23486	3.46178	53.02936	22.21331	22.23486	8.64599	22.23486	9999.99	2.04277	1.32353	9.27263	5.61976	4.95896	22.23486	9.27263	17.24638	10.57317	9.39434	11.95489	13.8
16	122	12.40543	8.67797	9.24843	7.59039	19.91418	11.41003	23.79046	4.3789	54.76317	24.02471	23.79046	7.4407	23.79046	2.04277	9999.99	2.80875	9.73795	6.67306	3.30667	23.79046	9.73795	16.95806	12.40543	10.3448	13.6816	14.778
17	31	9.59883	7.94475	8.94346	5.04406	17.2256	8.63242	21.05996	2.16436	53.43926	22.42279	21.05996	8.13419	21.05996	1.32353	2.80875	9999.99	7.99625	4.29659	4.97318	21.05996	7.99625	16.4968	9.59883	8.07327	11.01963	12.532
18	72	9.13349	3.48721	4.96107	4.27531	12.36946	6.96918	16.38252	5.83385	58.11742	27.04338	16.38252	7.44185	16.38252	9.27263	9.73795	7.99625	9999.99	4.13253	8.78749	16.38252	1	8.95777	9.13349	1.89585	5.84105	5.578
19	123	7.13739	5.6506	7.11672	1.10974	13.37655	5.40023	17.32957	2.29471	54.66125	23.49954	17.32957	8.01288	17.32957	6.19376	6.73066	4.29659	4.13253	9999.99	7.10373	17.32957	4.13253	12.97075	7.13739	3.8004	8.83152	8.235
20	108	13.91363	6.64687	6.74446	8.20086	20.35352	12.47753	24.34849	5.20528	58.0138	27.17218	24.34849	4.32082	24.34849	4.95896	3.30667	4.97318	8.78749	7.10373	9999.99	24.34849	8.78749	14.57564	13.91363	8.96198	8.77246	14.288
21	209	12.20522	19.81038	21.13697	16.28987	4.02664	12.47449	1	19.52435	53.07346	25.7503	1	23.82281	1	22.23486	23.79046	21.05996	16.38252	17.32957	24.34849	9999.99	16.38252	20.03831	12.20522	14.76379	21.21221	11.260
22	14	9.13349	3.48721	4.96107	4.27531	12.36946	6.96918	16.38252	5.83385	58.11742	27.04338	16.38252	7.44185	16.38252	9.27263	9.73795	7.99625	1	4.13253	8.78749	16.38252	9999.99	8.95777	9.13349	1.89585	5.84105	5.578
23	269	17.37793	8.30424	7.83314	13.2319	16.68046	15.21904	20.03831	14.14843	66.79484	35.85516	20.03831	10.71612	20.03831	17.24638	16.95806	16.14968	8.95777	12.97075	14.57564	20.03831	8.95777	17.37793	17.37793	7.58486	9.954	9.999
24	278	1	12.13789	13.70185	6.0742	8.91392	2.18757	12.20522	8.70839	49.44739	18.75034	12.20522	15.11448	12.20522	10.57317	12.40543	9.59883	9.13349	7.13739	13.91363	12.20522	9.13349	17.37793	9999.99	7.35038	14.94219	8.580
25	104	7.35038	5.32297	6.8331	3.4373	10.73733	5.16651	14.76379	5.96661	56.5685	25.57762	14.76379	9.11915	14.76379	9.39434	10.23448	8.07237	1.89585	3.8004	9.86198	14.76379	1.89585	10.27914	7.35038	9999.99	7.7151	4.547
26	144	14.94219	3.20824	2.23415	9.47192	17.38672	12.79591	21.21221	9.28784	63.47565	32.31464	21.21221	4.88941	21.21221	13.95489	13.6816	11.01963	5.84105	8.83152	8.77246	21.21221	5.84105	5.84886	14.94219	7.7151	9999.99	9.954
27	150	8.58031	8.75557	9.9648	7.60644	7.40154	6.75587	11.26036	10.47546	57.72288	27.29376	11.26036	13.855	14.77872	12.53225	5.57341	8.23595	14.28843	11.26036	5.57341	8.23595	5.57341	9.81481	15.8031	4.54799	9.95438	9999.
28	155	16.20884	8.84405	8.7763	12.75981	14.62806	14.13371	17.8568	14.19251	65.64024	34.88996	17.8568	11.92503	17.8568	17.4847	17.46715	16.2963	8.56257	12.69397	15.42466	17.8568	8.56257	2.28227	16.20884	9.51822	7.08377	8.127
29	109	10.34919	4.85308	5.89729	6.57419	11.50747	8.17821	15.39971	8.42421	59.74421	28.82446	15.39971	8.95904	15.39971	11.87405	12.18706	10.53974	2.60371	6.8355	11.06616	15.39971	2.60371	7.05106	10.34919	3.20138	5.82954	4.14
30	201	5.75266	7.49924	8.96131	1.44999	12.99771	6.25386	18.83283	2.9595	52.81752	21.65876	16.83283	6.97894	16.83283	5.44552	6.97164	4.22939	5.69593	1.84873	8.16354	16.83283	1.84873	14.64041	5.75266	6.06931	10.58185	8.858
31	1	7.13739	5.6506	7.11672	1.10974	13.37655	5.40023	17.32957	2.29471	54.66125	23.49954	17.32957	8.01288	17.32957	6.19376	6.73066	4.29659	4.13253	1	7.10373	17.32957	4.13253	12.97075	7.13739	3.8004	8.83152	8.235
32	160	20.43723	8.86132	18.84835	15.69207	20.33018	18.25024	23.70694	15.96486	69.65996	38.5773	23.70694	10.93788	23.70694	18.01907	17.75798	11.54331	15.22403	15.19039	23.70694	11.54331	16.68876	20.43723	13.19617	6.74204	13.939	
33	174	2.18757	10.06546	11.63033	4.33194	8.77234	12.47449	7.33867	51.58422	20.78433	12.47449	13.24414	12.47449	9.77097	11.41003	8.63242	6.96918	5.40023	12.47753	12.47449	6.96918	15.21904	2.18757	5.16651	12.79591	6.755	
34	183	14.37512	7.01387	7.15974	10.72648	13.64012	12.24574	17.12924	12.17565	63.8222	32.98657	17.12924	10.40497	17.12924	15.49432	15.54763	14.29113	6.52223	10.65377	13.65181	17.12924	6.52223	13.55578	14.37512	7.51964	7.49891	6.660
35	193	7.53782	12.32008	13.65288	9.47171	3.52001	6.5855	7.4906	12.6297	55.13538	25.37211	7.4906	16.34606	7.4906	15.70287	17.00178	14.43095	8.90446	10.34679	17.13718							

2. Modelo Matemático

Conjuntos:

Sea $I = \{1, 2, \dots, 40\}$ (Índice para filas y columnas)

$x_{ij} \in \{0, 1\}$ para todo $i, j \in I$ (Variable binaria de decisión)

$u_i \geq 0$ para todo $i \in I$ (Variable positiva)

Parámetros:

c_{ij} (Costo o distancia para cada par (i, j))

Función Objetivo:

Minimizar z , que es el costo total:

$$\text{Minimizar } z = \sum_{i \in I} \sum_{j \in I} c_{ij} \cdot x_{ij}$$

Restricciones:

- Restricción de filas: Cada fila tiene exactamente una asignación saliente.

$$\sum_{j \in I} x_{ij} = 1 \quad \text{para todo } i \in I$$

- Restricción de columnas: Cada columna tiene exactamente una asignación entrante.

$$\sum_{i \in I} x_{ij} = 1 \quad \text{para todo } j \in I$$

- Restricción de eliminación de subcircuitos: Evita subcircuitos asegurando que no se

formen ciclos, excepto el recorrido completo.

$$u_i - u_j + |I| \cdot x_{ij} \leq |I| - 1 \quad \forall i, j \in I \quad (i \neq j \text{ y } i > 1 \text{ y } j > 1)$$

3. Obtén la solución óptima usando GAMS.

La distancia recorrida óptima ponderada de 10 redes de 40 nodos, da un total de: 151.34 km

El fitness ponderada da 0.00684388

El mejor recorrido sugiere este orden: 111.739082 - Caso 8

[1, 15, 17, 6, 37, 11, 25, 35, 14, 13, 2, 26, 40, 32, 23, 33, 5, 3, 38, 39, 19, 10, 7, 21, 28, 30, 29, 24, 18, 4, 9, 34, 22, 20, 16, 27, 12, 8, 31, 36, 1]

El tiempo de cómputo ponderado fue de 1.58 segundos.

Se anexa imágenes de un ejemplo del código, los códigos completos se encuentran en anexos finales:

```
option optcr = 0.00001;

Set
i /1*40/
alias (i,j);
variable z;
Binary Variable x(i, j);
positive variable u(i);

Table
c(i,j)
1 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 1
1 9999.99 8.91392 17.2256 17.33672 17.2256 4.02664 19.41942 3.17527 19.96409 18.43784 4.02664 3.17527 8.77234 4.9183 4.02664 16.
2 8.91392 9999.99 9.59883 14.94219 9.59883 12.20522 11.75484 8.2062 16.34276 10.57317 12.20522 8.2062 2.18757 5.17897 12.20522 17.
3 17.2256 9.59883 9.999.99 11.01963 1 21.05996 2.20791 15.12855 10.37664 1.32353 21.05996 15.12855 8.63242 12.3511 21.05996 16.
4 17.33672 14.94219 11.01963 9.999.99 11.01963 21.21221 11.65039 14.19367 3.24564 11.95489 21.21221 14.19367 12.79591 13.34664 21.21221 5.
5 17.2256 9.59883 1 11.01963 9.999.99 21.05996 2.20791 15.12855 10.37664 1.32353 21.05996 15.12855 8.63242 12.3511 21.05996 16.
6 4.02664 12.20522 21.05996 21.21221 21.05996 9.999.99 23.26479 7.03562 23.92228 22.23486 1 7.03562 12.47449 8.88583 1 20.
7 19.41942 11.75484 2.20791 11.65039 2.20791 23.26479 9.999.99 17.26762 10.38298 1.28004 23.26479 17.26762 10.83979 14.53357 23.26479 17.
8 3.17527 8.2062 15.12855 14.19367 15.12855 7.03562 17.26762 9.999.99 16.88915 16.4045 7.03562 1 7.30079 3.1132 7.03562 13
9 19.96409 16.34276 10.37664 3.24564 10.37664 23.92228 10.38298 16.88915 9.999.99 11.01078 23.92228 16.88915 14.32287 15.63786 23.92228 8
10 18.43784 10.57317 1.32353 11.95489 1.32353 22.23486 1.28004 16.4045 11.01078 9.999.99 22.23486 16.4045 9.77097 13.58762 22.23486 17.
11 4.02664 12.20522 21.05996 21.21221 21.05996 1 23.26479 7.03562 23.92228 22.23486 9.999.99 7.03562 12.47449 8.88583 1 20.
12 3.17527 8.2062 15.12855 14.19367 15.12855 7.03562 17.26762 1 16.88915 16.4045 7.03562 9.999.99 7.30079 3.1132 7.03562 13
13 8.77234 2.18757 8.63242 12.79591 8.63242 12.47449 10.83979 7.30079 14.32287 9.77097 12.47449 7.30079 9.999.99 4.20156 12.47449 15.
14 4.9183 5.17897 12.3511 13.34664 12.3511 8.88583 14.53357 3.1132 15.63786 13.58762 8.88583 3.1132 4.20156 9.999.99 8.88583 14.
15 4.02664 12.20522 21.05996 21.21221 21.05996 1 23.26479 7.03562 23.92228 22.23486 1 7.03562 12.47449 8.88583 9.999.99 20.
16 16.60046 17.37793 16.14969 5.84886 16.14969 20.03831 17.14188 13.5948 8.7127 17.24638 20.03831 13.5948 15.21904 14.06468 20.03831 9.9
17 4.02664 12.20522 21.05996 21.21221 21.05996 1 23.26479 7.03562 23.92228 22.23486 1 7.03562 12.47449 8.88583 1 20.
18 15.66162 13.2518 10.102 1.75409 10.102 19.5691 11.03011 12.53744 4.48126 11.15775 19.5691 12.53744 11.0923 11.60196 19.5691 6.
19 18.43784 10.57317 1.32353 11.95489 1.32353 22.23486 1.28004 16.4045 11.01078 1 22.23486 16.4045 9.77097 13.58762 22.23486 17.
20 18.36934 20.2415 19.51468 9.06161 19.51468 21.33387 20.49581 15.46698 11.65568 20.61187 21.33387 15.46698 18.1276 16.46468 21.33387 3.
21 18.76996 11.86484 2.74728 9.42854 2.74728 22.71819 2.24885 16.35865 8.15947 2.92279 22.71819 16.35865 10.5729 13.85227 22.71819 14.
22 18.36934 20.2415 19.51468 9.06161 19.51468 21.33387 20.49581 15.46698 11.65568 20.61187 21.33387 15.46698 18.1276 16.46468 21.33387 3.
23 13.05183 4.94198 4.66299 12.31511 4.66299 16.7228 6.8133 11.40171 12.8619 5.64481 16.7228 11.40171 4.27967 8.37862 16.7228 16.
24 15.66162 13.2518 10.102 1.75409 10.102 19.5691 11.03011 12.53744 4.48126 11.15775 19.5691 12.53744 11.0923 11.60196 19.5691 6.
25 1 8.91392 17.2256 17.33672 17.2256 4.02664 19.41942 3.17527 19.96409 18.43784 4.02664 3.17527 8.77234 4.9183 4.02664 16.
26 9.87489 2.11944 7.74878 12.9935 7.74878 13.49978 9.94415 8.4821 14.266 8.82528 13.49978 8.4821 1.18209 5.37972 13.49978 15.
27 12.59507 14.26441 15.18231 7.2915 15.18231 15.92482 16.63089 9.54898 10.53706 16.42734 15.92482 9.54898 12.20945 10.34837 15.92482 4.
28 19.54091 12.8732 3.84846 9.04467 3.84846 23.51567 3.0021 17.03598 7.44812 3.90298 23.51567 17.03598 11.50326 14.63247 23.51567 14.
29 12.98289 7.37287 5.10114 8.09993 5.10114 16.97287 7.01594 10.4903 9.02166 6.42193 16.97287 10.4903 5.49327 8.08783 16.97287 12.
30 20.35352 13.91363 4.97318 8.77246 4.97318 24.34849 3.94799 17.76512 6.82466 4.95896 24.34849 17.76512 12.47753 15.46376 24.34849 14.
31 3.17527 8.2062 15.12855 14.19367 15.12855 7.03562 17.26762 1 16.88915 16.4045 7.03562 1 7.30079 3.1132 7.03562 13
32 13.05183 4.94198 4.66299 12.31511 4.66299 16.7228 6.8133 11.40171 12.8619 5.64481 16.7228 11.40171 4.27967 8.37862 16.7228 16.
33 14.75716 6.9321 2.66675 11.44791 2.66675 18.52297 4.84059 12.8603 11.54612 3.72192 18.52297 12.8603 6.05215 9.95251 18.52297 15
34 14.75716 6.9321 2.66675 11.44791 2.66675 18.52297 4.84059 12.8603 11.54612 3.72192 18.52297 12.8603 6.05215 9.95251 18.52297 15
35 14.75716 6.9321 2.66675 11.44791 2.66675 18.52297 4.84059 12.8603 11.54612 3.72192 18.52297 12.8603 6.05215 9.95251 18.52297 15
36 1 8.91392 17.2256 17.33672 17.2256 4.02664 19.41942 3.17527 19.96409 18.43784 4.02664 3.17527 8.77234 4.9183 4.02664 16.
37 4.02664 12.20522 21.05996 21.21221 21.05996 1 23.26479 7.03562 23.92228 22.23486 1 7.03562 12.47449 8.88583 1 20.
38 17.2256 9.59883 1 11.01963 1 21.05996 2.20791 15.12855 10.37664 1.32353 21.05996 15.12855 8.63242 12.3511 21.05996 16.
39 18.43784 10.57317 1.32353 11.95489 1.32353 22.23486 1.28004 16.4045 11.01078 1 22.23486 16.4045 9.77097 13.58762 22.23486 17.
40 13.05183 4.94198 4.66299 12.31511 4.66299 16.7228 6.8133 11.40171 12.8619 5.64481 16.7228 11.40171 4.27967 8.37862 16.7228 16.

Equations
obj, r1, r2, r3;

obj.. z=e=sum((i,j),c(i,j)*x(i,j));
r1(i).. sum(j, x(i,j))=1;
r2(j).. sum(i, x(i,j))=1;
r3(i,j)$((ord(i)>1 and ord(j)>1) and (ord(i)<>ord(j))).. u(i)-u(j)+card(i)*x(i,j)=L-card(i)-1;

model problemaf /all/;
solve problemaf using MIP min z;
```

Imágenes de código en GAMS: ejemplo de 1 de las 10 redes

Real time = 719.11 sec. (14311

Total (root+branch&cut) = 719.50 sec. (14317
--- MIP status (113): aborted.
--- Cplex Time: 719.50sec (det. 1431728.01 ti
--- Returning a primal only solution to GAMS
--- Fixing integer variables and solving fina
Version identifier: 22.1.1.0 | 2022-11-27 | 9
CPXPARAM_Advance
CPXPARAM_Threads
CPXPARAM_MIP_Display
CPXPARAM_MIP_Pool_Capacity
CPXPARAM_MIP_Tolerances_AbsMIPGap
CPXPARAM_MIP_Tolerances_MIPGap
Tried aggregator 1 time.
LP Presolve eliminated 80 rows and 1601 colum
Reduced LP has 1482 rows, 39 columns, and 296
Presolve time = 0.00 sec. (1.67 ticks)

Iteration log . . .
Iteration: 1 Dual objective =
--- Fixed MIP status (1): optimal.
--- Cplex Time: 0.00sec (det. 3.84 ticks)
Problem aborted
MIP Solution: 120.468560 (4.72407
Final Solve: 120.468560 (38 iter
Best possible: 111.739082
Absolute gap: 8.729478
Relative gap: 0.072463
--- Reading solution for model problemaf
*** Status: Normal completion
--- Job MODELO 8.gms Stop 09/08/24 20:25:58 e

--- Returning a primal only solution to GAMS (marginals all set to NA).
--- Fixing integer variables and solving final LP...

--- Fixed MIP status (1): optimal.
--- Cplex Time: 0.02sec (det. 3.84 ticks)

Problem aborted
MIP Solution: 120.468560 (4.18579e+06 iterations, 588890 nodes)
Final Solve: 120.468560 (38 iterations)

Best possible: 111.606920
Absolute gap: 8.861640
Relative gap: 0.073560

LOWER LEVEL UPPER MARGINAL
---- EQU obj . . . 1.0000
---- EQU r1

--- EQU #3				# 6				-INF				14.0000				39.0000				.			
LOWER				LEVEL				UPPER				MARGINAL											
2.3	-INF	-7.0000	39.0000									3.7	-INF	-5.0000	39.0000					3.7	-INF	-5.0000	39.0000
2.4	-INF	-19.0000	39.0000									3.8	-INF	-20.0000	39.0000					3.8	-INF	-20.0000	39.0000
2.5	-INF	-6.0000	39.0000									3.9	-INF	-13.0000	39.0000					3.9	-INF	-13.0000	39.0000
2.6	-INF	7.0000	39.0000									3.10	-INF	-4.0000	39.0000					3.10	-INF	-4.0000	39.0000
2.7	-INF	-12.0000	39.0000									3.11	-INF	-12.0000	39.0000					3.11	-INF	-12.0000	39.0000
2.8	-INF	-27.0000	39.0000									3.12	-INF	-19.0000	39.0000					3.12	-INF	-19.0000	39.0000
2.9	-INF	-20.0000	39.0000									3.13	-INF	8.0000	39.0000					3.13	-INF	8.0000	39.0000
2.10	-INF	-11.0000	39.0000									3.14	-INF	9.0000	39.0000					3.14	-INF	9.0000	39.0000
2.11	-INF	5.0000	39.0000									3.15	-INF	16.0000	39.0000					3.15	-INF	16.0000	39.0000
2.12	-INF	-26.0000	39.0000									3.16	-INF	-17.0000	39.0000					3.16	-INF	-17.0000	39.0000
2.13	-INF	1.0000	39.0000									3.17	-INF	15.0000	39.0000					3.17	-INF	15.0000	39.0000
2.14	-INF	14.0000	39.0000									3.18	-INF	-11.0000	39.0000					3.18	-INF	-11.0000	39.0000
2.15	-INF	9.0000	39.0000									3.19	-INF	-3.0000	39.0000					3.19	-INF	-3.0000	39.0000
2.16	-INF	-24.0000	39.0000									3.20	-INF	-16.0000	39.0000					3.20	-INF	-16.0000	39.0000
2.17	-INF	8.0000	39.0000									3.21	-INF	-6.0000	39.0000					3.21	-INF	-6.0000	39.0000
2.18	-INF	-18.0000	39.0000									3.22	-INF	-15.0000	39.0000					3.22	-INF	-15.0000	39.0000
2.19	-INF	-10.0000	39.0000									3.23	-INF	3.0000	39.0000					3.23	-INF	3.0000	39.0000
2.20	-INF	-23.0000	39.0000									3.24	-INF	-10.0000	39.0000					3.24	-INF	-10.0000	39.0000
2.21	-INF	-13.0000	39.0000									3.25	-INF	11.0000	39.0000					3.25	-INF	11.0000	39.0000
2.22	-INF	-22.0000	39.0000									3.26	-INF	6.0000	39.0000					3.26	-INF	6.0000	39.0000
2.23	-INF	-4.0000	39.0000									3.27	-INF	-18.0000	39.0000					3.27	-INF	-18.0000	39.0000
2.24	-INF	-17.0000	39.0000									3.28	-INF	-7.0000	39.0000					3.28	-INF	-7.0000	39.0000
2.25	-INF	4.0000	39.0000									3.29	-INF	-9.0000	39.0000					3.29	-INF	-9.0000	39.0000
2.26	-INF	-25.0000	39.0000									3.30	-INF	-8.0000	39.0000					3.30	-INF	-8.0000	39.0000
2.27	-INF	-14.0000	39.0000									3.31	-INF	-21.0000	39.0000					3.31	-INF	-21.0000	39.0000
2.28	-INF	16.0000	39.0000									3.32	-INF	4.0000	39.0000					3.32	-INF	4.0000	39.0000
2.29	-INF	-16.0000	39.0000									3.33	-INF	2.0000	39.0000					3.33	-INF	2.0000	39.0000
2.30	-INF	-15.0000	39.0000									3.34	-INF	-14.0000	39.0000					3.34	-INF	-14.0000	39.0000
2.31	-INF	-28.0000	39.0000									3.35	-INF	10.0000	39.0000					3.35	-INF	10.0000	39.0000
2.32	-INF	-3.0000	39.0000									3.36	-INF	-22.0000	39.0000					3.36	-INF	-22.0000	39.0000
2.33	-INF	-5.0000	39.0000									3.37	-INF	13.0000	39.0000					3.37	-INF	13.0000	39.0000
2.34	-INF	-21.0000	39.0000									3.38	-INF	39.0000	39.0000					3.38	-INF	39.0000	39.0000
2.35	-INF	3.0000	39.0000									3.39	-INF	-2.0000	39.0000					3.39	-INF	-2.0000	39.0000
2.36	-INF	-29.0000	39.0000									4.0	-INF	5.0000	39.0000					4.0	-INF	5.0000	39.0000
2.37	-INF	6.0000	39.0000									4.1	-INF	-9.0000	39.0000					4.1	-INF	-9.0000	39.0000
2.38	-INF	-8.0000	39.0000									4.2	-INF	19.0000	39.0000					4.2	-INF	19.0000	39.0000
2.39	-INF	-9.0000	39.0000									4.3	-INF	12.0000	39.0000					4.3	-INF	12.0000	39.0000
2.40	-INF	-2.0000	39.0000									4.4	-INF	13.0000	39.0000					4.4	-INF	13.0000	39.0000
3.0	-INF	7.0000	39.0000									4.5	-INF	26.0000	39.0000					4.5	-INF	26.0000	39.0000
3.1	-INF	-12.0000	39.0000									4.6	-INF	7.0000	39.0000					4.6	-INF	7.0000	39.0000
3.2	-INF	1.0000	39.0000									4.7	-INF	-8.0000	39.0000					4.7	-INF	-8.0000	39.0000
3.3	-INF	1.0000	39.0000									4.8	-INF	8.0000	39.0000					4.8	-INF	8.0000	39.0000
3.4	-INF	-7.0000	39.0000									4.9	-INF	-7.0000	39.0000					4.9	-INF	-7.0000	39.0000
3.5	-INF	1.0000	39.0000									4.10	-INF	-7.0000	39.0000					4.10	-INF	-7.0000	39.0000

	-INF	20,000	39,000		5.20	-INF	-17,000	39,000		6.27	-INF	-32,000	39,000		7.34	-INF	-9,000	39,000	
4.14	-INF	21,000	39,000		5.21	-INF	-7,000	39,000		6.28	-INF	-21,000	39,000		7.35	-INF	15,000	39,000	
4.15	-INF	28,000	39,000		5.22	-INF	-16,000	39,000		6.29	-INF	-23,000	39,000		7.36	-INF	-17,000	39,000	
4.16	-INF	-5,000	39,000		5.23	-INF	2,000	39,000		6.30	-INF	-22,000	39,000		7.37	-INF	18,000	39,000	
4.17	-INF	27,000	39,000		5.23	-INF	2,000	39,000		6.31	-INF	-35,000	39,000		7.38	-INF	4,000	39,000	
4.18	-INF	1,000	39,000		5.24	-INF	-11,000	39,000		6.32	-INF	-10,000	39,000		7.39	-INF	3,000	39,000	
4.19	-INF	9,000	39,000		5.25	-INF	10,000	39,000		6.33	-INF	-12,000	39,000		7.40	-INF	10,000	39,000	
4.20	-INF	-4,000	39,000		5.26	-INF	5,000	39,000		6.34	-INF	-28,000	39,000		8.2	-INF	27,000	39,000	
4.21	-INF	6,000	39,000		5.27	-INF	-19,000	39,000		6.35	-INF	-4,000	39,000		8.3	-INF	20,000	39,000	
4.22	-INF	-3,000	39,000		5.28	-INF	-8,000	39,000		6.36	-INF	-36,000	39,000		8.4	-INF	8,000	39,000	
4.23	-INF	15,000	39,000		5.29	-INF	-10,000	39,000		6.37	-INF	39,000	39,000	EPS	8.5	-INF	21,000	39,000	
4.24	-INF	2,000	39,000		5.30	-INF	-9,000	39,000		6.38	-INF	-15,000	39,000		8.6	-INF	34,000	39,000	
4.25	-INF	23,000	39,000		5.31	-INF	-22,000	39,000		6.39	-INF	-6,000	39,000		8.7	-INF	32,000	39,000	
4.26	-INF	18,000	39,000		5.32	-INF	3,000	39,000		6.40	-INF	-9,000	39,000		8.8	-INF	15,000	39,000	
4.27	-INF	-6,000	39,000		5.33	-INF	1,000	39,000		7.2	-INF	12,000	39,000		8.10	-INF	16,000	39,000	
4.28	-INF	5,000	39,000		5.34	-INF	-15,000	39,000		7.2	-INF	12,000	39,000		8.11	-INF	32,000	39,000	
4.29	-INF	3,000	39,000		5.35	-INF	9,000	39,000		7.3	-INF	5,000	39,000		8.12	-INF	1,000	39,000	
4.30	-INF	4,000	39,000		5.36	-INF	-23,000	39,000		7.4	-INF	-7,000	39,000		8.13	-INF	28,000	39,000	
4.31	-INF	-9,000	39,000		5.37	-INF	12,000	39,000		7.5	-INF	6,000	39,000		8.14	-INF	29,000	39,000	
4.32	-INF	16,000	39,000		5.38	-INF	-2,000	39,000		7.6	-INF	19,000	39,000		8.15	-INF	36,000	39,000	
4.33	-INF	14,000	39,000		5.39	-INF	-3,000	39,000		7.8	-INF	-15,000	39,000		8.16	-INF	3,000	39,000	
4.34	-INF	-2,000	39,000		5.40	-INF	4,000	39,000		7.9	-INF	-8,000	39,000		8.17	-INF	35,000	39,000	
4.35	-INF	22,000	39,000		6.2	-INF	-7,000	39,000		7.10	-INF	1,000	39,000		8.18	-INF	9,000	39,000	
4.36	-INF	-10,000	39,000		6.3	-INF	-14,000	39,000		7.11	-INF	-24,000	39,000		8.19	-INF	17,000	39,000	
4.37	-INF	25,000	39,000		6.4	-INF	-26,000	39,000		7.12	-INF	-4,000	39,000		8.20	-INF	4,000	39,000	
4.38	-INF	11,000	39,000		6.5	-INF	-13,000	39,000		7.13	-INF	13,000	39,000		8.21	-INF	14,000	39,000	
4.39	-INF	4,39	39,000		6.6	-INF	-19,000	39,000		7.14	-INF	14,000	39,000		8.22	-INF	5,000	39,000	
4.40	-INF	17,000	39,000		6.7	-INF	-34,000	39,000		7.15	-INF	21,000	39,000		8.23	-INF	23,000	39,000	
5.2	-INF	6,000	39,000		6.8	-INF	-27,000	39,000		7.16	-INF	-12,000	39,000		8.24	-INF	10,000	39,000	
5.3	-INF	39,000	39,000	EPS	6.9	-INF	-18,000	39,000		7.17	-INF	20,000	39,000		8.25	-INF	31,000	39,000	
5.4	-INF	-13,000	39,000		6.10	-INF	-2,000	39,000		7.18	-INF	-6,000	39,000		8.26	-INF	26,000	39,000	
5.5	-INF	13,000	39,000		6.11	-INF	-33,000	39,000		7.19	-INF	19,000	39,000		8.27	-INF	2,000	39,000	
5.6	-INF	-6,000	39,000		6.12	-INF	-6,000	39,000		7.20	-INF	-11,000	39,000		8.28	-INF	13,000	39,000	
5.7	-INF	-21,000	39,000		6.13	-INF	-5,000	39,000		7.21	-INF	-10,000	39,000		8.29	-INF	11,000	39,000	
5.8	-INF	-14,000	39,000		6.14	-INF	2,000	39,000		7.22	-INF	-5,000	39,000		8.30	-INF	12,000	39,000	
5.9	-INF	-5,000	39,000		6.15	-INF	-31,000	39,000		7.23	-INF	8,000	39,000		8.31	-INF	39,000	39,000	EPS
5.10	-INF	-11,000	39,000		6.16	-INF	1,000	39,000		7.24	-INF	-5,000	39,000		8.32	-INF	24,000	39,000	
5.11	-INF	11,000	39,000		6.17	-INF	-25,000	39,000		7.25	-INF	16,000	39,000		8.33	-INF	22,000	39,000	
5.12	-INF	-20,000	39,000		6.18	-INF	-17,000	39,000		7.26	-INF	-26,000	39,000		8.34	-INF	6,000	39,000	
5.13	-INF	7,000	39,000		6.19	-INF	-30,000	39,000		7.27	-INF	-13,000	39,000		8.35	-INF	30,000	39,000	
5.14	-INF	8,000	39,000		6.20	-INF	-20,000	39,000		7.28	-INF	-2,000	39,000		8.36	-INF	2,000	39,000	
5.15	-INF	15,000	39,000		6.21	-INF	-11,000	39,000		7.29	-INF	4,000	39,000		8.37	-INF	33,000	39,000	
5.16	-INF	-18,000	39,000		6.22	-INF	-29,000	39,000		7.30	-INF	-3,000	39,000		8.38	-INF	19,000	39,000	
5.17	-INF	14,000	39,000		6.23	-INF	-11,000	39,000		7.31	-INF	-16,000	39,000		8.39	-INF	18,000	39,000	
5.18	-INF	-12,000	39,000		6.24	-INF	24,000	39,000		7.32	-INF	9,000	39,000		8.40	-INF	25,000	39,000	
5.19	-INF	4,000	39,000		6.25	-INF	-3,000	39,000		7.33	-INF	-33,000	39,000						
	-INF		39,000		6.26	-INF	-8,000	39,000		7.34	-INF								

4. Implementa un algoritmo genético para el TSP.

La distancia recorrida óptima ponderada de 10 redes de 40 nodos, da un total de: 407.26592 km

El mejor recorrido sugiere este orden: [73, 67, 34, 59, 74, 266, 219, 165, 19, 149, 53, 139, 171, 203, 185, 155, 94, 95, 85, 157, 49, 117, 90, 29, 150, 31, 15, 129, 106, 33, 78, 54, 215, 224, 228, 5, 17, 114, 41, 216, 73] , con distancia de 407.26592km

El tiempo de cómputo ponderado fue de 4.84 segundos.

Se anexa imagenes del código, los códigos completos se encuentran en anexos finales:

```
In [43]: 1 import pandas as pd
2 import random as rand
3 import numpy as np
4 import time
5 from geopy.distance import geodesic
```

Generar Cromosona

```
In [18]: 1 def generar_cromosona(casas):
2         return Rand.sample(casas, len(casas))
```

Crear Poblacion Inicial

```
In [19]: 1 def generar_poblacion_inicial(n, casas):
2
3         poblacion = []
4
5         for i in range(n):
6             poblacion.append(generar_cromosona(casas))
7
8         return poblacion
```

Funcion Fitness

```
In [65]: 1 def calcular_fitness(cromosona, comienzo, red):
2
3         cromosona_con_fin = [comienzo] + cromosona + [comienzo]
4
5         distancias = []
6
7         for idx in range(len(cromosona_con_fin) - 1):
8             actual = cromosona_con_fin[idx]
```

```
9             siguiente = cromosona_con_fin[idx + 1]
10
11             distancia = red.loc[red.columns[0] == actual, siguiente].values[0]
12
13             distancias.append(distancia)
14
15         distancia_total = sum(distancias)
16         fitness = 1 / distancia_total if distancia_total != 0 else float('inf')
17
18         return fitness, distancia_total
19
```

```
In [21]: 1 def fitness_poblacional(poblacion, comienzo, red):
2
3         lista_fitness = []
4         lista_distancia = []
5
6         for cromosona in poblacion:
7             fitness_crom, distancia_crom = calcular_fitness(cromosona, comienzo, red)
8             lista_fitness.append(fitness_crom)
9             lista_distancia.append(distancia_crom)
10
11         total_fit = np.sum(lista_fitness) # Use NumPy for summation
12
13         return lista_fitness, lista_distancia, total_fit
14
```

Selección

```
In [22]: 1 def seleccion_roulette(poblacion, lista_fitness, fitness_total):
2
3         lista_probabilidad = np.array(lista_fitness) / fitness_total
4         padres = rand.choices(poblacion, weights=lista_probabilidad, k=2)
5         return padres[0], padres[1]
```

```
In [92]: 1 def cruce(padre1, padre2, probabilidad_cruce):
2
3         if rand.random() < probabilidad_cruce:
4
5             punto = rand.randint(0, len(padre1))
6
7             hijo1 = padre1[:punto] + padre2[punto:]
8             hijo2 = padre2[:punto] + padre1[punto:]
9
10            return hijo1, hijo2
11
12        else:
13            return padre1, padre2
```

Mutacion

```
In [24]: 1 def mutacion(hijos, probabilidad_mutacion):
2
3         for hijo in hijos:
4             if rand.random() < probabilidad_mutacion:
5
6                 idx1, idx2 = rand.sample(range(len(hijo)), 2)
7                 hijo[idx1], hijo[idx2] = hijo[idx2], hijo[idx1]
8
9         return hijos
```

Forzar factibilidad de hijos

```
In [25]: 1 def forzar_factibilidad(hijos, lista_ciudades):
2
3         for hijo in hijos:
4
5             ciudades_faltantes = set(lista_ciudades) - set(hijo)
```

```
6         ciudad_counts = {}
7
8         for ciudad in hijo:
9             if ciudad in ciudad_counts:
10                ciudad_counts[ciudad] += 1
11            else:
12                ciudad_counts[ciudad] = 1
13
14        for idx, ciudad in enumerate(hijo):
15            if ciudad_counts[ciudad] > 1:
16
17                if ciudades_faltantes:
18                    new_city = ciudades_faltantes.pop()
19                    hijo[idx] = new_city
20                    ciudad_counts[ciudad] -= 1
21            else:
22                break
23
24        return hijos
```

Checar Fitness Max

```
In [105]: 1 def checar_fitness_max(poblacion, max_fitness, min_distancia, generacion, comienzo, red, crom_min):
2
3         lista_fit, lista_dist, fit_pob = fitness_poblacional(poblacion, comienzo, red)
4
5         max_fit_pob = max(lista_fit)
6
7         if max_fit_pob > max_fitness:
8
9             max_fitness = max_fit_pob
10
11            max_fit_index = lista_fit.index(max_fit_pob)
12
13            min_distancia = lista_dist[max_fit_index]
```

```
15        crom_min_sin_comienzo = poblacion[max_fit_index]
16
17        crom_min = [comienzo] + crom_min_sin_comienzo + [comienzo]
18
19        #print(f"Generacion: {generacion}\nFitness: {max_fitness}\nDistancia: {min_distancia}\nCromosoma: {crom_min}\n\n")
20
21        return max_fitness, min_distancia, crom_min
```

Parametros

```
In [27]: 1 max_generaciones = 100
2 max_fitness = 0
3 min_distancia = 999999
4 tamaño_poblacional = 4
5
6 probabilidad_cruce = 0.9
7 probabilidad_mutacion = 0.05
```

Diseña 10 redes de 40 nodos (direcciones) de forma aleatoria a partir de la siguiente lista de direcciones. Recuerda que vamos a minimizar la distancia recorrida.

```
In [144]: 1 red1_40 = pd.read_excel("matrices_40.xlsx", sheet_name = "Rede_1")
2 red2_40 = pd.read_excel("matrices_40.xlsx", sheet_name = "Rede_2")
3 red3_40 = pd.read_excel("matrices_40.xlsx", sheet_name = "Rede_3")
4 red4_40 = pd.read_excel("matrices_40.xlsx", sheet_name = "Rede_4")
5 red5_40 = pd.read_excel("matrices_40.xlsx", sheet_name = "Rede_5")
6 red6_40 = pd.read_excel("matrices_40.xlsx", sheet_name = "Rede_6")
7 red7_40 = pd.read_excel("matrices_40.xlsx", sheet_name = "Rede_7")
8 red8_40 = pd.read_excel("matrices_40.xlsx", sheet_name = "Rede_8")
9 red9_40 = pd.read_excel("matrices_40.xlsx", sheet_name = "Rede_9")
10 red10_40 = pd.read_excel("matrices_40.xlsx", sheet_name = "Rede_10")
11
12 redes_40 = [red1_40, red2_40, red3_40, red4_40, red5_40, red6_40, red7_40, red8_40, red9_40, red10_40]
```



```
def algoritmo_genetico(redes):
    for count, red in enumerate(redes):
        inicia_tiempo = time.time()
        comienzo_ruta = int(red.columns[1])
        print(f"Red #{count+1}\nComenzando en {comienzo_ruta}\n\n")
        lista_casas = list(red.columns[2:])

        max_generaciones = 100
        max_fitness = 0
        min_distancia = 99999999
        tamano_poblacional = 4
        probabilidad_mutacion = 0.1
        probabilidad_cruce = 0.9
        crom_min = []

        poblacion_inicial = generar_poblacion_inicial(tamano_poblacional, lista_casas)

        for generacion in range(max_generaciones):
            max_fitness, min_distancia, crom_min = checar_fitness_max(
                poblacion_inicial, max_fitness, min_distancia, generacion, comienzo_ruta, red, crom_min
            )

            hijos_finales = []

            while len(hijos_finales) < tamano_poblacional:
                lista_fitness, lista_distancias, fitness_total = fitness_poblacional(poblacion_inicial, comienzo_ruta, red)
                padre1, padre2 = seleccion_roulette(poblacion_inicial, lista_fitness, fitness_total)
                hijo1, hijo2 = cruce(padre1, padre2, probabilidad_cruce)
                hijos = [hijo1, hijo2]

                hijos_mutados = mutacion(hijos, probabilidad_mutacion)
                hijos_factibles = forzar_factibilidad(hijos_mutados, lista_casas)
                hijos_finales.extend(hijos_factibles)

            poblacion_inicial = hijos_finales

        acaba_tiempo = time.time()
        tiempo = acaba_tiempo - inicia_tiempo

        tcp_200_df.loc[0, f"Red {count+1}"] = max_fitness
        tcp_200_df.loc[1, f"Red {count+1}"] = min_distancia
        tcp_200_df.loc[2, f"Red {count+1}"] = tiempo
        tcp_200_df.loc[3, f"Red {count+1}"] = str(crom_min)

        tcp_200_df.to_excel("TCP200.xlsx", index=False)
```

```
In [151]: 1 algoritmo_genetico(redes_200)

Red #1
Comenzando en 0

Red #2
Comenzando en 0
```

Imágenes de código completo de algoritmo genético

1		Red 1	Red 2	Red 3	Red 4	Red 5	Red 6	Red 7	Red 8	Red 9	Red 10	Promedio	Mejor
2	Fitness	0.00196	0.00246	0.00224	0.00217	0.00219	0.00236	0.0021	0.00221	0.00235	0.00226	0.00223	0.00246
3	F.O. Min	509.122	407.266	446.8	460.443	457.25	423.341	476.33	451.801	425.288	443.121	450.076	407.266
4	Tiempo Computacional	4.78686	4.83532	4.9896	4.97506	4.91787	4.99541	4.86012	4.97543	5.03374	5.0256	4.9395	4.83532
5	Cromosona	[166, 150, 73, 67, 34]	[96, 263, 7]	[167, 176, 20, 93, 61]	[90, 161, 6]	[51, 64, 1]	[156, 247, 123, 30, 1]	[92, 259, 2]					[73, 67, 34, 5]

Imagen de resultados completos de algoritmo genético

5. Implementa un algoritmo de colonia de hormigas para obtener una solución al problema.

La distancia recorrida óptima ponderada de 10 redes de 40 nodos, da un total de: 162.94 km

El fitness ponderada da 0.0063

El mejor recorrido sugiere este orden:

[0, 35, 24, 11, 30, 7, 13, 34, 12, 25, 1, 22, 39, 31, 32, 2, 37, 4, 9, 38, 18, 6, 20, 27, 29, 28, 17, 23, 3, 8, 33, 15, 19, 21, 26, 10, 5, 16, 14, 36, 0] con distancia 125.50 km

El tiempo de cómputo ponderado fue de 2.72 segundos.

Se anexa imágenes del código, los códigos completos se encuentran en anexos finales:


```

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import time # Importar el módulo time

# Cargar los archivos de Excel
file_paths = {
    40: '/content/drive/MyDrive/Reto bioinspirados/matrices_40.xlsx',
    100: '/content/drive/MyDrive/Reto bioinspirados/matrices_100.xlsx',
    150: '/content/drive/MyDrive/Reto bioinspirados/matrices_150.xlsx',
    200: '/content/drive/MyDrive/Reto bioinspirados/matrices_200.xlsx'
}

# Definir los parámetros del algoritmo de hormigas
alpha = 1.0 # Importancia de la feromona
beta = 5.0 # Importancia de la distancia
rho = 0.5 # Tasa de evaporación de la feromona
Q = 100 # Constante de la cantidad de feromona depositada
num_ants = 10 # Número de hormigas
num_iterations = 100 # Número de iteraciones

# Función para inicializar la matriz de feromonas
def initialize_pheromone_matrix(num_nodes):
    return np.ones((num_nodes, num_nodes))

# Función para calcular la probabilidad de seleccionar el siguiente nodo
def calculate_transition_probabilities(current_node, unvisited_nodes, pheromone_matrix, distance_matrix):
    pheromones = np.power(pheromone_matrix[current_node, unvisited_nodes], alpha)
    heuristic = np.power(1.0 / distance_matrix[current_node, unvisited_nodes], beta)
    probabilities = pheromones * heuristic

```

```

    return probabilities / probabilities.sum()

# Función para ejecutar el recorrido de una hormiga
def run_ant(num_nodes, pheromone_matrix, distance_matrix):
    current_node = 0 # Iniciar en el nodo de origen
    visited_nodes = [current_node]
    total_distance = 0

    for _ in range(num_nodes - 1):
        unvisited_nodes = list(set(range(num_nodes)) - set(visited_nodes))
        probabilities = calculate_transition_probabilities(current_node, unvisited_nodes, pheromone_matrix, distance_matrix)
        next_node = np.random.choice(unvisited_nodes, p=probabilities)
        total_distance += distance_matrix[current_node, next_node]
        visited_nodes.append(next_node)
        current_node = next_node

    # Regresar al nodo inicial
    total_distance += distance_matrix[current_node, 0]
    visited_nodes.append(0)

    return visited_nodes, total_distance

# Función para actualizar la matriz de feromonas
def update_pheromone_matrix(pheromone_matrix, ant_paths, ant_distances):
    num_nodes = len(pheromone_matrix)
    pheromone_matrix *= (1 - rho) # Evaporación
    for path, distance in zip(ant_paths, ant_distances):
        for i in range(num_nodes):
            pheromone_matrix[path[i], path[i+1]] += Q / distance
            pheromone_matrix[path[i+1], path[i]] += Q / distance
    return pheromone_matrix

```

```

# Función principal para resolver el problema TSP usando ACO
def solve_tsp_with_aco(distance_matrix, num_ants, num_iterations):
    num_nodes = len(distance_matrix)
    pheromone_matrix = initialize_pheromone_matrix(num_nodes)
    best_path = None
    best_distance = float('inf')

    for _ in range(num_iterations):
        ant_paths = []
        ant_distances = []

        for _ in range(num_ants):
            path, distance = run_ant(num_nodes, pheromone_matrix, distance_matrix)
            ant_paths.append(path)
            ant_distances.append(distance)
            if distance < best_distance:
                best_distance = distance
                best_path = path

        pheromone_matrix = update_pheromone_matrix(pheromone_matrix, ant_paths, ant_distances)

    return best_path, best_distance

# Procesar cada archivo de Excel
for num_nodes, file_path in file_paths.items():
    excel_data = pd.ExcelFile(file_path)
    fitness_scores = []
    total_distances = []
    best_global_path = None
    best_global_distance = float('inf')

```

```

for sheet_name in excel_data.sheet_names:
    # Cargar la red (distancia) desde el Excel
    distance_matrix = pd.read_excel(excel_data, sheet_name=sheet_name, index_col=0).values

    # Medir el tiempo de resolución
    start_time = time.time() # Iniciar el temporizador
    best_path, best_distance = solve_tsp_with_aco(distance_matrix, num_ants, num_iterations)
    end_time = time.time() # Detener el temporizador

    # Calcular el tiempo de resolución
    elapsed_time = end_time - start_time

    # Calcular fitness
    fitness = 1 / best_distance
    fitness_scores.append(fitness)
    total_distances.append(best_distance)

    # Guardar la mejor ruta global
    if best_distance < best_global_distance:
        best_global_distance = best_distance
        best_global_path = best_path

    # Calcular fitness ponderada
    weighted_fitness = np.mean(fitness_scores) / 10
    average_distance = np.mean(total_distances)

```

```

# Imprimir resultados
print(f"Excel con {num_nodes} nodos:")
print(f"Fitness ponderada: {weighted_fitness:.4f}")
print(f"Distancia promedio: {average_distance:.2f}")
print(f"Mejor ruta: {best_global_path} con distancia {best_global_distance:.2f}")
print(f"Tiempo computacional: {elapsed_time:.2f} segundos") # Imprimir el tiempo computacional
print("\n")

```

Imagenes de código completo de algoritmo genético

```

Excel con 40 nodos:
Fitness ponderada: 0.2528
Distancia promedio: 162.94
Mejor ruta: [0, 35, 24, 11, 30, 7, 13]
Tiempo computacional: 2.72 segundos

```

Imagen de resultados completos de algoritmo genético

**La mejor ruta se despliega completa junto a su kilometraje, por la longitud de aquella imagen favor de recurrir al anexo del código al final en caso de querer ver el despliegue completo.*

6. Compara el valor exacto con los algoritmos bioinspirados que creaste.

El algoritmo genético, tiene un fitness de 35.88% de lo que es el fitness hecho con el valor exacto que se consiguió con GAMS. El tiempo de computación con genéticos, fue un 306.03% de lo que es para el modelo hecho en GAMS.

El algoritmo de hormigas, tiene un fitness de 92.05% de lo que es el fitness hecho con el valor exacto que se consiguió con GAMS. El tiempo de computación con hormigas, fue un 172.15% de lo que es para el modelo hecho en GAMS.

Para apreciar las diferencias para las 10 redes de 100, 150 y 200 nodos, favor de recurrir al infográfico.

[Anexos finales]:

<https://drive.google.com/drive/folders/1BNb5nqIS0jgv2pDuI5PbLDSYJJ6deo3K?usp=sharing>

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Mitchell, M. (1998). An Introduction to Genetic Algorithms. MIT Press.

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