



# MODELLING WEEK

## MODELLING THE PATIENTS DEMAND IN OPHTHALMOLOGICAL CLINICS

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Vissum Corporación

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# DESCRIPTION OF THE PROBLEM

The problem we were asked to deal with consists in creating a mathematical model to analyze the behaviour of patients visiting an ophthalmological clinic:

	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	V12
1	1330575	001PA000000	20001	VISSUM SANTA HORTENSIA	8	OFTALMOLOGIA GENERAL	802	DRA. ALVAREZ	2	REVISIONES LARGAS	2	REVISION ANUAL
2	415600	001PA000242	20001	VISSUM SANTA HORTENSIA	8	OFTALMOLOGIA GENERAL	1162	DRA IGLESIAS	1	PRIMERAS	1	PRIMERA VISITA
3	415985	001PA000242	20001	VISSUM SANTA HORTENSIA	8	OFTALMOLOGIA GENERAL	1162	DRA IGLESIAS	5	REVISION SEGUIMIENTO	11	REVISION SEGUIMIENTO
4	432305	001PA000242	20001	VISSUM SANTA HORTENSIA	6	CATARATAS	1098	DRA.CIANCAS	4	POSTOPERATORIOS	37	REV POSTOP HASTA 1 M
5	144856	001PA001607	20001	VISSUM SANTA HORTENSIA	6	CATARATAS	1099	DRA.DE BENITO	2	REVISIONES LARGAS	4	REVISION 3 MESES
6	208701	001PA005798	20001	VISSUM SANTA HORTENSIA	6	CATARATAS	802	DRA. ALVAREZ	4	POSTOPERATORIOS	37	REV POSTOP HASTA 1 M
7	1840290	001PA007647	20001	VISSUM SANTA HORTENSIA	10	BAJA VISION	1115	JOSE LUIS HDEZ	5	REVISION SEGUIMIENTO	11	REVISION SEGUIMIENTO
8	1840695	001PA008046	20001	VISSUM SANTA HORTENSIA	1	CIRUGIA REFRACTIVA	1145	DR.GIMENEZ VAL	4	POSTOPERATORIOS	18	REV POSTOP 24H
9	1841009	001PA008046	20001	VISSUM SANTA HORTENSIA	8	OFTALMOLOGIA GENERAL	1162	DRA IGLESIAS	5	REVISION SEGUIMIENTO	11	REVISION SEGUIMIENTO
10	1467508	001PA008228	20001	VISSUM SANTA HORTENSIA	6	CATARATAS	1099	DRA.DE BENITO	2	REVISIONES LARGAS	2	REVISION ANUAL
11	1442602	001PA009711	20001	VISSUM SANTA HORTENSIA	8	OFTALMOLOGIA GENERAL	802	DRA. ALVAREZ	1	PRIMERAS	1	PRIMERA VISITA
12	1532656	001PA009711	20001	VISSUM SANTA HORTENSIA	6	CATARATAS	802	DRA. ALVAREZ	4	POSTOPERATORIOS	38	REV POSTOP DE 1 A 3M
13	74497	001PA010088	20001	VISSUM SANTA HORTENSIA	6	CATARATAS	1096	DRA.ARRANZ	4	POSTOPERATORIOS	18	REV POSTOP 24H
14	172215	001PA013013	20001	VISSUM SANTA HORTENSIA	8	OFTALMOLOGIA GENERAL	1100	DRA.GARCIA GONZ	2	REVISIONES LARGAS	2	REVISION ANUAL
15	1749628	001PA014933	20001	VISSUM SANTA HORTENSIA	6	CATARATAS	802	DRA. ALVAREZ	5	REVISION SEGUIMIENTO	11	REVISION SEGUIMIENTO
16	1787455	001PA014933	20001	VISSUM SANTA HORTENSIA	7	GLAUCOMA	1096	DRA.ARRANZ	5	REVISION SEGUIMIENTO	11	REVISION SEGUIMIENTO
17	1811348	001PA014933	20001	VISSUM SANTA HORTENSIA	7	GLAUCOMA	1096	DRA.ARRANZ	2	REVISIONES LARGAS	3	REVISION 6 MESES
18	1437075	001PA015171	20001	VISSUM SANTA HORTENSIA	8	OFTALMOLOGIA GENERAL	1096	DRA.ARRANZ	2	REVISIONES LARGAS	2	REVISION ANUAL
19	1440879	001PA015171	20001	VISSUM SANTA HORTENSIA	8	OFTALMOLOGIA GENERAL	1096	DRA.ARRANZ	2	REVISIONES LARGAS	3	REVISION 6 MESES
20	1593707	001PA015171	20001	VISSUM SANTA HORTENSIA	8	OFTALMOLOGIA GENERAL	1096	DRA.ARRANZ	2	REVISIONES LARGAS	3	REVISION 6 MESES
21	1746121	001PA015171	20001	VISSUM SANTA HORTENSIA	8	OFTALMOLOGIA GENERAL	1096	DRA.ARRANZ	2	REVISIONES LARGAS	4	REVISION 3 MESES
22	98518	001PA015171	20001	VISSUM SANTA HORTENSIA	8	OFTALMOLOGIA GENERAL	1096	DRA.ARRANZ	5	REVISION SEGUIMIENTO	11	REVISION SEGUIMIENTO
23	140426	001PA015171	20001	VISSUM SANTA HORTENSIA	8	OFTALMOLOGIA GENERAL	1096	DRA.ARRANZ	2	REVISIONES LARGAS	3	REVISION 6 MESES
24	287581	001PA015171	20001	VISSUM SANTA HORTENSIA	7	GLAUCOMA	1096	DRA.ARRANZ	2	REVISIONES LARGAS	3	REVISION 6 MESES
25	1872530	001PA015171	20001	VISSUM SANTA HORTENSIA	6	CATARATAS	1145	DR.GIMENEZ VAL	4	POSTOPERATORIOS	18	REV POSTOP 24H
26	1875549	001PA015171	20001	VISSUM SANTA HORTENSIA	8	OFTALMOLOGIA GENERAL	1145	DR.GIMENEZ VAL	5	REVISION SEGUIMIENTO	11	REVISION SEGUIMIENTO
27	1888381	001PA015171	20001	VISSUM SANTA HORTENSIA	7	GLAUCOMA	1096	DRA.ARRANZ	5	REVISION SEGUIMIENTO	11	REVISION SEGUIMIENTO
28	133714	001PA017779	20001	VISSUM SANTA HORTENSIA	8	OFTALMOLOGIA GENERAL	1099	DRA.DE BENITO	2	REVISIONES LARGAS	3	REVISION 6 MESES
29	153710	001PA017779	20001	VISSUM SANTA HORTENSIA	8	OFTALMOLOGIA GENERAL	1099	DRA.DE BENITO	5	REVISION SEGUIMIENTO	11	REVISION SEGUIMIENTO
30	216726	001PA017779	20001	VISSUM SANTA HORTENSIA	8	OFTALMOLOGIA GENERAL	1099	DRA.DE BENITO	3	REVISIONES LARGAS	3	REVISION 6 MESES

Our problem consists in optimizing patients demand for an ophthalmological clinic; we have a database containing all the following information about any visit:

1. V1 - visit ID
2. V2 - client ID
3. V3 - clinic ID
4. V4 - Name of the clinic
5. V5 - Department ID
6. V6 - Name of the department
7. V7 - Doctor ID
8. V8 - Doctor Name
9. V9 - Family ID
10. V10 - Family Name
11. V11 - Kind of visit ID
12. V12 - Kind of visit
13. V13 - Date of the visit

14. V14 - Date of the call

15. V15 - Indicates if the visit was or not performed.

The clinic has many departments (15) with several doctors (32), but all the patients have to follow almost the same procedure. The first time they come to the clinic they have to follow a FIRST VISIT protocol. Then they may have to proceed with surgery or just continue with a normal sequence of visits such as check-up or other kinds of visit. Some patients drop out of the process, because they never showed up to the visitor just because they don't need any other visit although, there are many patients that remain in the process for several years. One thing which is very important is that every type of visit has a different demand in time.

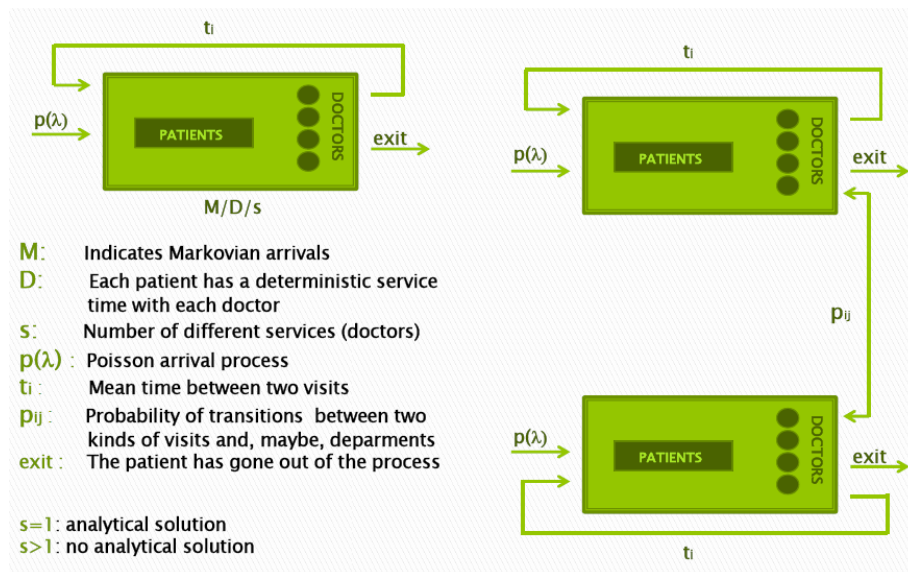
The total amount of visits is **147.992**. Vissum Corporation gave us the data in an excel file. We used them to create our model.

The company gave us this working plan:

1. Create a mathematical model describing the new patients demand. Ideally, the model should offer an estimate of the demand in the future.
2. Create a mathematical model for the behaviour of consolidated patients. This might be done using Markov Models.
3. Using the developed models and simulation techniques, estimate a model for the aggregated demand month by month. This final model should allow the optimization of the doctor's agendas.
4. Identify the asymptotic behaviour of the demand. Analyse whether the patients demand is growing or, on the other hand, we've reached a stationary state, in order to decide whether or not new doctors should be recruited.

We observed that we could identify two different problems (1-4 e 2-3). The first one is to estimate the demand and its asymptotic behaviour. This may be done by using time series. The second problem is to study the behaviour of consolidated patients, supposing to know the demand. Because of the few time we had at our disposition, we focused only on the 2 and 3.

## MODEL SCHEME



Our aim was to study all the departments together but, always because of the lack of time, we were able to analyse only one of them. Each department may be studied by using two different models: an analytical one or a simulation. The analytical one is a Markov process: there is a network of queues (the departments); in each department there is a queue of patients with a Poisson arrival process; each patient is attended by a doctor, with a deterministic time of visit  $D$ . After the visit, the patient may simply exit the process or he may come back to the department; this happens in a time  $t$  with a probability  $p$ . When we add others departments, we also have a probability of transition between two departments. We indicated with  $s$  the number of services (in this case doctors); the model has an analytical solution only if  $s=1$  and if we don't consider the transition time. This analytical model appeared to be too much complicated, so we decided to use a simulator. In order to do this, we needed to know:

- The distribution of the arrivals: we assumed it to be an exponential one;
- The probabilities of transitions between the kinds of visit: we estimated them by using a Matlab program from the data we had at disposition;
- The mean times between visits: we estimated them by using a Matlab program too.

## WORKING WITH THE DATA

First of all, we decided deal with the data with Matlab.

Our aim was to create a simulator for all the departments, but it became complicated and we didn't have enough time to do it. That's why we decided to begin studying two departments: "General Ophthalmology" and "Cataracts". We've chosen them because of two reasons:

- The amount of data is large enough (96.073, about 65% of the total data);
- There weren't kind of visits specific of these departments (i.e., all the kind of visits of these departments appear also in other departments).

First, we started with the study of departments one by one; in fact the simulator will use only one of them. Then we studied the two departments together.

Before focusing on these two departments, we made some general studies: we firstly made a program to count how many times each patient changes from one department to another and then we calculated how many new arrivals each doctor has. We obtained the two following sets of data.

### DOCTOR ID

```
610  801  802 1092 1094 1095 1096 1098 1099 1100 1101
1103 1105 1106 1107 1108 1112 1114 1121 1128 1129 1145
1146 1161 1162 1182
```

### NUMBER OF NEW ARRIVALS

```
    0  256  599  769    0  0 1287  376  718 1904   90
1358    0  131   82  22  0    0  197  52  960 1106
248   97  821    0
```

As we have mentioned before, we have studied the case of one department for the simulation and we've also studied two departments together, as we are going to see.

## DEPARTMENT 8: “OFTALMOLOGIA GENERAL”

This department is the one which contains the biggest number of visits (58.344, about the 40% of all the data). We ordered them firstly by their ID and then by the date of the visit.

We did a program to count how many times each patient change kind of visit; then we used it to calculate the probabilities of changes between kind of visits in the same department and we obtained the following matrix:

	1	2	3	4	5	6	7	8	9	10
1	0	0.1375	0.0291	0.0290	0.1405	0	0.0009	0.0004	0.0010	0.6615
2	0	0.4278	0.0579	0.0407	0.0915	0	0.0002	0	0.0005	0.3813
3	0	0.1504	0.3639	0.2017	0.1199	0	0.0009	0.0002	0.0011	0.1617
4	0	0.0797	0.2261	0.3245	0.2023	0	0.0002	0.0002	0.0020	0.1650
5	0	0.0609	0.0790	0.1489	0.4551	0.0003	0.0014	0.0010	0.0040	0.2494
6	0	0.0833	0.0500	0.2000	0.3333	0	0	0	0	0.3333
7	0	0.0270	0.0541	0.0270	0.4595	0.0495	0.0270	0.0405	0	0.3243
8	0	0.0721	0.0360	0.1081	0.1712	0	0	0.0180	0	0.5946
9	0	0.0721	0.0496	0.1322	0.3636	0	0	0	0.0083	0.3967

### LEGEND

- |                                |   |
|--------------------------------|---|
| <b>1</b> - First visit         | <b>6</b> - 24h post-operative revision        |
| <b>2</b> - One year revision   | <b>7</b> - 1 month post-operative revision    |
| <b>3</b> - 6 month revision    | <b>8</b> - 1-3 month post-operative revision  |
| <b>4</b> - 3 month revision    | <b>9</b> - Discharged post-operative revision |
| <b>5</b> - Monitoring revision | <b>10</b> - Patient out of the system         |

In general, the program works as it follow: it asks Matlab to read the data from an excel sheet; looking through these data, it checks firstly if there are two or more following records for the same patient. If this happens, it controls the kind of visit: if there are two different kind of visit or if the kind is the same but is not a “first visit”, it adds 1 in the corresponding position of the matrix; although, it adds one in the exit column.

If in two following records there are two different patients, if the date of visit is before 01/01/2011 the case is considered as an exit.

Then, by dividing each row by the sum of all the elements it contains, we obtain the probability requested.

Below the matrix, we've got the names of the 9 different kind of visits bellow the matrix. In each position we have the probability of change from one kind of visit to other kind of visit.

The matrix isn't square because we have added an extra column to count people who never come back to the clinic, so this column has the probability of change from one kind of visit to exit.

Also, we can see that the first column contains just zeros because a patient can not be a first visit again. In fact, we have found some special cases that we will explain later.

The lowest probabilities are in the columns 6 to 9 because we are in a clinic department, so the probability to change from any kind of visit to a post-surgery visit is very small.

The highest probabilities are in the fifth and the tenth column. For the last one is obvious because if not the system would be very busy. For the fifth column, the company told us that the monitoring check-up (number 5) is a kind of visit that doctors use a lot when they don't know well how to classify a new patient.

Then, with these probabilities we have calculated the next matrix which contains the mean times, in days, between two kind of visits.

Firstly, we've assumed that the transition time depended on the initial and final kind of visit of the patients.

	1	2	3	4	5	6	7	8	9
1	0	545,930	274,480	194,959	73,494	0,000	18,571	75,333	163,750
2	0	414,993	285,246	247,453	148,709	0,000	43,000	0,000	160,833
3	0	377,734	226,104	211,926	142,017	0,000	94,250	191,000	223,000
4	0	413,774	239,152	174,884	122,797	0,000	11,000	98,000	186,600
5	0	480,326	275,117	189,877	81,821	37,500	65,706	63,250	113,813
6	0	585,800	638,667	379,000	125,600	0,000	0,000	0,000	0,000
7	0	682,000	197,500	147,500	67,706	33,000	29,333	36,000	0,000
8	0	492,000	589,250	146,583	256,263	0,000	0,000	42,000	0,000
9	0	508,333	194,167	191,250	146,955	0,000	0,000	0,000	0,000



These times are not that we expected, for example, the columns corresponding to the 3 month check-up (the fourth) has, in average, more than 90 days (number of days in three months). In fact, the mean times in all columns are higher than it should be because it's possible that the patients go to other departments before they come back to this one. We will check it when we see the calculations with two departments together.

Also, we have done the calculations of the mean times in a vector in order to not spend much time with the simulator. In this vector, we are supposing that the time only depends on the final kind of visit and not on the original.

1	2	3	4	5	6	7	8	9
0	435,396	251,164	195,156	97,319	36,000	52,914	66,636	137,423

## DEPARTMENT 6: “CATARATAS”

This department contains 37.729 visits (about the 25% of all the data). As we did for department 8, we ordered them firstly by their ID and then by the date of the visit. The program is quite similar to the one we used for department 8. Below we show the data obtained:

MATRIX OF PROBABILITIES OF CHANGES BETWEEN TWO KIND OF VISIT

	1	2	3	4	5	6	7	8	9
1	0	0,102	0,023	0,027	0,093	0,110	0,078	0,097	0,009
2	0	0,371	0,054	0,045	0,074	0,062	0,053	0,023	0,002
3	0	0,222	0,142	0,135	0,091	0,068	0,055	0,039	0,004
4	0	0,110	0,140	0,195	0,127	0,074	0,055	0,046	0,009
5	0	0,082	0,053	0,098	0,258	0,072	0,093	0,065	0,009
6	0	0,051	0,030	0,045	0,150	0,186	0,190	0,102	0,015
7	0	0,073	0,027	0,047	0,192	0,089	0,178	0,115	0,018
8	0	0,119	0,047	0,086	0,123	0,085	0,048	0,115	0,015
9	0	0,151	0,095	0,095	0,147	0,060	0,030	0,078	0,026

MEAN TIMES MATRIX, IN DAYS

	1	2	3	4	5	6	7	8	9
1	0	538,731	286,358	233,454	81,699	67,664	56,275	80,043	92,605
2	0	431,916	303,647	220,457	127,362	126,700	87,746	135,478	151,118
3	0	423,418	246,980	223,549	148,558	155,454	91,759	130,732	159,800
4	0	462,670	262,270	225,645	135,310	167,380	91,858	123,910	163,882
5	0	456,801	309,464	196,005	82,470	103,990	66,072	88,295	119,778
6	0	486,718	362,802	249,688	91,105	93,264	31,434	95,570	53,527
7	0	451,906	331,207	224,487	76,735	96,141	36,000	64,815	53,517
8	0	466,409	290,232	207,495	111,115	145,044	103,490	100,675	104,710
9	0	388,600	242,500	170,955	82,294	112,429	58,143	79,278	19,833

MEAN TIMES VECTOR

	1	2	3	4	5	6	7	8	9
0	450,716	292,053	218,404	96,097	104,973	55,638	91,278	89,034	

## TWO DEPARTMENTS TOGETHER

We did the calculations with these two departments together because both had the same kind of visit and we could study the transition between two departments. In this case, we will have more rows because here we are considered the kind of visit of the two departments.

Firstly, we filtered the data by selecting only the ones concerning departments 6 and 8 and we asked Matlab to read them. Then we calculated the probabilities of changes between two different kinds of visit. Firstly, the program looks through the data and separates two cases: there is the same patient ID in two following records or there isn't. In the first case it checks the kind of visit and if the patient has gone to the visit or not. If the kind of visit is "first visit" it is considerate as an exit. If the patient hasn't gone to the visit, we put 1 in the column of the exit. Otherwise, we put 1 in the corresponding column. If the kinds of visit are different, also if it is not a first visit we consider it as an exit.

In the case the ID patient are different, we check if the date of the visit is before 01/01/2011 and, in that case, we add one in the exit column.

The following step is to calculate the probabilities and the time matrix. It was done in the same way as the previous programs. Below we show the results:

MATRIX OF PROBABILITIES OF CHANGES BETWEEN TWO KINDS OF VISIT

	1	2	3	4	5	6	7	8
1	0	0,129	0,023	0,022	0,115	0	0,001	0
2	0	0,399	0,048	0,031	0,070	0	0	0
3	0	0,129	0,301	0,163	0,080	0	0,001	0
4	0	0,068	0,179	0,247	0,133	0	0	0
5	0	0,048	0,054	0,105	0,331	0	0,001	0,001
6	0	0,067	0,017	0,050	0,267	0	0	0
7	0	0,014	0,041	0,027	0,378	0,014	0,027	0,041
8	0	0,063	0,009	0,090	0,108	0	0	0,018
9	0	0,032	0,048	0,080	0,224	0	0	0
10	0	0,021	0,018	0,022	0,126	0	0	0
11	0	0,094	0,029	0,025	0,096	0	0	0
12	0	0,073	0,121	0,099	0,088	0	0	0,001
13	0	0,033	0,118	0,149	0,115	0	0	0

14	0	0,027	0,034	0,066	0,240	0	0,001	0
15	0	0,032	0,062	0,068	0,192	0	0,001	0
16	0	0,023	0,020	0,039	0,276	0,001	0,001	0
17	0	0,029	0,046	0,079	0,149	0	0,001	0
18	0	0,022	0,045	0,082	0,142	0	0	0

	9	10	11	12	13	14	15	16	17	18	19
1	0,001	0	0,010	0,004	0,004	0,028	0,015	0,022	0,014	0,001	0,612
2	0,000	0	0,059	0,009	0,007	0,017	0,015	0,015	0,006	0,001	0,324
3	0,001	0	0,041	0,051	0,038	0,020	0,038	0,009	0,010	0	0,119
4	0,001	0	0,031	0,038	0,060	0,038	0,049	0,021	0,015	0,003	0,116
5	0,003	0	0,034	0,016	0,035	0,080	0,046	0,044	0,032	0,005	0,168
6	0	0	0,017	0,017	0,100	0,067	0,100	0,017	0,017	0	0,267
7	0	0	0,027	0	0,014	0,108	0,000	0,027	0,014	0	0,270
8	0	0	0,108	0	0,036	0,054	0,036	0,063	0,018	0	0,396
9	0,008	0	0,040	0,016	0,064	0,056	0,048	0,080	0,024	0	0,280
10	0,001	0	0,084	0,015	0,014	0,077	0,095	0,065	0,085	0,007	0,367
11	0	0	0,313	0,038	0,032	0,054	0,048	0,040	0,017	0,002	0,212
12	0,002	0	0,157	0,092	0,085	0,061	0,043	0,040	0,026	0,001	0,111
13	0,002	0	0,074	0,086	0,108	0,078	0,043	0,036	0,030	0,005	0,124
14	0,002	0	0,058	0,032	0,056	0,177	0,048	0,062	0,042	0,005	0,150
15	0,003	0	0,031	0,011	0,021	0,107	0,137	0,163	0,074	0,011	0,086
16	0,003	0	0,044	0,011	0,020	0,128	0,058	0,137	0,092	0,015	0,134
17	0,003	0	0,094	0,030	0,055	0,078	0,056	0,029	0,091	0,011	0,250
18	0	0	0,123	0,063	0,063	0,108	0,037	0,019	0,060	0,022	0,213

MATRIX OF MEAN TIMES

	1	2	3	4	5	6	7	8
1	0	544,693	242,067	169,751	57,472	0	17,500	75,333
2	0	404,925	255,970	206,974	106,794	0	54,500	0
3	0	361,202	199,289	183,579	89,402	0	102,000	191,000
4	0	398,504	210,537	140,146	86,498	0	11,000	0
5	0	456,184	223,058	151,483	53,328	15,000	69,083	63,250
6	0	603,250	98,000	159,000	78,688	0	0	0
7	0	1062,000	226,333	147,500	40,393	31,000	12,500	36,000
8	0	505,429	176,000	134,600	151,250	0	0	42,000
9	0	299,000	194,167	133,600	94,321	0	0	0
10	400,000	516,925	239,217	160,514	58,091	69,000	10,500	0
11	0	413,003	226,400	185,800	75,544	0	0	0
12	0	361,725	196,442	166,778	86,104	0	0	68,000
13	0	398,542	193,262	138,119	80,810	0	0	0
14	0	439,358	217,142	141,370	58,111	33,000	21,600	35,500
15	0	409,090	227,060	173,694	50,838	0	9,333	98,000
16	0	426,684	230,739	155,947	47,006	14,000	41,000	0
17	0	413,697	220,683	147,033	72,293	0	13,667	0
18	0	542,000	178,917	153,727	64,184	0	0	0

	9	10	11	12	13	14	15	16	17	18
1	79,250	0	571,066	226,000	176,471	55,362	53,496	45,817	74,596	60,500
2	104,600	0	401,981	272,713	191,375	114,507	144,946	43,642	87,377	96,833
3	123,667	0	327,510	186,528	169,335	111,152	129,257	34,951	93,778	70,000
4	123,143	0	397,994	176,831	128,212	90,722	110,386	71,888	81,684	90,706
5	99,156	0	432,941	228,328	138,041	56,283	86,439	38,332	74,607	84,509
6	0	0	206,000	189,000	206,667	69,250	118,667	42,000	63,000	0
7	0	0	512,000	0	178,000	54,250	0	33,000	91,000	0
8	0	0	581,833	0	133,250	47,833	130,000	39,429	51,000	0
9	0	0	361,600	323,000	152,500	219,286	204,167	22,200	40,667	0
10	54,000	0	530,645	234,727	163,466	65,900	50,498	39,401	69,977	76,135

11	142,667	0	411,664	256,097	173,826	91,516	80,700	46,606	92,803	117,429
12	121,333	0	370,754	179,707	160,239	89,253	99,225	49,446	86,721	70,000
13	95,000	0	421,716	185,112	142,924	84,246	84,617	43,718	78,758	148,818
14	83,800	0	440,679	240,034	136,891	51,094	56,644	34,052	63,593	73,240
15	75,455	0	471,419	242,048	151,148	58,121	43,965	17,424	55,586	50,419
16	52,583	0	399,227	236,459	159,271	45,448	52,472	19,962	46,858	46,400
17	104,667	0	435,009	217,735	152,766	69,331	100,709	48,758	71,893	74,000
18	0	0	385,970	208,588	136,118	51,345	71,400	38,200	65,313	19,833

As we can see in the matrix of the mean times, the times are lower than the cases studied independently as we have mentioned before, because in this case we have considered the transitions between these two departments. As more departments are considered better results we will obtain.

Finally, we have calculated the vector of mean times although we didn't use it for the simulator.

#### VECTOR OF MEAN TIMES

1	2	3	4	5	6	7	8	9
400,000	423,536	216,535	158,873	63,614	26,556	40,619	64,200	91,057

## SOME SPECIAL CASES

The next point in our project was to study some special cases. Dealing with the data and the output of some calculations that we did, we got some apparently strange cases, so we analysed them in order to improve the code and understand the output. As a first example we see the following table in which we collect the number of changes in patient between kind of visit:

	1	2	3	4	5	6	7	8	9
1	261	1054	223	222	1077	0	7	3	8
2	0	5135	695	488	1098	0	3	0	6
3	0	662	1602	888	528	0	4	1	5
4	0	393	1114	1599	997	0	1	1	10
5	0	730	947	1784	5454	4	17	12	48

Here we see that there are 261 transitions from the kind '1st visit' to the same kind '1st visit', and that cannot occur since a patient cannot be a first visit patient twice. So we are counting transitions in a bad way. What's happening here is that maybe a patient made an appointment but never showed up, and the made an appointment again. So for us, this is considered like two visits. We will see this in the next part considering two different departments.

### 1) In 'General Ophthalmology':

We have considered a special kind of patients: those who went out of the process because they didn't show up in his/her first visit. With that we mean patients that have made a first-visit appointment but never showed up. In practice, the doctor had reserved the time for attending this patient. This is an exit of the system even though he/she has made a new appointment and he/she has actually showed up. For example, we have the next table for a patient:

001PA65 3634	8	OFTALMOLOGIA GENERAL	11 29	DRA.DRAKE	1	PRIMERAS	1	PRIMERA VISITA	20120 307	20120 224	P
001PA65 3634	8	OFTALMOLOGIA GENERAL	11 00	DRA.GARCI A GONZ	1	PRIMERAS	1	PRIMERA VISITA	20120 315	20120 308	R
001PA65 3634	8	OFTALMOLOGIA GENERAL	11 00	DRA.GARCI A GONZ	5	REVISION SEGUIMIENTO	1 1	REVISION SEGUIMIENTO	20120 417	20120 403	R
001PA65 3634	8	OFTALMOLOGIA GENERAL	11 00	DRA.GARCI A GONZ	2	REVISIONES LARGAS	4	REVISION 3 MESES	20121 015	20120 417	P



For us, the second row of this table is a new arrival, because the first one didn't happen.

Likewise, we consider that one patient has gone out of the process if the date of his/her last appointment is before 01/01/2011 (no matter if that appointment was or not made). For example:

001PA600386	8	OFTALMOLOGIA GENERAL	1129	DRA.DRAK E	1	PRIMERA S	1	PRIMER A VISITA	20101124	20101013	R
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001PA593675	8	OFTALMOLOGIA GENERAL	1145	DR.GIMENEZ VAL	5	REVISION SEGUIMIENTO	11	REVISION SEGUIMIENTO	20101015	20100930	R
001PA593675	8	OFTALMOLOGIA GENERAL	1100	DRA.GARCIA GONZ	2	REVISIONES LARGAS	2	REVISION ANUAL	20120213	20120210	R

## 2) In 'Cataracts':

As before, we consider that first and second rows are patients that went out of the process, in spite of being the same patient, because he/she never came to the clinic.

001TM780925	6	CATARATAS	1092	DR.TEUS	1	PRIMERAS	29	PRIMERA MAYORES 65	20110726	20110722	P
001TM780925	6	CATARATAS	1161	DR. PAZ MORENO	1	PRIMERAS	29	PRIMERA MAYORES 65	20120217	20120209	P

The same with the first row of the following table:

001PA650325	6	CATARATAS	1092	DR.TEUS	1	PRIMERAS	29	PRIMERA MAYORES 65	20120213	20120130	P
001PA650325	6	CATARATAS	1092	DR.TEUS	1	PRIMERAS	29	PRIMERA MAYORES 65	20120224	20120214	R

## 3) First visits in departments 'General ophthalmology' and 'Cataracts':

Here, we take into account that we can have the **two first-visit kind in the same patient** ('FIRST VISIT' and 'FIRST VISIT OVER 65'). If the first one wasn't made, we consider it as an exit of the system. This can be possible because one patient made an appointment in 'General Ophthalmology' but never came to the clinic. Then, he/she made a new appointment but for something more specific (for example, for 'Cataracts'), so the new appointment is classified in that department as 'First visit over 65' (also, it could be the reverse situation):

001PA513	8	OFTALMOLOGIA	110	DRA.IBA	1	PRIMER	1	PRIMERA VISITA	200909	200908	P
----------	---	--------------	-----	---------	---	--------	---	----------------	--------	--------	---

MODELLING THE PATIENTS DEMAND IN OPHTHALMOLOGICAL CLINICS

999		GENERAL	3	RZ		AS			16	14	
001PA513 999	6	CATARATAS	109 2	DR.TEUS	1	PRIMER AS	2 9	PRIMERA MAYORES 65	200909 23	200909 18	P

001PA624 862	6	CATARATAS	109 2	DR.TE US	1	PRIMER AS	2 9	PRIMERA MAYORES 65	201105 06	201104 11	P
001PA624 862	8	OFTALMOLOGIA GENERAL	109 2	DR.TE US	1	PRIMER AS	1	PRIMERA VISITA	201206 25	201202 06	P

001PA51 4672	8	OFTALMOLOGIA GENERAL	10 92	DR.TEUS	1	PRIMERAS	1	PRIMERA VISITA	20090 909	20090 828	P
001PA51 4672	6	CATARATAS	10 92	DR.TEUS	1	PRIMERAS	2 9	PRIMERA MAYORES 65	20111 202	20111 130	R
001PA51 4672	8	OFTALMOLOGIA GENERAL	11 29	DRA.DR AKE	2	REVISIONES LARGAS	4	REVISION 3 MESES	20120 529	20120 507	R

001PA52 1164	8	OFTALMOLOGIA GENERAL	11 03	DRA.IBARZ	1	PRIMERAS	1	PRIMERA VISITA	20090 930	20090 828	P
001PA52 1164	6	CATARATAS	11 03	DRA.IBARZ	1	PRIMERAS	2 9	PRIMERA MAYORES 65	20091 110	20091 001	R
001PA52 1164	8	OFTALMOLOGIA GENERAL	11 03	DRA.IBARZ	2	REVISIONES LARGAS	4	REVISION 3 MESES	20100 218	20100 209	R
001PA52 1164	6	CATARATAS	11 03	DRA.IBARZ	4	POSTOPERAT ORIOS	1 8	REV POSTOP 24H	20100 317	20100 315	R
001PA52 1164	6	CATARATAS	11 03	DRA.IBARZ	4	POSTOPERAT ORIOS	3 7	REV POSTOP HASTA 1 M	20100 405	20100 317	R
001PA52 1164	6	CATARATAS	11 03	DRA.IBARZ	4	POSTOPERAT ORIOS	3 7	REV POSTOP HASTA 1 M	20100 503	20100 405	R
001PA52 1164	6	CATARATAS	11 03	DRA.IBARZ	2	REVISIONES LARGAS	2	REVISION ANUAL	20110 221	20100 922	R
001PA52 1164	6	CATARATAS	11 61	DR. PAZ MORENO	2	REVISIONES LARGAS	2	REVISION ANUAL	20111 221	20111 116	P
001PA52 1164	8	OFTALMOLOGIA GENERAL	11 61	DR. PAZ MORENO	2	REVISIONES LARGAS	2	REVISION ANUAL	20120 427	20120 417	R

001PA455 290	6	CATARATAS	109 2	DR.TEUS	1	PRIMER AS	2 9	PRIMERA MAYORES 65	200902 18	200901 07	P
001PA455 290	8	OFTALMOLOGIA GENERAL	110 6	DR.VLEMI NG	1	PRIMER AS	1	PRIMERA VISITA	200904 24	200903 06	R

Another situation that is in our database is patients that have two first appointments for different doctors and different departments:

001PA56 0140	6	CATARATAS	80 2	DRA. ALVAREZ	1	PRIMERAS	2 9	PRIMERA MAYORES 65	20100 415	20100 325	R
001PA56 0140	8	OFTALMOLOGIA GENERAL	10 96	DRA.ARR ANZ	1	PRIMERAS	1	PRIMERA VISITA	20100 415	20100 325	R
001PA56 0140	8	OFTALMOLOGIA GENERAL	10 96	DRA.ARR ANZ	5	REVISION SEGUIMIENTO	1 1	REVISION SEGUIMIENTO	20100 617	20100 415	P

001PA659 496	6	CATARAT AS	802	DRA. ALVAREZ	1	PRIMERAS	2 9	PRIMERA MAYORES 65	201205 30	201205 08	R
001PA659 496	6	CATARAT AS	109 2	DR.TEUS	1	PRIMERAS	2 9	PRIMERA MAYORES 65	201205 30	201205 08	R
001PA659 496	6	CATARAT AS	802	DRA. ALVAREZ	2	REVISIONES LARGAS	4	REVISION 3 MESES	201211 27	201205 30	P

#### 4) In general:

We firstly thought that the transitions between the general kind of visits (first check-up, 3 month check-up, 6 month check-up, 1 year check-up, monitoring check-up) could be stochastic in the sense that we could have any combination. Then, the company told us that maybe the process that a patient follows when he/she undergoes surgery is deterministic in the following way:

- 24 hour post-surgery check-up
- Until 1 month post-surgery check-up
- 1-3 months post-surgery check-up
- Final post-surgery check-up
- Monitoring check-up

But with the data we saw that this process is really stochastic since sometimes a patient just goes to one post-surgery revision, or not all of them. We can observe the following examples:

001PA341 005	6	CATARAT AS	80 2	DRA. ALVAREZ	4	POSTOPERATO RIOS	18	REV POSTOP 24H	20090519	2009051 3	R
001PA341 005	6	CATARAT AS	80 2	DRA. ALVAREZ	4	POSTOPERATO RIOS	38	REV POSTOP DE 1 A 3M	20090811	2009072 0	R
001PA341 005	6	CATARAT AS	80 2	DRA. ALVAREZ	4	POSTOPERATO RIOS	18	REV POSTOP 24H	20091020	2009100 5	R
001PA341 005	6	CATARAT AS	80 2	DRA. ALVAREZ	4	POSTOPERATO RIOS	38	REV POSTOP DE 1 A 3M	20100521	2010040 9	R
001PA341 005	6	CATARAT AS	80 2	DRA. ALVAREZ	4	POSTOPERATO RIOS	18	REV POSTOP 24H	20100713	2010052 1	R
001PA341 005	6	CATARAT AS	80 2	DRA. ALVAREZ	4	POSTOPERATO RIOS	37	REV POSTOP HASTA 1 M	20101209	2010120 2	R
001PA341 005	6	CATARAT AS	80 2	DRA. ALVAREZ	4	POSTOPERATO RIOS	38	REV POSTOP DE 1 A 3M	20110509	2011030 9	R
001PA341 005	6	CATARAT AS	80 2	DRA. ALVAREZ	4	POSTOPERATO RIOS	37	REV POSTOP HASTA 1 M	20120323	2012022 9	R

We can guess that this patient underwent surgery three times, but the post-surgery check-ups were different (sometimes a '24 hours post-surgery check-up' < '1-3 month post-surgery check up' and others, '24 hours post-surgery check-up' < 'Until 1 month post-surgery check-up'). Similarly, we can analyze the following:

001PA3 41005	5	RETINA-VITREO	1 0 9 4	DRA. FIGUEROA	5	REVISION SEGUIMIENTO	1 1	REVISION SEGUIMIENTO	2009 0107	2008 1215	R
001PA3 41005	8	OFTALMOLOGIA GENERAL	8 0 2	DRA. ALVAREZ	5	REVISION SEGUIMIENTO	1 1	REVISION SEGUIMIENTO	2009 0116	2008 1209	R
001PA3 41005	5	RETINA-VITREO	1 0 9 4	DRA. FIGUEROA	5	REVISION SEGUIMIENTO	1 1	REVISION SEGUIMIENTO	2009 0204	2009 0107	R
001PA3 41005	6	CATARATAS	8 0 2	DRA. ALVAREZ	4	POSTOPERATO RIOS	1 8	REV POSTOP 24H	2009 0519	2009 0513	R
001PA3 41005	5	RETINA-VITREO	1 0 9 4	DRA. FIGUEROA	2	REVISIONES LARGAS	4	REVISION 3 MESES	2009 0601	2009 0204	R
001PA3 41005	6	CATARATAS	8 0 2	DRA. ALVAREZ	4	POSTOPERATO RIOS	3 8	REV POSTOP DE 1 A 3M	2009 0811	2009 0720	R
001PA3 41005	6	CATARATAS	8 0 2	DRA. ALVAREZ	2	REVISIONES LARGAS	3 9	REV POSTOP PARA ALTA	2009 0925	2009 0811	R
001PA3 41005	6	CATARATAS	8 0 2	DRA. ALVAREZ	4	POSTOPERATO RIOS	1 8	REV POSTOP 24H	2009 1020	2009 1005	R
001PA3 41005	5	RETINA-VITREO	1 0 9 4	DRA. FIGUEROA	2	REVISIONES LARGAS	4	REVISION 3 MESES	2009 1130	2009 0601	R
001PA3 41005	8	OFTALMOLOGIA GENERAL	8 0 2	DRA. ALVAREZ	5	REVISION SEGUIMIENTO	1 1	REVISION SEGUIMIENTO	2010 0115	2009 1020	R
001PA3 41005	8	OFTALMOLOGIA GENERAL	8 0 2	DRA. ALVAREZ	5	REVISION SEGUIMIENTO	1 1	REVISION SEGUIMIENTO	2010 0330	2010 0209	P
001PA3 41005	6	CATARATAS	8 0 2	DRA. ALVAREZ	4	POSTOPERATO RIOS	3 8	REV POSTOP DE 1 A 3M	2010 0521	2010 0409	R
001PA3 41005	6	CATARATAS	8 0 2	DRA. ALVAREZ	4	POSTOPERATO RIOS	1 8	REV POSTOP 24H	2010 0713	2010 0521	R
001PA3 41005	6	CATARATAS	8 0 2	DRA. ALVAREZ	2	REVISIONES LARGAS	3 9	REV POSTOP PARA ALTA	2010 0924	2010 0729	R
001PA3 41005	6	CATARATAS	8 0 2	DRA. ALVAREZ	5	REVISION SEGUIMIENTO	1 1	REVISION SEGUIMIENTO	2010 1122	2010 1102	R
001PA3 41005	6	CATARATAS	8 0 2	DRA. ALVAREZ	4	POSTOPERATO RIOS	3 7	REV POSTOP HASTA 1 M	2010 1209	2010 1202	R

001PA3 41005	6	CATARATAS	8 0 2	DRA. ALVAREZ	5	REVISION SEGUIMIENTO	1 1	REVISION SEGUIMIENTO	2011 0309	2011 0128	R
001PA3 41005	6	CATARATAS	8 0 2	DRA. ALVAREZ	4	POSTOPERATO RIOS	3 8	REV POSTOP DE 1 A 3M	2011 0509	2011 0309	R
001PA3 41005	6	CATARATAS	8 0 2	DRA. ALVAREZ	5	REVISION SEGUIMIENTO	1 1	REVISION SEGUIMIENTO	2011 0613	2011 0518	R
001PA3 41005	6	CATARATAS	8 0 2	DRA. ALVAREZ	5	REVISION SEGUIMIENTO	1 1	REVISION SEGUIMIENTO	2011 0802	2011 0704	R
001PA3 41005	8	OFTALMOLOGIA GENERAL	8 0 2	DRA. ALVAREZ	5	REVISION SEGUIMIENTO	1 1	REVISION SEGUIMIENTO	2012 0111	2011 1018	R
001PA3 41005	8	OFTALMOLOGIA GENERAL	8 0 2	DRA. ALVAREZ	5	REVISION SEGUIMIENTO	1 1	REVISION SEGUIMIENTO	2012 0229	2012 0130	R
001PA3 41005	9	CIRUGIA PLASTICA OCULAR	1 0 9 5	DRA.SANZ LOPEZ	5	REVISION SEGUIMIENTO	1 1	REVISION SEGUIMIENTO	2012 0229	2012 0130	R
001PA3 41005	6	CATARATAS	8 0 2	DRA. ALVAREZ	4	POSTOPERATO RIOS	3 7	REV POSTOP HASTA 1 M	2012 0323	2012 0229	R
001PA3 41005	8	OFTALMOLOGIA GENERAL	8 0 2	DRA. ALVAREZ	5	REVISION SEGUIMIENTO	1 1	REVISION SEGUIMIENTO	2012 0418	2012 0323	R
001PA3 41005	9	CIRUGIA PLASTICA OCULAR	1 0 9 5	DRA.SANZ LOPEZ	5	REVISION SEGUIMIENTO	1 1	REVISION SEGUIMIENTO	2012 0418	2012 0418	R
001PA3 41005	6	CATARATAS	8 0 2	DRA. ALVAREZ	5	REVISION SEGUIMIENTO	1 1	REVISION SEGUIMIENTO	2012 0523	2012 0418	P
001PA3 41005	8	OFTALMOLOGIA GENERAL	8 0 2	DRA. ALVAREZ	5	REVISION SEGUIMIENTO	1 1	REVISION SEGUIMIENTO	2012 0606	2012 0425	P

Since we had these cases, and we can have any combination between the kind of visits, we had to calculate the probabilities of changing between any kind of visit.

# SIMULATOR

## FIRST SIMULATION MODEL

In this part we are going to explain the simulation model. At first, we consider a single department and a single queue, and we will not consider people who do not return to the doctor.

### VARIABLES

These are the variables that we use in this simulation:

#### 1. STATE VARIABLES

The state variables give information about the state of the system:

**TPD:** kind of patient who is being attending for each doctor.

**TP:** vector of the kind of patient in the queue.

**NP:** number of patients in the queue.

**NDO:** number of busy doctors

#### 2. EVENT VARIABLES

An event variable represents the instant when an event happens:

**TD:** next final of doctor consultation.

**TL:** arrival time.

**MTP:** matrix of the next time revision.

**TF:** vector of final time of each doctor consultation.

#### 3. OTHERS VARIABLES

**i:** type of visit.

**j:** doctor.

**DL:** time between arrivals.

**TM:** simulation time.

#### 4. DATA

**TC:** vector of consultation times.

**Tmax:** maximal simulation time.

**lambda:** arrival rate of new customers.

### MODEL

#### MAIN PROGRAM

First of all we initialize the variables that we are going to use in the simulation model and we generate the first arrival. Then we have to update the simulation time. Now we have to check if the next event is an arrival or an end of service. If it is an arrival, we go to the arrival subroutine and if it is a final doctor service we go to the subroutine end of service. When the subroutine has finished, we check if the simulation time has arrived to the final simulation time. In that case, the process ends. If not, we update the simulation time and we continue in the same way.

#### ARRIVALS SUBROUTINE

We have to identify the type of visit and we have to study 2 cases:

If there are not patients in the queue and there are some free doctors, then we update the variables NOD (number of busy doctors) and TF (the time when this doctor is going to be free again). Otherwise, the patient goes to the queue. Then we update number of patients in the queue NP.

Afterwards, if it's the first visit of this patient, we generate another new first visit arrival.

Otherwise, we update the matrix with the arrivals that are not first visit.

#### END OF DOCTOR SERVICE SUBROUTINE

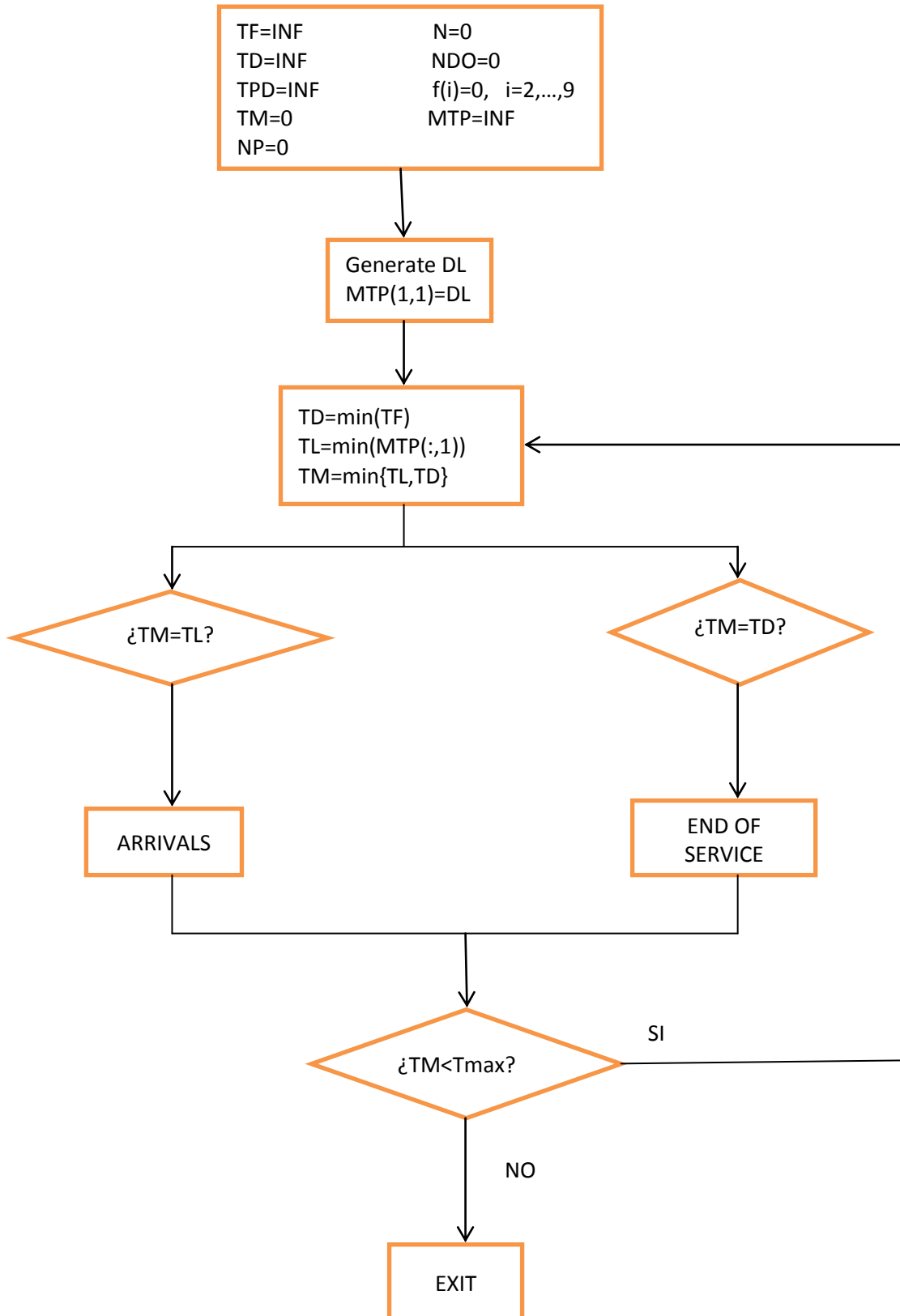
When a doctor service ends, the patient can become in a new type of patient. So, in this subroutine, we are changing the type of the patient.

After doing this, if there are patients in the queue, a new patient starts his consult. In this case we update the kind of patient who is being attending for each doctor (TPD) and the number of patients in the queue (NP).

Otherwise, we update the number of busy doctors NDO.

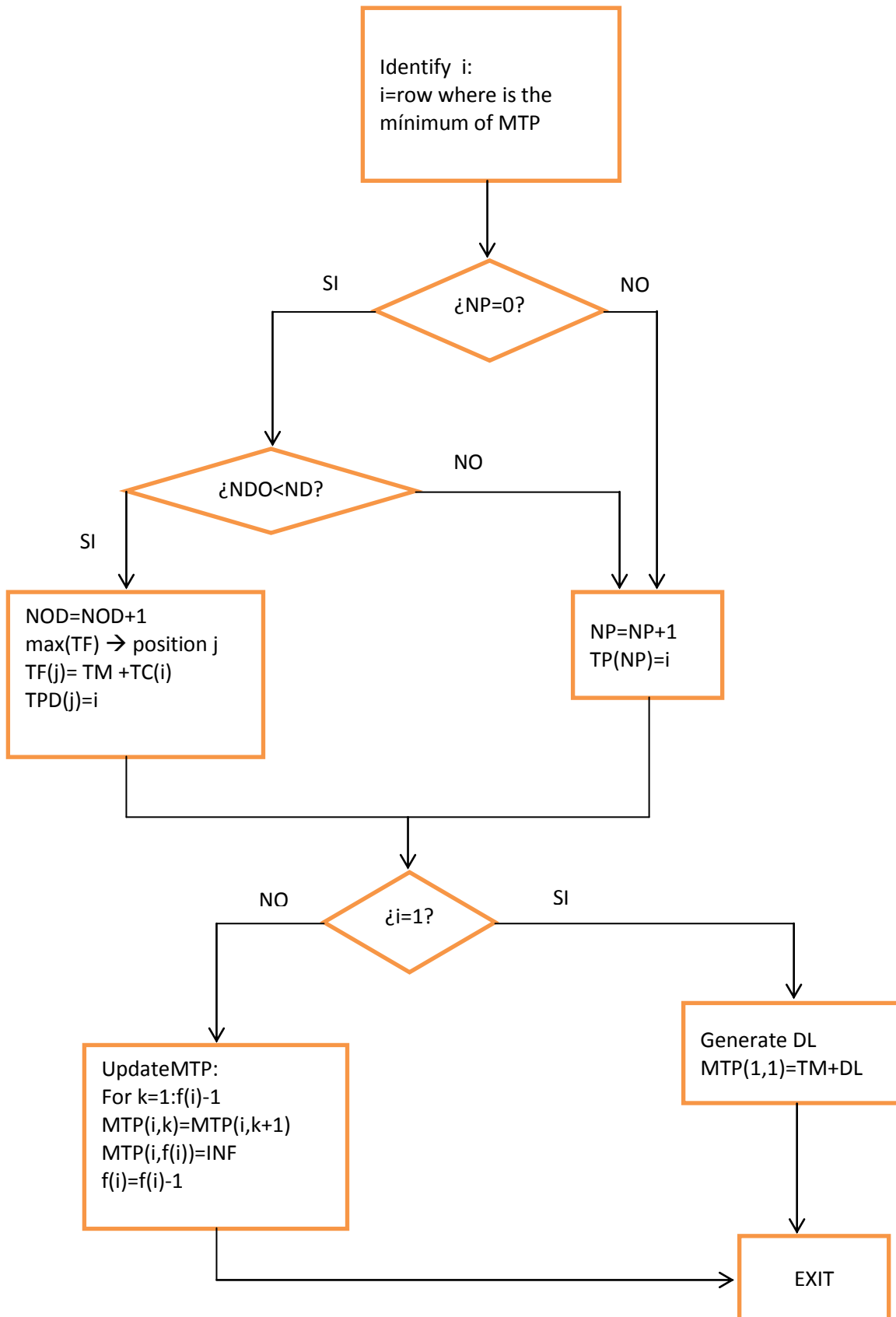
## MODEL SCHEME

### MAIN PROGRAM

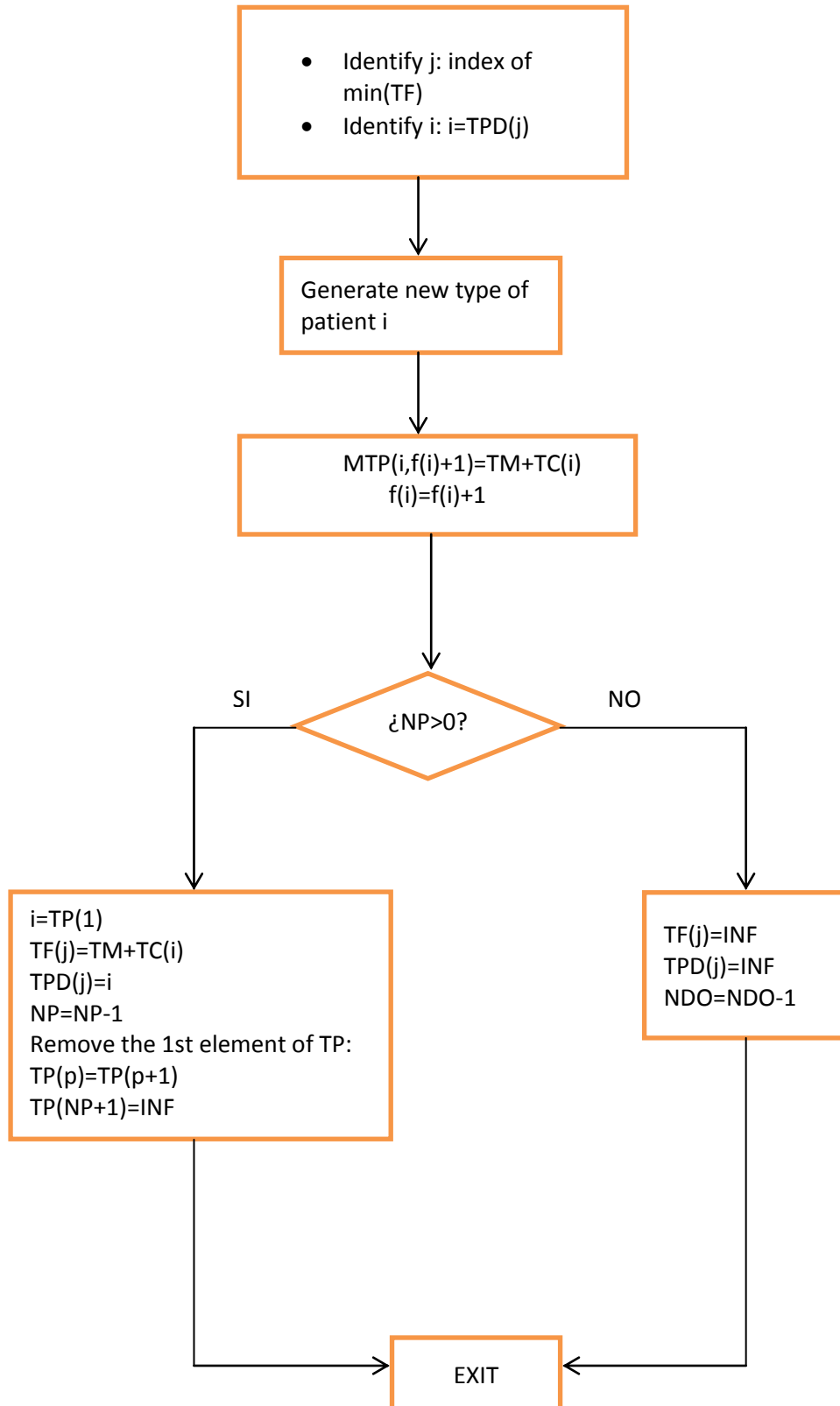




**ARRIVALS SUBROUTINE**



**END OF DOCTOR SERVICE SUBROUTINE**



## RESULTS

We have obtained that, with  $\lambda$  and the number of doctors fixed, we have 2 possibilities:

If there are not enough doctors, the queue size grows all the time. Otherwise, we have a stationary state with a number of patients near to 0.

Then, it seems we are using too many or too few doctors.

The interesting question should be, How can we adjust the number of doctors for a given arrival rate  $\lambda$ ? Because  $\lambda$  is fixed in this model.

So we decided to do a new simulation model.

## SECOND SIMULATION MODEL

In this new simulation program model we have added a new event related to recruit a new doctor. In order to decide if it is necessary to increase the number of doctors, we calculate the utilization factors for each doctor that represents the proportion of time the doctor is actually working.

This is checked at the end of each month when we evaluate these factors and then we decide if a new doctor is recruiting.

### MODEL'S ELEMENTS

#### 1. STATE VARIABLES

**TPD:** kind of patient who is being attending for each doctor.

**TP:** vector of the kind of patient in the queue.

**NP:** number of patients in the queue.

**NDO:** number of busy doctors

**NAB:** number of patients that exit the system.

#### 2. EVENT VARIABLES

**TD:** next final of doctor consultation.

**TL:** arrival time.

**MTP:** matrix of the next time revision.

**TF:** vector of final time of each doctor consultation.

**TCD:** recruiting a new doctor.

#### 3. OTHERS VARIABLES

**i:** type of visit.

**j:** doctor.

**DL:** time between arrivals.

**TM:** simulation time.

**UF:** utilization factor of each doctor (time working over total time).

**WT:** working time of each doctor.

**cont:** auxiliary variable to count a month

**mes:** number of month that elapse

**Tant:** last simulation time

**NPM:** auxiliary variable of average number of patients during a month

**NPCM:** vector of average number of patients during a month

**NDOM:** vector of average number of busy doctors

**GFU:** auxiliary vector of minimum utilization factors of all the doctors in the system during a month

**perc:** minimum utilization factor that all the doctors have to overstep for recruiting a new doctor next month

**ind:** auxiliary index for the number of patient in the queue

**ind2:** auxiliary vector for each kind of patient that we keep the next column index in matrix MTP.

**f:** auxiliary vector for each kind of patient that we keep the last column index in matrix MTP

#### 4. DATA

**ND:** number of doctors.

**TC:** vector of consultation times.

**Tmax:** maximal simulation time.

**p(i,j):** probability to become from patient i to patient j.

**PV(i):** vector of elapsed times until the next visit of patient i.

**v:** number of type of patients.

**lambda:** arrival rate of new customers.

#### 5. EVENTS

These are the possible events that could occur:

- **New doctor:** if the utilization factors of all the doctors is enough higher, we have to add a new doctor in the system.
- **New Arrival:** the same as in the first model.
- **End of doctor's service:** the same as in the first model.

#### 6. MODEL

##### MAIN PROGRAM

##### 0. Initialize variables:

TF=INF; TD=INF; TPD=INF; MTP=INF; MD=INF; TCD=INF;

N=0; NDO=0; TM=0; NP=0; NAB=0; TP=0; DO=0;

WT=zeros(1,ND);

ind2 = ones(v,1); ind=1;

f(i)=0, i=2,...,9

Generate DL; MTP(1,1)=DL; TL = MTP(1,1);

##### 1. Next event time:

$TD = \min(TF)$ ;

$TM = \min(TL, TD, TCD)$ ;

**2. Event identification:**

If  $TM = TCD \rightarrow$  call to: *New doctor subroutine.*

If  $TM = TD \rightarrow$  call to: *End of doctor's service subroutine.*

If  $TM = TL \rightarrow$  call to: *New arrival subroutine.*

**3. Check point: Recruiting doctors:**

If a month has passed  $\rightarrow$  calculate utilization factors for each doctor.

If all the utilization are greater than the coefficient perc  $\rightarrow$  add a new doctor

$\rightarrow TCD = TM$

**4. Check point: Stop:**

If  $TM < T_{max} \rightarrow$  Go to 1. If not, Stop.

SUBROUTINES

**New doctor:**

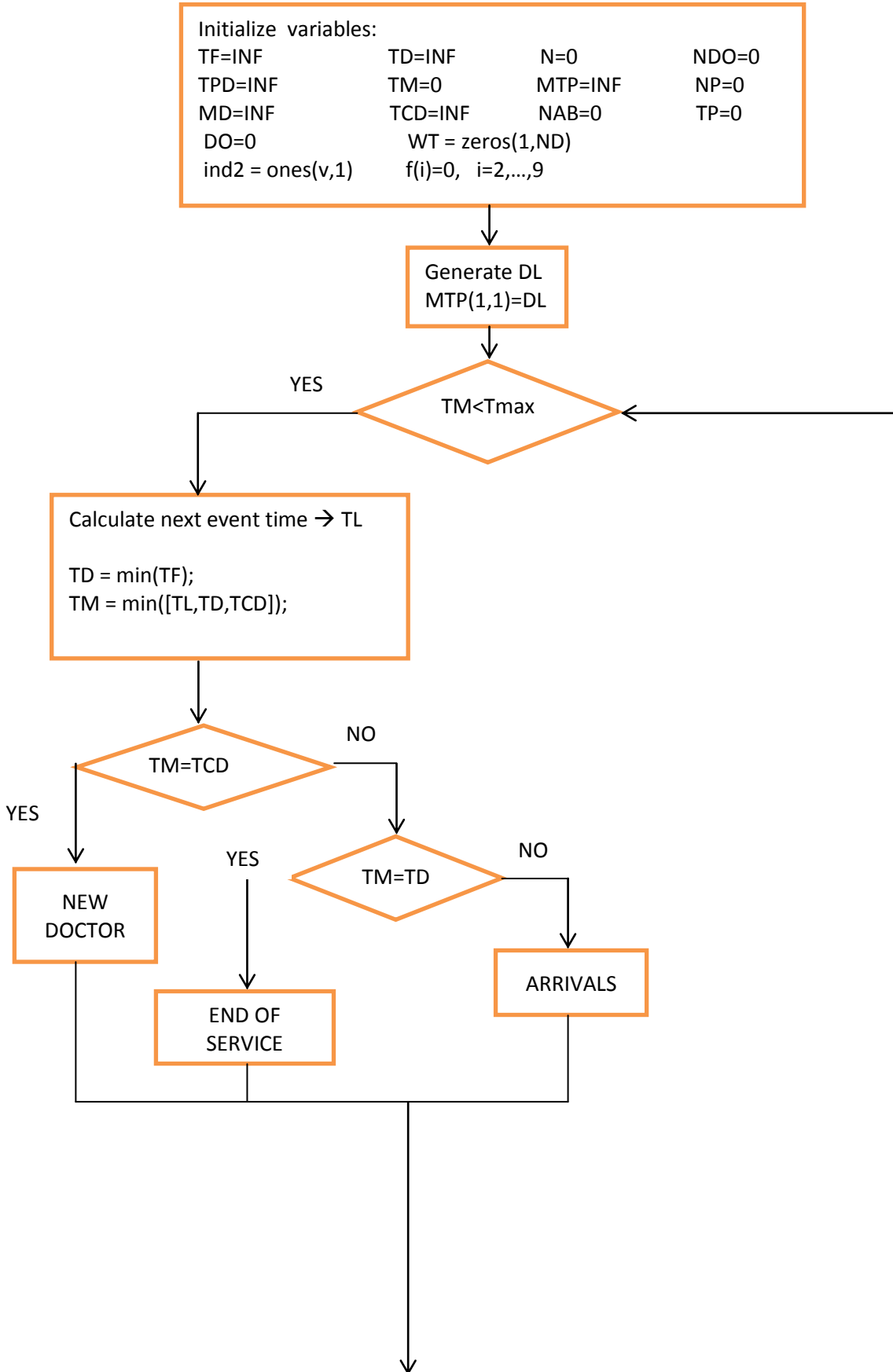
1.  $ND = ND + 1$ ;
2.  $TF = [TF, INF]$ ;
3.  $TPD = [TPD, INF]$ ;
4. If  $NP > 0 \rightarrow$  Go to 5. If not, go to 10;
5.  $I = TP(ind)$ ;
6.  $TF(ND) = TM + TC(i)$ ;
7.  $TPD(ND) = i$ ;
8.  $NP = NP - 1$ ;
9.  $ind = ind + 1$ ;
10.  $TCD = INF$ ;
11.  $WT = [WT, 0]$ ;
12. EXIT: Go to main program.

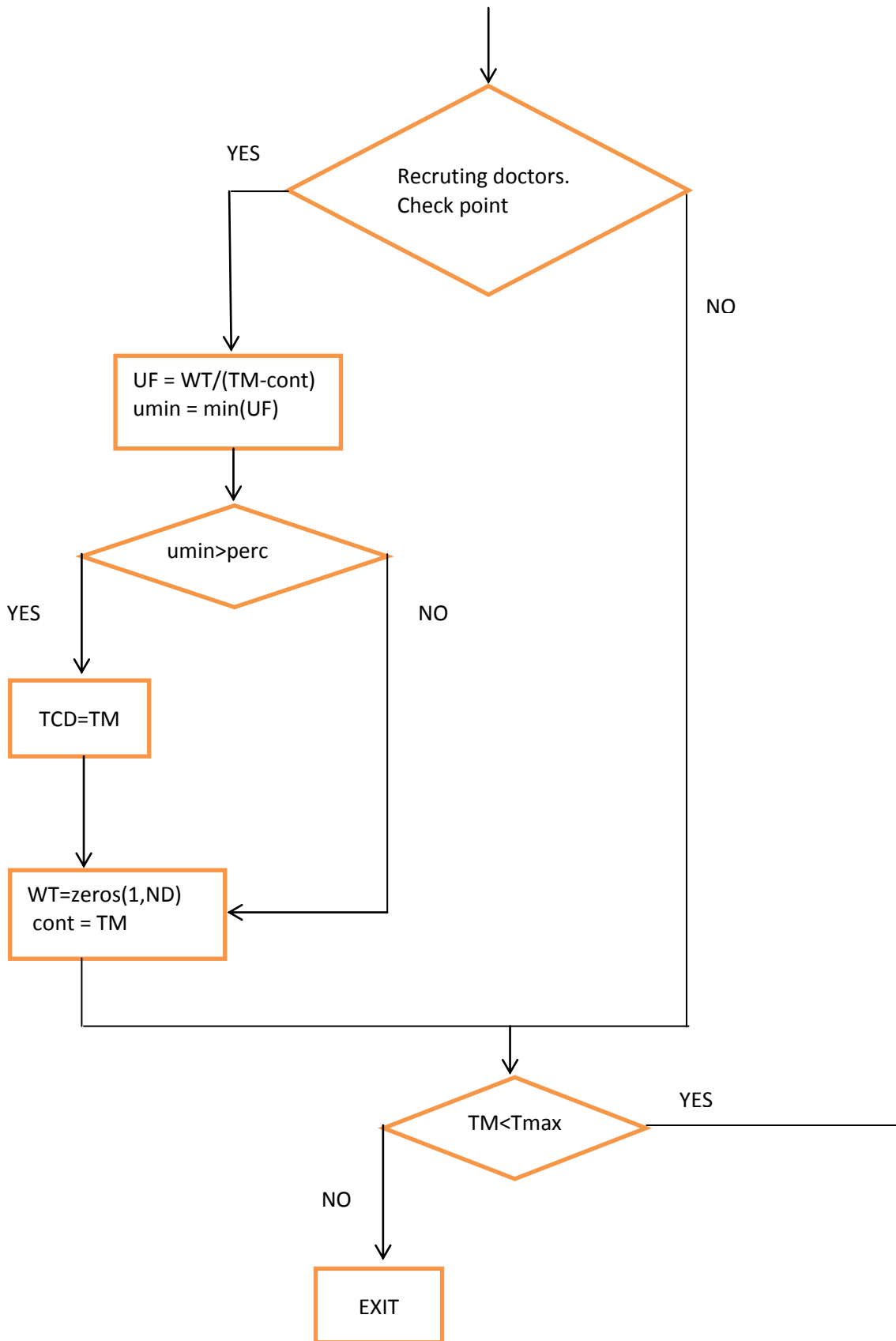
**New arrival:** the same as in the first simulation model.

**End of doctor's service:** the same as in the first simulation model.

## MODEL SCHEME

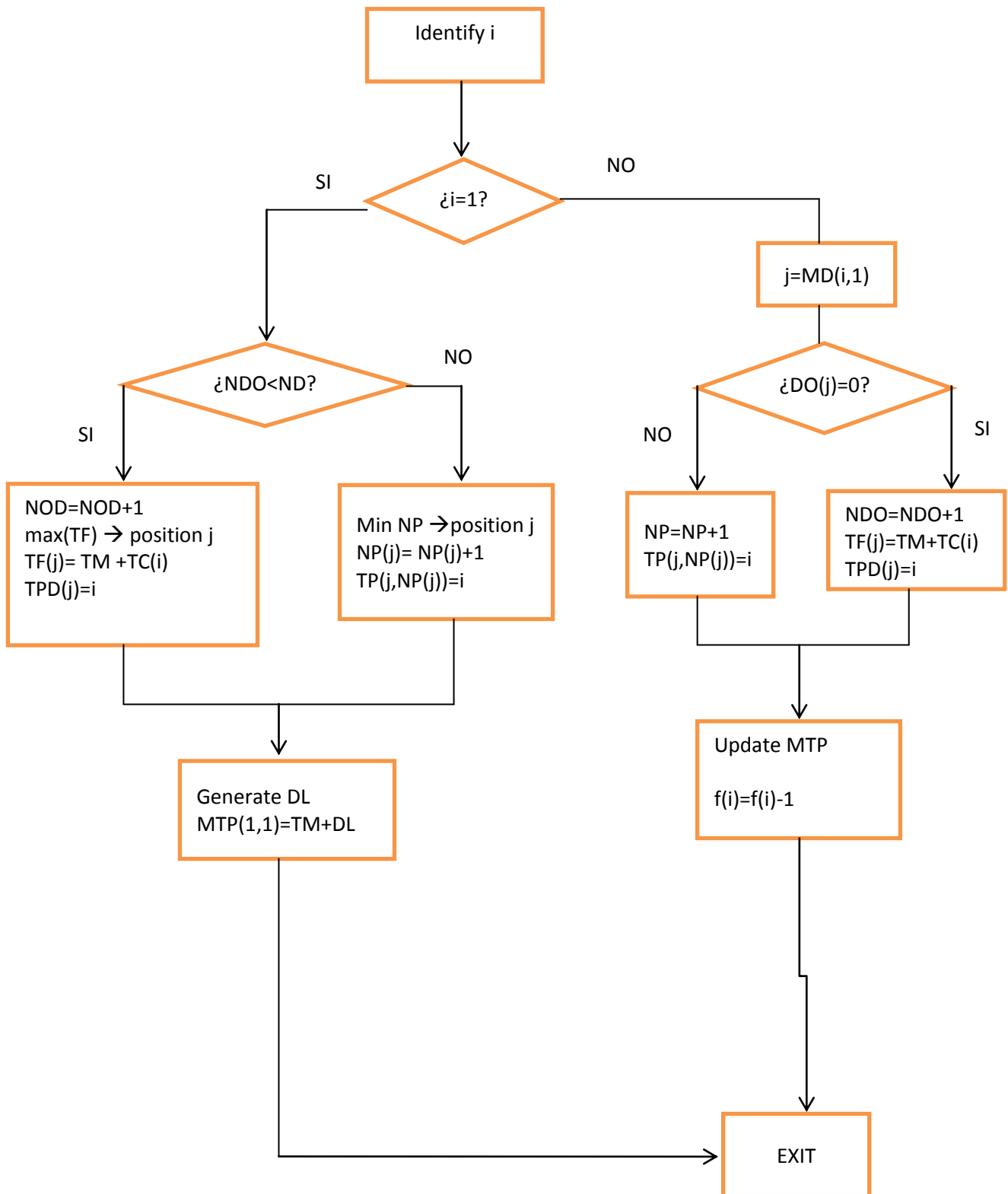
### MAIN PROGRAM



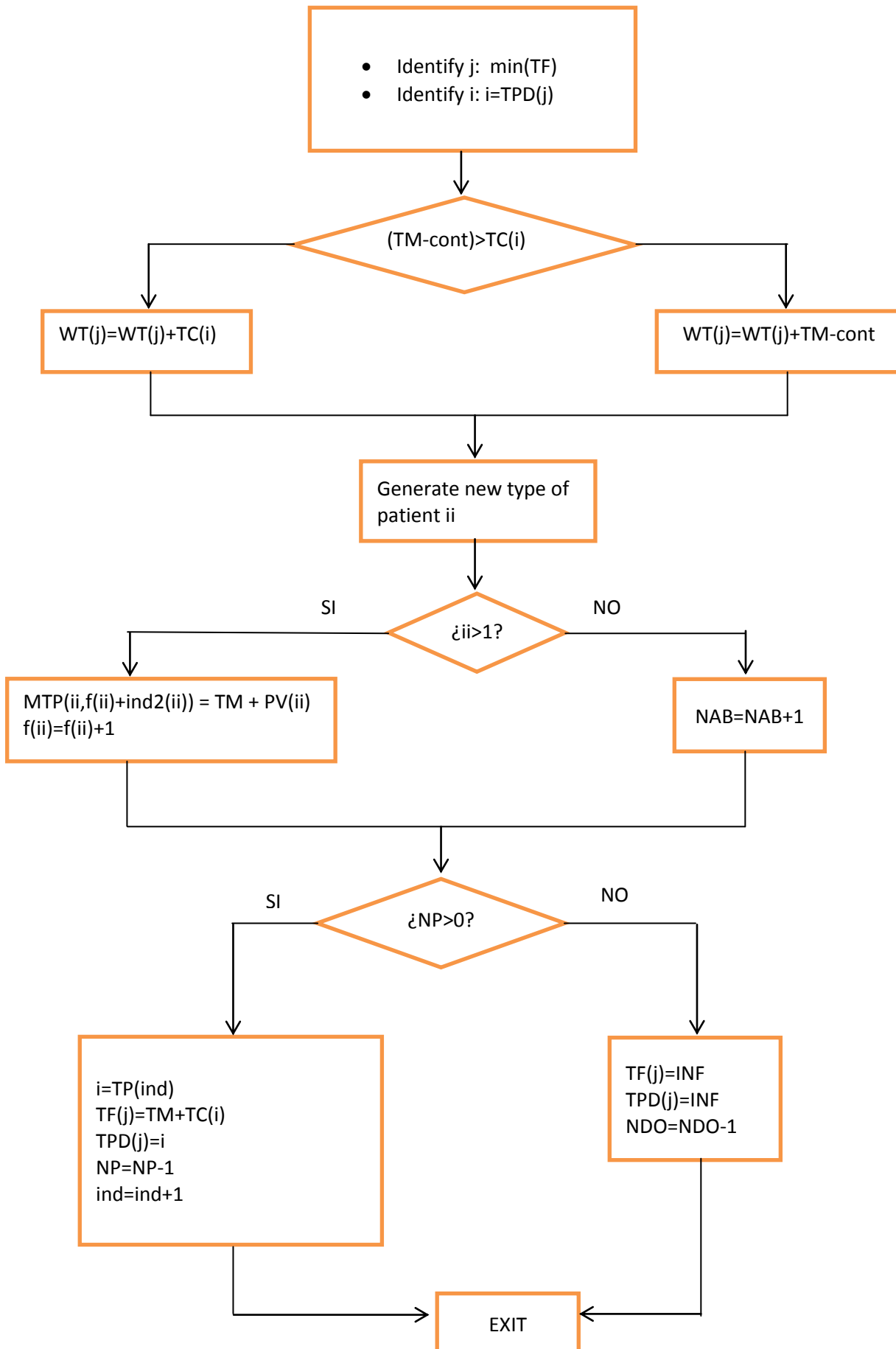




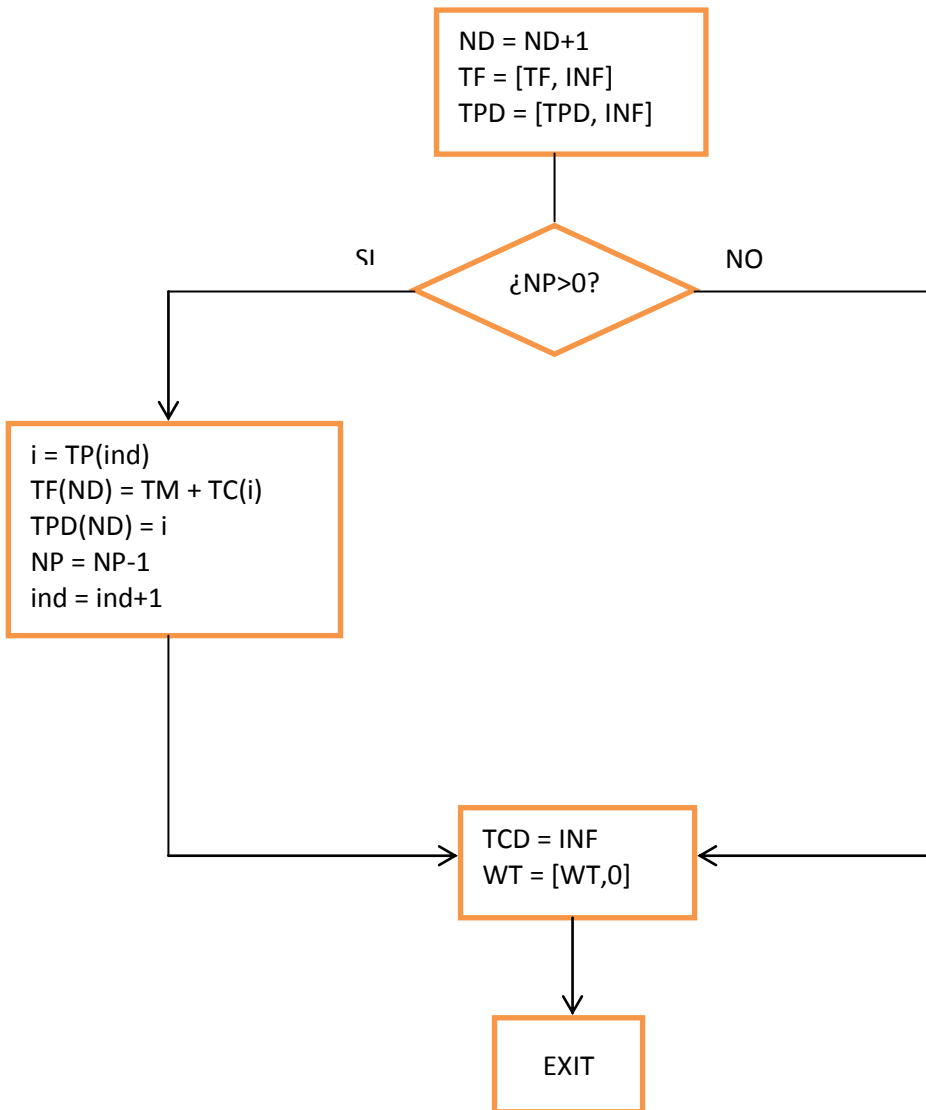
**ARRIVALS SUBROUTINE**



**END OF DOCTOR SERVICE SUBROUTINE**

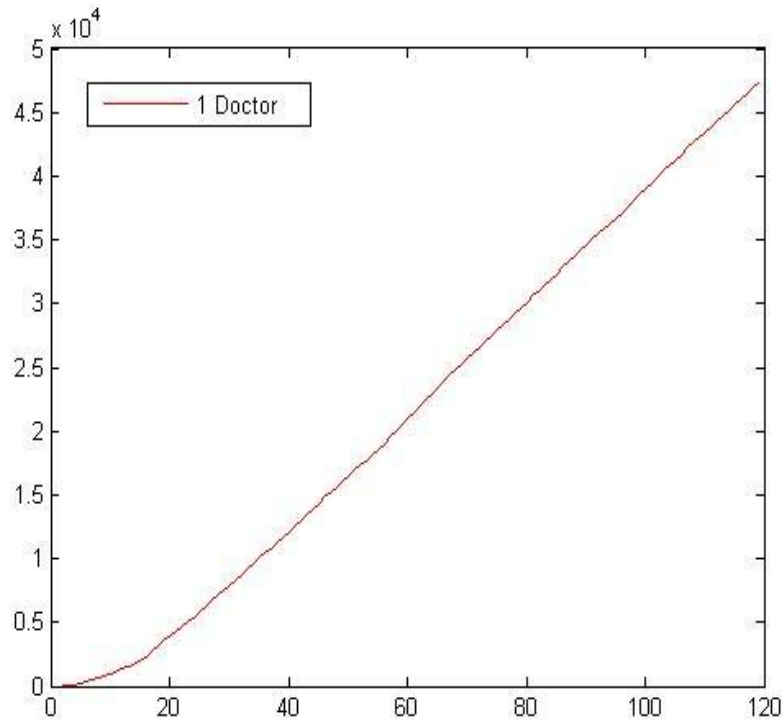


**NEW DOCTOR SUBROUTINE**



## RESULTS

We have developed some numerical results, only for the “One-department model”, to show which kind of numerical experiments could be performed for the whole clinic model.

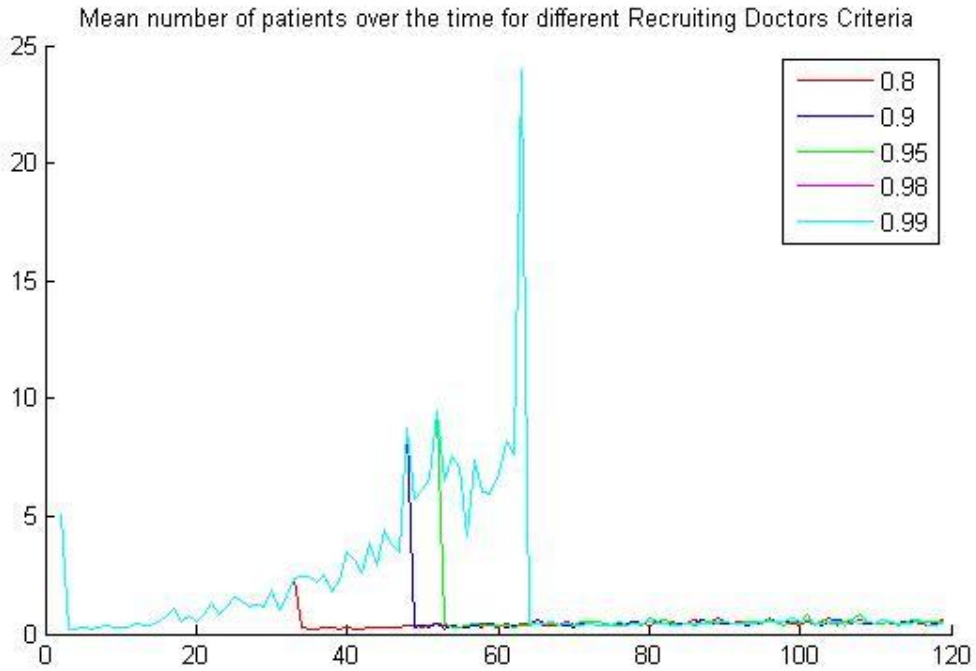


The figure above shows what we have already said, if there is only one doctor, then for our arrival rate we obtained an explosion in the number of patients in the system.

Now the interesting study is to obtain the appropriate number of doctors for a given arrival rate. So, we start with one doctor in the system and we recruit new doctors depending on different criteria based on the utilization factors of all the doctors.

For example, the criteria 0.8 means that a new doctor is recruited if all the doctor’s utilization factors are greater than 0.8.

In the following figure we show the mean number of patients that are in the queue at the end of each month during 10 years. When the number of patients in the queue decreases suddenly, that means that a new doctor has been recruiting.



In that figure we see that the recruiting instants for each criterion are different and how they determined the number of patients in the queue.

In the table below, we show the average number of patients in the queue – 1<sup>st</sup> column- and the number of recruited doctors -2<sup>nd</sup> columns- at the end of each period for different criteria.

U. Factor	1 month	1 year	2 years	3 years	4 years	5 years	6 years	7 years	8 years	9 years	10 years
Criterion 1 0.8	44.70 1	0.44 2	1.17 2	0.21 3	0.35 3	0.29 3	0.51 3	0.33 3	0.65 3	0.56 3	0.60 3
Criterion 2 0.9	44.70 1	0.44 2	1.17 2	2.21 2	8.72 2	0.37 3	0.45 3	0.43 3	0.60 3	0.47 3	0.55 3
Criterion 3 0.95	44.70 1	0.44 2	1.17 2	2.21 2	8.72 2	0.38 3	0.48 3	0.32 3	0.58 3	0.82 3	0.56 3
Criterion 4 0.98	44.70 1	0.44 2	1.17 2	2.21 2	8.72 2	6.80 2	0.43 3	0.35 3	0.52 3	0.46 3	0.42 3
Criterion 5 0.99	44.70 1	0.44 2	1.17 2	2.21 2	8.72 2	6.80 2	0.43 3	0.35 3	0.52 3	0.46 3	0.42 3
Criterion 6 >1 (In thousands)	44.70 1	1.32 1	5.37 1	10.43 1	15.58 1	20.95 1	26.57 1	31.85 1	37.10 1	42.55 1	47.36 1

However, as expected, the final number of doctors and patients are the same order in the stationary state -as you can see in the tenth year-.

Utilization Factors
0.590407062
0.575726807
0.560456648
0.5550857
0.5550857
1

Here we are also showing the utilization factors in the stationary state.

## CONCLUSIONS

Our problem, the study of the patient arrivals to an ophthalmological clinic, and their behaviour in the system –coming back to the system or going definitively out-, should become in a complex network of queues, which seems to be intractable from an analytical point of view. For this reason, we have proposed a simulation model.

In order to deal with the data, we have decided to start with a “One-department model”, using the data of the “General Ophthalmology” department, that joins about a 40% of all visits.

The numerical results presented, obtained for only one department, show the kind of experiments that could be performed with a multi-department version of the simulator representing the whole clinic.