

# Modeling of Emergency Medical Service in Flu Season: Algorithm for Dispatching Ambulance Units

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**ABSTRACT.** Flu-season causes increase number of calls for emergency medical service, so that number of calls received by dispatchers are usually much larger, than the number of available ambulance units. Often it is very hard for dispatchers to get the right decision, as they have to compare sometimes more than 50 cases in the current set. We decided to work out the model of emergency medical service and apply the algorithm for dispatching ambulance units in flu season. The programming language Python is used for implementing the algorithms. Applying algorithms should be a practical help for dispatchers assisting them make the best possible decisions without losing precious time. The dataset is collected from the usual case-cards filled by operators of Georgian Emergency and Operative Response Center. The algorithms make possible to compute objective value of risk factor for each case. The accuracy of revealing urgent cases using algorithms presented in the work is sufficiently high, being the same as that of experienced medics for the analyzed flu-case set. © 2018 Bull. Georg. Natl. Acad. Sci.

**Key words:** algorithm for dispatching, dispatch priority, flu, risk factor

Emergency case messages for medical service usually enter the “112” center. “112” operators register the case-cards containing information about each patient. Afterwards such cards are sent to dispatchers of ambulance units.

Greatly increased number of calls for ambulance units, as it usually happens in flu seasons, causes serious complication of their dispatching. Sometimes more than 50 calls may be waiting in line for the emergency units. Besides the permanent deficiency of ambulance cars, dispatchers have usually got problems in defining case urgency in a reasonably short period of time. Having in mind certain human factors such as nervousness, being tired, stressed etc. [1], dispatchers cannot avoid errors in the process of estimating case urgency and are not always able to reveal the most urgent cases not losing precious time.

The recent research aims at the optimization of emergency medical service by modeling dispatching process and applying algorithms computing urgency of each case.

## Model of Getting Medical Information

First of all, we worked out the model of getting necessary medical information from standard case-cards registered by call-takers.

After consulting highly experienced medics the following parameters were chosen: age of a patient, temperature, dangerous clinical symptoms (shortness of breath, heart pain, vomiting, diarrhea) [2,3], accompanying chronic diseases and conditions that increase risk factor of influenza case (asthma, chronic lung disease, pregnancy, neurologic conditions, heart diseases and hypertension, diabetes, weak immune system, kidney/liver disorders, severe headache or some other problems) [2] (Tables 1 – 4).

As influenza is the most dangerous for newborns, quite dangerous for infants and little children [4], as well as aged people, risk-factor  $r_a$  is estimated differently for different age groups, being highest for newborns and infants (Table 1).

**Table 1. Risk factor  $r_a$  for different age groups.**

age	newborns	infants	children	Adults & child.	aged
t	$t \leq 40d$	$40d < t \leq 2y$	$2 < t \leq 5$	$5 < t \leq 65$	$t > 65$
$r_a$ %	30	25	18	10	17
$r_a$	3	2.5	1.8	1	1.7

As high fever increases the risk of flu complication, especially in case of accompanying chronic diseases or conditions [5], the values of risk-factor  $r_c$  caused by abnormal meanings of temperature are different for different temperature groups (Table 2).

**Table 2. Risk factor  $r_c$  for different temperature groups.**

T	$T \leq 35^\circ C$	$35 < T \leq 37$	$37 < T \leq 38$	$38 < T \leq 39$	$T > 39^\circ C$
$r_c$ %	30	0	10	20	40

Some clinical symptoms known as dangerous greatly increase urgency of the case. The values of risk-factor  $r_s$  caused by them are presented in Table 3.

**Table 3. Risk factor  $r_s$  for dangerous clinical symptoms.**

Clin. Sympt.	Shortn.breath	Heart pain	Diarrhea	Vomiting	Age
$r_s$ %	40	-	30	30	$t \leq 2y$
		35	15	10	$t > 2y$

The fragment of Python code for computing weights of clinical symptoms is presented below:

```

for i, row in df.iterrows():
    if 0 <= row['AGE'] <= 2 :
    if row['SYMP'] == "Vomit.":
df.loc[i,'SYMP_CAT'] = 30
    elif row['SYMP'] == "Diar.":
df.loc[i,'SYMP_CAT'] = 30
    elif row['SYMP'] == "Sh_Breath":
df.loc[i,'SYMP_CAT'] = 40
    elif 3 < row['AGE']:
    if row['SYMP'] == "Vomit.":
df.loc[i,'SYMP_CAT'] = 10

```

```

elif row['SYMP'] == "Diar.":
df.loc[i,'SYMP_CAT'] = 15
elif row['SYMP'] == "Sh_Breath":
df.loc[i,'SYMP_CAT'] = 40
elif row['SYMP'] == "Heart_Pain":
df.loc[i,'SYMP_CAT'] = 35
    
```

Some chronic diseases and conditions accompanying flu case increase the risk of complications. The values of risk-factor  $r_d$  of such states are presented in Table 4.

**Table 4. Risk factor  $r_d$  for accompanying chronic diseases and conditions.**

Asthma	Chr. lung d.	Pregn.	Neural. condit.	Heart dis. & hypertension	Diabet.	Weak immun.	Kidney/liver disorders	Other probl.
50	45	40	35	30	25	20	15	10

Risk factor  $r_d = 0$ , if patient has no additional problems.

Dataset. Our dataset is formed using medical information of 20 typical flu cases.

**Table 5. Medical information of 20 influenza cases (patients 1 - 20)**

Patient	Age (years) a	Temp °C c	Other clinical symptoms s	Accomp. diseases and conditions d	Med. diagn. urgency score $D_m$ 1-10	Med. priority Number $P_m$
1	62	39.2			1	20
2	3	38.3	Vomit.		5-6	14
3	5	38.5	Diar.		3-4	17
4	75	38.7	Sh. breath	Heart Dis.	10	1-5
5	61	39.2	Sh. breath	Heart Dis.	10	1-5
6	8	39.1	Sh. breath		9	8-10
7	55	38.2		Diabet	2-3	18-19
8	12	39.5	Sh. breath	Asthma	10	1-5
9	0.2	37.9	Diar.		10	1-5
10	36	37.8		Pregn.	5	15-16
11	80	34.5	Diar.		6-7	13
12	0.1	38.9	Sh. breath	Heart Dis.	10	1-5
13	40	39.7	Sh. breath		9	7-10
14	70	38.1	Vomit.		5	15-16
15	47	39.4		Heart Dis.	8	11-12
16	66	37.7		Diabet	2-3	18-19
17	39	38.4	Sh. Breath	Diabet	9-10	6
18	50	38.3	Vomit.	Heart Dis.	9	7-10
19	15	39.8	Sh. breath		9	7-10
20	24	38.6	Vomit.	Pregn.	8	11-12

The  $D_m$  score of each patient was estimated by the experienced doctor using 1 – 10 scale, showing the urgency of the case (Table 5). Priority line number  $P_m$  corresponds to the  $D_m$  score of the patient. The more urgent is the case, the more  $D_m$  score and the less  $P_m$  number is in the priority line of cases for emergency service. It should be mentioned that  $D_m$  score depends only on the urgency of the case, while priority line number  $P_m$  depends as well on the urgency of other cases in the current set, particularly on the number of cases with the same or higher  $D_m$  values.

#### Algorithms Applied for Estimating the Risk Factor of Flu-cases

Having in mind to automate the process of evaluating the risk factor, it is necessary to create the algorithm for calculating the risk factor for each flu-case based on parameters predefined as mentioned above.

The calculated values of risk factor are compared with  $D_m$  scores defined by highly qualified medics. The medics' diagnosis is considered to be correct. So the optimal decision is assumed to be the one closest to the line of cases made up according to the medics' opinion.

At first, a simple algorithm Alg1 was applied to provide the emergency dispatchers with objective information about the urgency of each case from currently active set.

$$\text{Alg 1:} \quad r_1 = r_a + r_c + r_s + r_d \quad (1)$$

To enhance the risk factor of newborn and infant age groups, another algorithm Alg2 is applied.

$$\text{Alg 2:} \quad r_2 = r_a (r_c + r_s + r_d) \quad (2)$$

It is to be mentioned that  $r_a$  in formula (1) is presented in percentage ( $r_a$  % in Table 1), while in formula (2)  $r_a = \{3; 2.5; \dots\}$  (the lower line in Table 2).

**for** i, row **in** df.iterrows():

df.loc[i,'Alg1'] = (row.AGE\_CAT + row.TEMP\_CAT + row.SYMP\_CAT + row.COND\_CAT)

df.loc[i,'Alg2'] = row.AGE\_CAT\*(row.COND\_CAT + row.TEMP\_CAT + row.SYMP\_CAT)/10

#### Results and Discussion

The results of applying above described algorithms for flu-cases are shown in Table 6.

The values of risk factor  $r_1$  and  $r_2$  computed using algorithms Alg 1 and Alg 2, as well as the priority line numbers  $P_1$  and  $P_2$  based on them are presented in Table 6.

As it is seen from Table 6, a simple model of dispatching emergency units (Alg 1) describes dispatching process done by a medic sufficiently well. The difference  $D_1$  is insignificant in 13 cases  $D_1 = |P_m - P_1| \leq 1$  As for Alg 2,  $D_2 \leq 1$  in 14 flu-cases.

The most urgent cases scored  $D_m = 10$  (patients 4,5,8,9,12), are revealed by applied algorithms as well. Alg 1 reveals 4 cases (patients 4,5,8,12) as having  $r_1 \geq 95$  and being the first in priority line  $P_1 = \{1;2;3;4\}$ . Patient 9 is the only one exception. It is not revealed as urgent using Alg 1:  $r_1(9) = 65$ , patient 9 being infant (0.2y) with diarrhea.

As it is mentioned above, Alg 2 is applied to enhance the risk factor of influenza for newborns and infants. Using Alg 2, patient 9 is also revealed as being in urgent group:  $r_2(9) = 100$ ,  $P_2 = 5$ .

So Alg 2 reveals all 5 urgent cases as having the highest values of risk factor  $r_2 \geq 100$ ,  $P_2 = \{1;2;3;4;5\}$ .

To increase the accuracy of automated dispatching, we decided to apply both algorithms and provide dispatchers with the most urgent cases revealed at least by one of them.

#### Conclusion

The results of the preliminary research show that application of presented system of data analysis and the special algorithms computing risk factor values make it possible to improve the work of ambulance brigade

dispatchers providing them with the most urgent influenza cases defined quite accurately and objectively. The accuracy of revealing the most urgent cases using the applied algorithms appears to be the same as that of experienced medics. For further adjustment of the algorithms and improvement of their reliability, the research should be carried out on larger sets.

**Table 6.** Risk factors of 20 flu-cases computed using algorithms Alg 1 and Alg 2

Patient	Med. diagn. urgency score $D_m$ 1-10	Med. priority Number $P_m$	Comput. risk factor $r_1$	Comput. priority number $P_1$	Comput. risk factor $r_2$	Comput. priority number $P_2$	Differ. $ P_m - P_1 $ $D_1$	Differ. $ P_m - P_2 $ $D_2$
1	1	20	50	19	40	20	1	0
2	5-6	14	68	12	90	6	2	8
3	3-4	17	53	17	63	14	0	3
4	10	1-5	107	4	153	2	0	0
5	10	1-5	120	2-3	110	4	0	0
6	9	8-10	90	6-8	80	8-10	2	0
7	2-3	18-19	55	16	45	19	2	0
8	10	1-5	140	1	130	3	0	0
9	10	1-5	65	13	100	5	8	0
10	5	15-16	60	15	50	18	0	2
11	6-7	13	62	14	76.5	11	1	2
12	10	1-5	120	2-3	270	1	0	0
13	9	7-10	90	6-8	80	8-10	1	0
14	5	15-16	47	20	51	17	4	1
15	8	11-12	80	9-10	70	12-13	2	1
16	2-3	18-19	52	18	59.5	16	0	2
17	9-10	6	95	5	85	7	1	1
18	9	7-10	70	11	60	15	1	5
19	9	7-10	90	6-8	80	8-10	1	0
20	8	11-12	80	9-10	70	12-13	2	1

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## ინფორმატიკა

## სასწრაფო სამედიცინო მომსახურების მოდელირება გრიპის ეპიდემიის დროს: ალგორითმი სასწრაფო დახმარების ბრიგადების ეფექტური მართვისათვის

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§ საქართველოს ტექნიკური უნივერსიტეტი, მართვის ავტომატიზებული სისტემების დეპარტამენტი, თბილისი, საქართველო

გრიპის ეპიდემია იწვევს სასწრაფო სამედიცინო მომსახურების მოთხოვნის გაზრდას. ამ დროს სამედიცინო სასწრაფო დახმარების ბრიგადების გამგზავნი დისპეტჩერები იღებენ არსებული თავისუფალი ბრიგადების რაოდენობაზე გაცილებით მეტ ზარს. მათთვის ძნელია სწორი გადაწყვეტილების სწრაფად მიღება, რადგან ხშირად 50-ზე მეტი მიმდინარე გამოძახება აქვთ შესადარებელი. სასწრაფო სამედიცინო მომსახურების დისპეტჩერების დასახმარებლად შექმნილი გრიპის სეზონის შემთხვევებზე მორგებული მოდელი და ალგორითმები თითოეული შემთხვევის სასწრაფო სამედიცინო მომსახურების გადაუდებლობის დასადგენად. პროგრამული რეალიზაციის მიზნით გამოყენებულია მულტიპარადიგმული ენა Python. ალგორითმების საფუძველზე შესაძლებელია ობიექტურად დადგინდეს გრიპის შემთხვევათა მომსახურების რიგი. დისპეტჩერს წარედგინება ყველაზე მაღალი რისკ ფაქტორის მქონე შემთხვევები, რის საფუძველზეც მას შეუძლია სწრაფად მიიღოს ადეკვატური გადაწყვეტილება სასწრაფო დახმარების მანქანებისა და ექიმთა ბრიგადების გაგზავნის თაობაზე. საჭირო მონაცემთა მოპოვება შესაძლებელია ჩვეულებრივი ბარათებიდან, რომლებიც ივსება შსს სსიპ „112“-ის ოპერატორების მიერ თითოეული გამოძახების შემთხვევაზე. აღნიშნული ალგორითმების საშუალებით შესაძლებელია გამოვავლინოთ ყველა შემთხვევა, რომლებსაც გამოცდილი ექიმი სასწრაფოდ მისახედად მიიჩნევს.

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