Evaluating the Effectiveness of Electrocardiological Study Using Cardiological Decision Support Systems

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Abstract. This work is devoted to evaluating the effectiveness of the electrocardiological study process without using and using cardiological decision support systems. To assess the effectiveness, analytical expressions of the probabilistic-time characteristics of the developed structural model of the electrocardiological study process are used. An analysis of the time characteristics of the model is performed when different initial conditions are set for three different types of electrocardiological studies: the study is conducted for the first time, the study is repeated as a result of screening, the study is repeated after treatment. The work shows that the use of cardiological decision support systems based on the developed methods for analyzing biomedical signals with locally concentrated features reduced the average time required for the electrocardiological study of each of the considered types.

Keywords: Electrocardiological study; Cardiological decision support system; Probabilistic-time characteristic; Biomedical signals with locally concentrated features

1 Introduction

Currently, a sharp increase in the amount of information processed in solving traditional medical problems has led to the introduction of various medical information systems (MIS) into modern medicine, from simple electronic medical records to complex decision support systems (DSS) [1-3]. The electrocardiological (ECG) study process is based on the analysis of biomedical signals (BMS) with locally concentrated features (LCF) associated with the cyclic work of the heart and cardiovascular system [4]. Various computerized cardiological systems, including cardiological DSS, are used to automate the collection and processing of such information. The authors developed the structural model of the ECG study process in the form of a probabilis-

tic-time graph, which made it possible to obtain analytical expressions for the analysis of this process given initial conditions (the presence or absence of previous examinations and treatment), as well as determine the criteria for the effectiveness of ECG studies [5].

2 Literature review

A review of the literature showed that most often attention is paid to the analysis of individual stages of the ECG study process, among which the following:

- detection of indications for examination;
- recording and digitization of BMS with LCF;
- preprocessing of BMS with LCF;
- morphological analysis of BMS with LCF;
- detection of diagnostic indicators;
- diagnostics and issuing a diagnostic report.

The quality and effectiveness of the ECG study depend on the quality of the recording BMS with LCF.

As a result of preprocessing of BMS with LCF, there are most often performed removing artifacts from the signal by methods based on the use of various types of filters [6, 7] and of wavelet transform [8-10], compensation of the isoline drift by methods based on interpolation of the ECG isoelectric line [11, 12].

One of the difficult and critical stages is the stage of the morphological analysis of BMS with LCF for which various methods are used:

– analysis of BMS with LCF in the time domain using modern classification methods such as cluster analysis and pattern recognition [13, 14], probabilistic classification [15], neural networks [16], fuzzy clustering [17, 18];
– analysis of BMS with LCF in the time-frequency domain, for example, local (window) Fourier transform (spectral-time mapping) and wavelet transform [19, 20], as well as in the phase plane [4];
– morphological filtration of BMS with LCF using the multichannel matched morphological filter proposed by the authors [21].

Diagnostic features are formed in the form of parameters of the found structural elements based on the morphological analysis of BMS with LCF [22, 23]. Thus, errors at the stage of the morphological analysis of BMS with LCF can lead to the incorrect diagnostic solutions.

Therefore, the quality of the ECG study directly depends on the quality of the morphological analysis of BMS with LCF.

Different MISs are used with varying degrees of effectiveness at each of the listed stages. However, a systematic analysis of the ECG study process without using and using cardiological DSS is not found in literary sources.

3 Formal problem statement

The aim of the work is to analyze the effectiveness of the ECG study process without using and using cardiological DSS based on the morphological analysis of BMS with LCF.

To achieve this goal, the following tasks are solved:

- to determine the average examination time under various initial conditions by the developed structural model;
- to evaluate the effectiveness of ECG studies without using and using cardiological DSS by the developed criterion.

4 A structural model of a patient's ECG study

Let us consider the structural model developed in [5] for the process of ECG study, shown in Fig. 1.

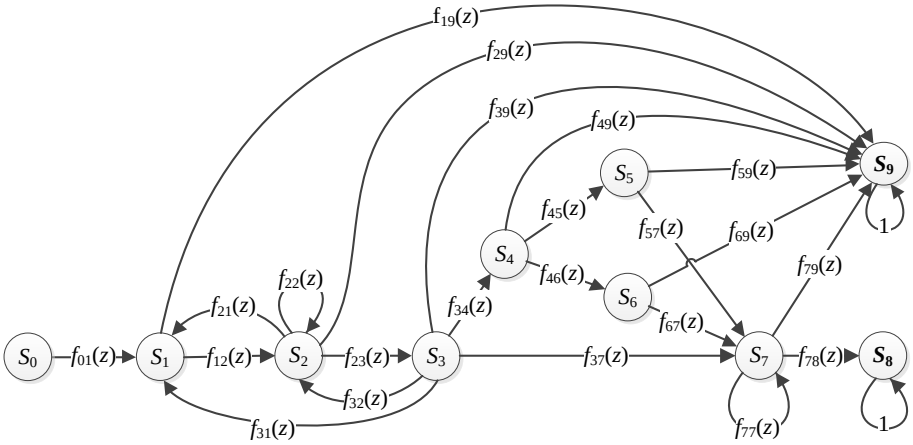

Fig. 1. The structural model M_S of the ECG study

To describe the passage of the ECG study process from the initial state to the final state the arc function $f(p_{ij}, t_{ij}) = f_{ij}(z)$ of a probabilistic-time graph is defined such that when finding the products of the arc functions, the probabilities p_{ij} are multiplied and the times t_{ij} are summed:

$$f_{ij}(z) = p_{ij} z^{t_{ij}}, \tag{1}$$

where z – a parameter of the arc function, the degree of which characterizes the time of transition from one state to another ($|z| \le 1$).

The following states are identified in the structural model M_S: S_0 – the beginning of the study; S_1 – indications were defined; S_2 – morphological analysis of BMS with LCF was performed; S_3 – pathological changes were identified; S_4 – comparison with previous ECG studies was performed; S_5 – dynamics evaluation was completed; S_6 – evaluation of treatment effectiveness was completed; S_7 – the diagnostic decision was made; S_8 – recommendations were issued (the end of the ECG study); S_9 – a set of states that do not lead to the goal (the state of uncertainty); $f_{ij}(z)$, $\forall i, j = \overline{0;9}$ – arc function by (1).

In [5], it is indicated that the structural model M_S is no state associated with the direct recording of the ECG signal because the duration of the ECG signal recording is strictly regulated by the protocol of the type of the ECG study and can vary from several minutes to several hours and days. That is, this time cannot be optimized, and the duration of the recording process does not affect the effectiveness of the ECG study.

The generating function of the graph shown in Fig. 1 has the following form:

$$F(z) = F_{08}(z) + F_{09}(z), \tag{2}$$

where

$$F_{08}(z) = \frac{p_{01}p_{12}p_{23}p_{78}\left(p_{34}z^{t_{34}}\left(p_{45}p_{57}z^{t_{45}+t_{57}} + p_{46}p_{67}z^{t_{46}+t_{67}}\right) + p_{37}z^{t_{37}}\right)z^{t_{01}+t_{12}+t_{23}+t_{78}}}{\left(1-p_{77}z^{t_{77}}\right)} \Bigg/$$
$$\Big/\left(1-p_{12}\left(p_{21}\left(1+p_{23}p_{32}z^{t_{23}+t_{32}}\right)z^{t_{21}} + p_{23}p_{31}z^{t_{23}+t_{31}}\right)z^{t_{12}} - p_{23}p_{32}z^{t_{23}+t_{32}} - p_{22}z^{t_{22}}\right);$$

$$F_{09}(z) = p_{01}\Big(\left(1-p_{12}\right)z^{t_{19}} + p_{12}\Big(\left(1-p_{21}-p_{22}-p_{23}\right)z^{t_{29}} +$$
$$+ p_{23}\Big(\left(1-p_{31}-p_{32}-p_{34}-p_{37}\right)z^{t_{39}} + p_{34}\Big(\left(1-p_{45}-p_{46}\right)z^{t_{49}} +$$
$$+ p_{45}\Big(\left(1-p_{57}\right)z^{t_{59}} + p_{57}\left(1-p_{77}-p_{78}\right)z^{t_{57}+t_{79}}\Big)z^{t_{45}} +$$
$$+ p_{46}\Big(\left(1-p_{67}\right)z^{t_{69}} + p_{67}\left(1-p_{77}-p_{78}\right)z^{t_{67}+t_{79}}\Big)z^{t_{46}}\Big)z^{t_{34}} +$$
$$+ p_{37}\left(1-p_{77}-p_{78}\right)z^{t_{37}+t_{79}}\Big)z^{t_{23}}\Big)z^{t_{12}}\Big)z^{t_{01}} \Big/ \left(1-p_{77}z^{t_{77}}\right)\Big/$$
$$\Big/\left(1-p_{12}\left(p_{21}\left(1+p_{23}p_{32}z^{t_{23}+t_{32}}\right)z^{t_{21}} + p_{23}p_{31}z^{t_{23}+t_{31}}\right)z^{t_{12}} - p_{23}p_{32}z^{t_{23}+t_{32}} - p_{22}z^{t_{22}}\right).$$

Using the generating function (2), it is possible to determine the probability and the average time of an ECG study by following expressions:

$$P_{ECG} = F(z)\big|_{z=1};$$

$$T_{ECG} = \left.\frac{dF(z)}{dz}\right|_{z=1}.$$

Since the analytical expressions for the probability P_{ECG} and the average time T_{ECG} of an ECG study are too cumbersome, in [5] the authors developed a program in the Matlab language for getting these analytical expressions as well as an analytical expression of the probability P_{ECG}^{+} of a successful ECG study which has the following form taking into account restrictions:

$$\begin{cases} P_{ECG}^{+} = \dfrac{p_{01}p_{12}p_{23}p_{78}\left(p_{34}\left(p_{45}p_{57}+p_{46}p_{67}\right)+p_{37}\right)}{\left(1-p_{77}\right)\left(1-p_{12}\left(p_{21}\left(1+p_{23}p_{32}\right)+p_{23}p_{31}\right)-p_{23}p_{32}-p_{22}\right)}; \\ p_{34}p_{37}=0; \\ p_{34}+p_{37}\in(0;1]; \\ p_{45}p_{46}=0; \\ p_{45}+p_{46}\in(0;1]. \end{cases} \tag{3}$$

Also in [5], there were proposed the following criteria for the effectiveness of the ECG study process by the average time taken to complete the study and the probability of its successful completion:

$$\begin{cases} T_{ECG}\to\min; \\ p_{34}p_{37}=0; \\ p_{34}+p_{37}\in(0;1]; \\ p_{45}p_{46}=0; \\ p_{45}+p_{46}\in(0;1]; \end{cases}$$

$$\begin{cases} P_{ECG}^{+}\to\max; \\ p_{34}p_{37}=0; \\ p_{34}+p_{37}\in(0;1]; \\ p_{45}p_{46}=0; \\ p_{45}+p_{46}\in(0;1]. \end{cases}$$

Let us use the obtained analytical expressions that describe the probabilistic-time characteristics of the ECG study process under given initial conditions (the presence or absence of previous examinations and treatment), as well as use the proposed criteria of the effectiveness for analysis and optimization of the entire process and its individual stages.

5 Experiments and results

To analyze the probabilistic-time characteristics of the ECG study process, it is necessary to set the initial conditions.

According to the structural model M_S of the ECG study (Fig. 1), there are three alternative ways of transition from the initial state S_0 to the final state S_8 which correspond to three different types of ECG studies [5]:

- the study is conducted for the first time;
- the study is repeated as a result of screening;
- the study is repeated after treatment.

In this case, let us consider a simplified version of the model when the ECG study process does not go into a state of uncertainty S_9, that is $p_{19} = p_{29} = p_{39} = p_{49} = p_{59} = p_{69} = p_{79} = 0$ and $t_{19} = t_{29} = t_{39} = t_{49} = t_{59} = t_{69} = t_{79} = 0$. Since all transitions from the current state S_i form a complete group of events, the following expressions can be written:

$$p_{01} = p_{12} = p_{57} = p_{67} = 1; \tag{4}$$

$$p_{23} + p_{21} + p_{22} = 1; \tag{5}$$

$$p_{34} + p_{37} + p_{31} + p_{32} = 1; \tag{6}$$

$$p_{45} + p_{46} = 1; \tag{7}$$

$$p_{78} + p_{77} = 1. \tag{8}$$

Let us denote P_{ECG}^{-} – probability of transition to a state of uncertainty S_9, then, taking into account the simplified model ($p_{19} = p_{29} = p_{39} = p_{49} = p_{59} = p_{69} = p_{79} = 0$) $P_{ECG}^{-} = 0$, which means $P_{ECG}^{+} = 1$ for any admissible probability values in the expression (3), that is, the examination will surely end successfully. However, the time taken to complete the examination will depend not only on the time of each stage but also on the corresponding probabilities.

In this case, the analytical expression for the average time T_{simp} of the ECG study, calculated according to the simplified model, is too cumbersome, but it is easy to obtain using the program in the Matlab language, if, taking into account (4) and (8), the following substitution is made at the end of the program, given in [5]:

```
Tsimpl = subs(T,[p01, p12, p57, p67, p77, t19, t29, t39,
                 t49, t59, t69, t79],[1, 1, 1, 1, 1-p78,
                 0, 0, 0, 0, 0, 0, 0]);
```

Let us analyze the average time of conducting an ECG study using a simplified model M_S separately for each of the cases under different initial conditions. Moreover, in each of the cases we will consider the average execution time of each stage for three options:

– using cardiological DSS with the module of morphological analysis of BMS with LCF (DSS1) developed by the authors [21];
– using cardiological DSS in which the morphological analysis of BMS with LCF is performed in a semi-automatic mode (DSS2);
– without using any MIS (without MIS).

In all experiments, we take $p_{21} = p_{31} = 0$. Then according to (5) $p_{22} = 1 - p_{23}$.

5.1 Analysis of the time characteristics of the model for the case when the ECG study is conducted for the first time

If an ECG study is conducted for the first time, then $p_{34} = 0$, and then a simplified structural model of an ECG study has the form shown in Fig. 2.

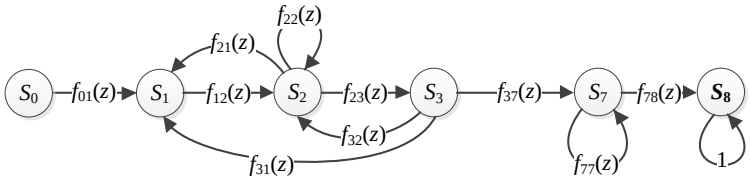

Fig. 2. Simplified structural model of an ECG study: the study is conducted for the first time

The analytical expression for the average time T_1 of the ECG study, which is conducted for the first time, was obtained from the Matlab, performing the following substitution at the end of the program given in [5]:

```
T1 = simplify(subs(Tsimpl, p34, 0));
```

Let us consider the dependence $T_1(p_{23})$ under the following initial conditions: $p_{37} = p_{78} = 1$. The initial conditions for the average execution time of each stage are given in Table 1. It should be noted here that only the time t_{12} differs when conducting an ECG study with DSS1 and DSS2 (Table 1).

Table 1. The average time of each stage (in minutes): the study is conducted for the first time

The average time	t_{01}	t_{12}	t_{23}	t_{37}	t_{78}	t_{22}	t_{32}
DSS1	7	2	2	2	2	$1.1t_{12}$	$1.2t_{37}$
DSS2	7	5	2	2	2		
without MIS	12	7	3	7	7		

Table 2 shows the minimum and maximum values of the average time T_1 of the ECG study without using and using cardiological DSS in experiments at different values p_{32}.

Table 2. Values T_1 (in the format mm:ss) in experiments at various values p_{32}

Values p_{32}	DSS1		DSS2		without MIS	
	$\min T_1$	$\max T_1$	$\min T_1$	$\max T_1$	$\min T_1$	$\max T_1$
0	15:00	17:12	18:00	23:30	36:00	43:42
0.1	15:26	17:53	18:26	24:33	37:06	45:40
0.3	16:42	19:51	19:42	27:34	40:17	51:17
0.5	19:00	23:23	22:00	33:00	46:00	61:23

Figure 3 shows the curves of the change in the average time $T_1(p_{23})$ of the ECG study without using and using cardiological DSS at various initial values p_{32}.

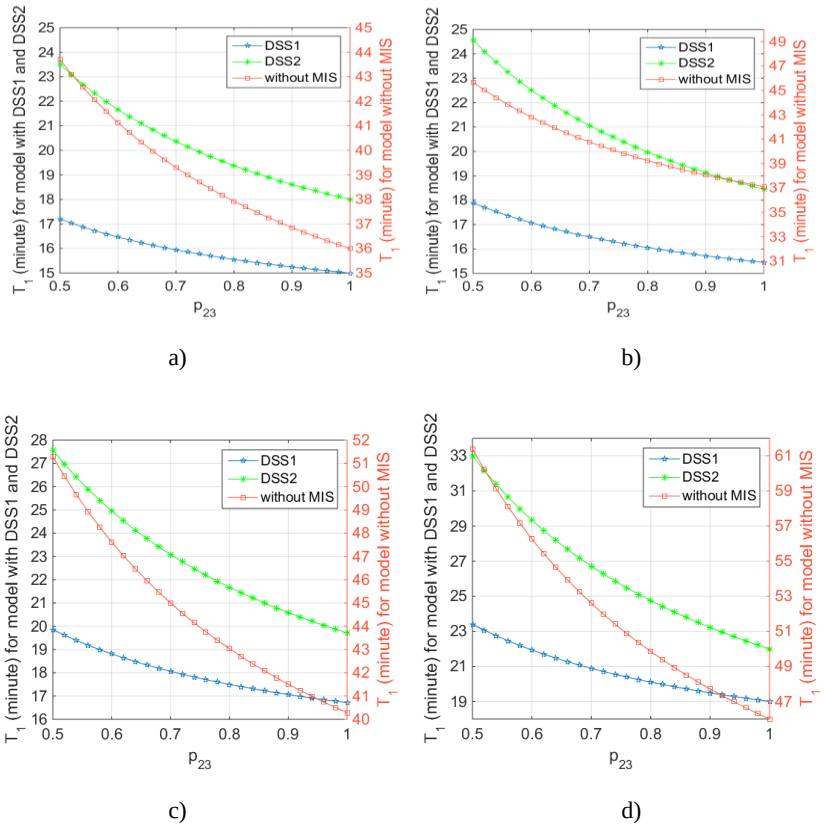

Fig. 3. Graphs of changes in the average time $T_1(p_{23})$ of the ECG study without using and using cardiological DSS:
a) $p_{32} = 0$; b) $p_{32} = 0.1$; c) ; $p_{32} = 0.3$ d) $p_{32} = 0.5$

From an analysis of the data presented (Table 2 and Fig. 3), we can conclude that in each of the experiments the following trend is observed:

– $\max T_1^{\text{DSS1}} < \min T_1^{\text{DSS2}}$ (for $p_{32} = 0$ and $p_{32} = 0.1$);
– $\max T_1^{\text{DSS1}} \approx \min T_1^{\text{DSS2}}$ (for $p_{32} = 0.3$);
– $\max T_1^{\text{DSS1}} < \min T_1^{\text{without MIS}}$ and $\max T_1^{\text{DSS2}} < \min T_1^{\text{without MIS}}$ (for all values p_{32}).

5.2 Analysis of the time characteristics of the model for the case when the ECG study is repeated as a result of screening

If the ECG study is repeated as a result of screening, then $p_{37} = 0$ and $p_{46} = 0$, and then the simplified structural model of the ECG study has the form shown in Fig. 4.

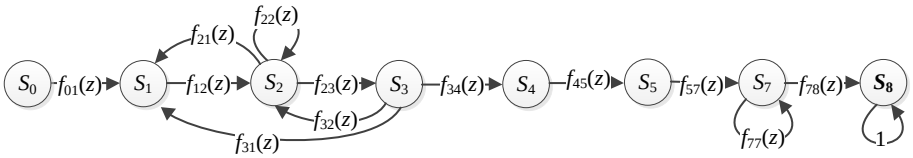

Fig. 4. Simplified structural model of an ECG study: the study is repeated as a result of screening

The analytical expression for the average time T_2 of the ECG study that is repeated as a result of screening was obtained from the Matlab, performing the following substitution at the end of the program given in [5]:

```
T2 = simplify(subs(Tsimpl,[p37, p45, p46],[0, 1, 0]));
```

Let us consider the dependence $T_2(p_{23})$ under the following initial conditions: $p_{34} = p_{45} = p_{57} = p_{78} = 1$. The initial conditions for the average execution time of each stage are given in Table 3. As in the first case, only the time t_{12} differs when conducting an ECG study with DSS1 and DSS2 (Table 3).

Table 3. The average time of each stage (in minutes): the study is repeated as a result of screening

The average time	t_{01}	t_{12}	t_{23}	t_{34}	t_{45}	t_{57}	t_{78}	t_{22}	t_{32}
DSS1	7	2	2	2	1	1	2	$1.1t_{12}$	$1.1t_{34}$
DSS2	7	5	2	2	1	1	2		
without MIS	12	7	3	10	3	2	7		

Table 4 shows the minimum and maximum values of the average time T_2 of the ECG study without using and using DSS in experiments at different values p_{32}.

Figure 5 shows the curves of the change in the average time $T_2(p_{23})$ of the ECG study without using and using cardiological DSS at various initial values p_{32}.

Table 4. Values T_2 (in the format mm:ss) in experiments at various values p_{32}

Values p_{32}	DSS1		DSS2		without MIS	
	$\min T_2$	$\max T_2$	$\min T_2$	$\max T_2$	$\min T_2$	$\max T_2$
0	17:00	19:12	20:00	25:30	44:00	51:42
0.1	17:26	19:53	20:26	26:33	45:26	54:00
0.3	18:42	21:51	21:42	29:34	49:34	60:34
0.5	21:00	25:23	24:00	35:00	57:00	72:24

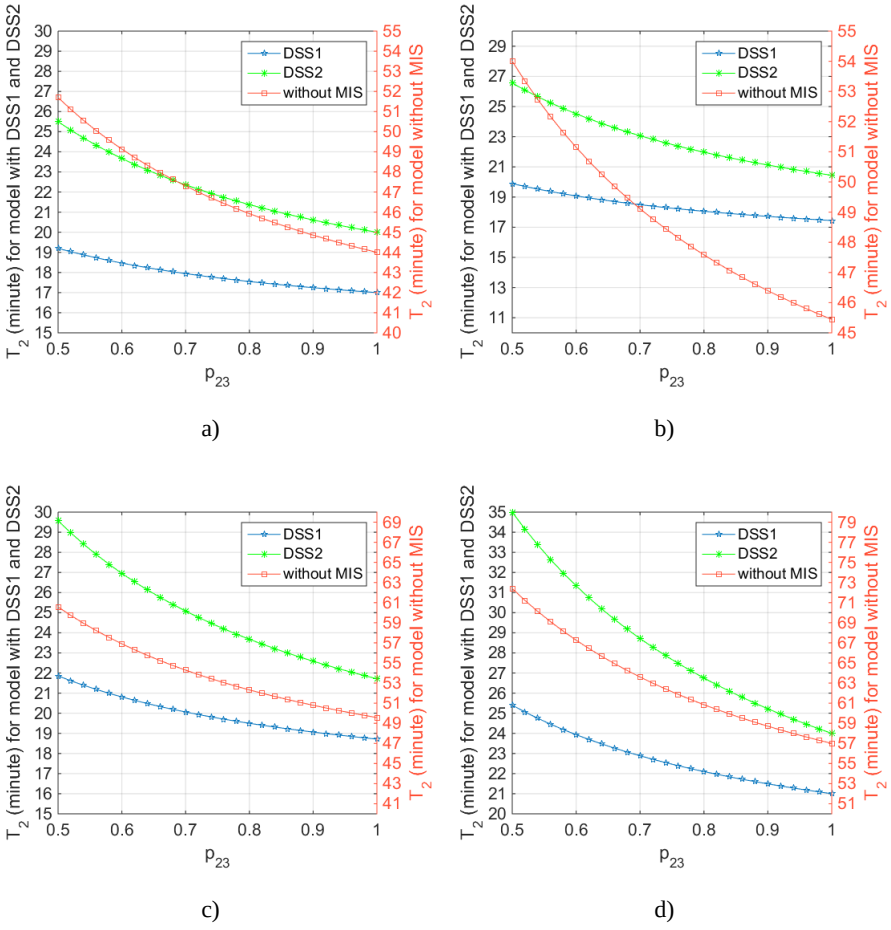

Fig. 5. Graphs of changes in the average time $T_2(p_{23})$ of the ECG study without using and using cardiological DSS:
a) $p_{32} = 0$; b) ; $p_{32} = 0.1$ c) $p_{32} = 0.3$; d) $p_{32} = 0.5$

From an analysis of the data presented (Table 4 and Fig. 5), we can conclude that in each of the experiments, the trend described for the first case remains:

– $\max T_2^{\text{DSS1}} < \min T_2^{\text{DSS2}}$ (for $p_{32} = 0$ and $p_{32} = 0.1$);
– $\max T_2^{\text{DSS1}} \approx \min T_2^{\text{DSS2}}$ (for $p_{32} = 0.3$);
– $\max T_2^{\text{DSS1}} < \min T_2^{\text{without MIS}}$ and $\max T_2^{\text{DSS2}} < \min T_2^{\text{without MIS}}$ (for all values p_{32}).

5.3 Analysis of the time characteristics of the model for the case when the ECG study is repeated after treatment

If the ECG study is repeated after treatment, then $p_{37} = 0$ and $p_{45} = 0$, and then the simplified structural model of the ECG study has the form shown in Fig. 6.

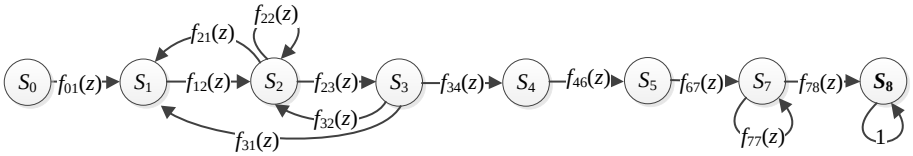

Fig. 6. Simplified structural model of an ECG study: the study is repeated after treatment

The analytical expression for the average time T_3 of the ECG study that is repeated as a result of screening was obtained from the Matlab, performing the following substitution at the end of the program given in [5]:

```
T3 = simplify(subs(Tsimpl,[p37, p45, p46],[0, 0, 1]));
```

Let us consider the dependence $T_3(p_{23})$ under the following initial conditions: $p_{34} = p_{46} = p_{67} = p_{78} = 1$. The initial conditions for the average execution time of each stage are given in Table 5. As in the first two cases, only the time t_{12} differs when conducting an ECG study with DSS1 and DSS2 (Table 5).

Table 5. The average time of each stage (in minutes): the study is repeated after treatment

The average time	t_{01}	t_{12}	t_{23}	t_{34}	t_{46}	t_{67}	t_{78}	t_{22}	t_{32}
DSS1	7	2	2	2	1,5	1	2	$1.1t_{12}$	$1.1t_{34}$
DSS2	7	5	2	2	1,5	1	2		
without MIS	12	7	3	10	3,5	2	7		

Table 6 shows the minimum and maximum values of the average time T_3 of the ECG study without using and using cardiological DSS in experiments at different values p_{32}.

Table 6. Values T_3 (in the format mm:ss) in experiments at various values p_{32}

Values p_{32}	DSS1		DSS2		without MIS	
	$\min T_3$	$\max T_3$	$\min T_3$	$\max T_3$	$\min T_3$	$\max T_3$
0	17:30	19:42	20:30	26:00	44:30	52:12
0.1	17:56	20:23	20:56	27:03	45:56	54:30
0.3	19:12	22:21	22:12	30:04	50:04	61:04
0.5	21:30	25:54	24:30	35:30	57:30	72:54

Figure 7 shows the curves of the change in the average time $T_3(p_{23})$ of the ECG study without using and using cardiological DSS at various initial values p_{32}.

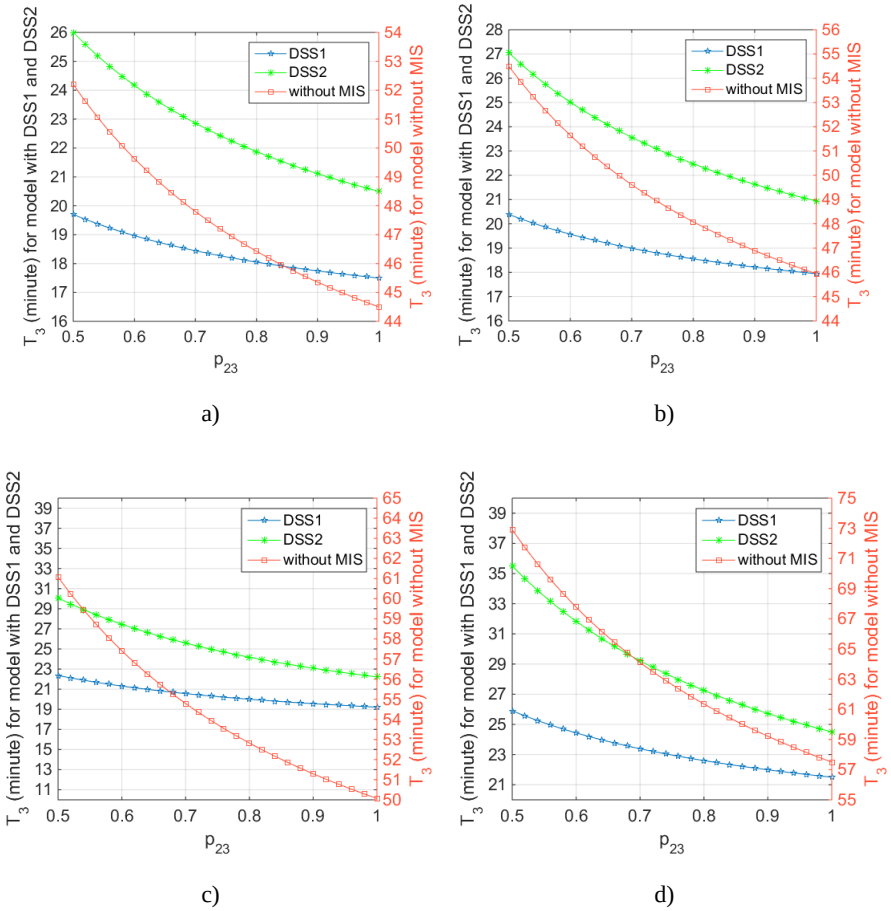

Fig. 7. Graphs of changes in the average time $T_3(p_{23})$ of the ECG study without using and using cardiological DSS:
a) $p_{32} = 0$; b) $p_{32} = 0.1$; c) $p_{32} = 0.3$; d) $p_{32} = 0.5$

From an analysis of the data presented (Table 6 and Fig. 7), we can conclude that in each of the experiments, the trend described for the first two cases remains:

- $\max T_3^{\text{DSS1}} < \min T_3^{\text{DSS2}}$ (for $p_{32} = 0$ and $p_{32} = 0.1$);
- $\max T_3^{\text{DSS1}} \approx \min T_3^{\text{DSS2}}$ (for $p_{32} = 0.3$);
- $\max T_3^{\text{DSS1}} < \min T_3^{\text{without MIS}}$ and $\max T_3^{\text{DSS2}} < \min T_3^{\text{without MIS}}$ (for all values p_{32}).

6 Conclusion

In this work, using the simplified structural model of an ECG study, analytical expressions were obtained to calculate the average execution time of this process for three different types of studies: the study is conducted for the first time, the study is repeated as a result of screening, the study is repeated after treatment.

Using the obtained analytical expressions, an analysis of the time characteristics of the ECG study was performed without using and using cardiological DSS separately for each of the considered study types. The above data show that the use of any cardiological DSS significantly reduces the time for the ECG study of each of the considered types, even if the worst option of the ECG study using any cardiological DSS was being compared with the best option of the ECG study without using any MIS. Moreover, if cardiological DSS is used with an improved module for the morphological analysis of BMS with LCF (DSS1) then even the best option for conducting the ECG study using DSS2 in almost all cases is inferior in time to the worst option for conducting the ECG study using DSS1.

Further studies are aimed at experimental verification of the effectiveness of ECG studies both in time and in the probability of successful completion of the considered process under various initial conditions using the proposed full structural model.

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