Building Counterterrorism Strategies for Intelligence Services: Early Warning Short Term Forecasting Model of Migrant Flow in Europe

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Abstract

The paper deals with the design of an early warning predictive system with the capability of short term forecasting of a future migrant flow time series. The study was focused on observing the migrant flow to the EU via the Balkan migration route passing the Greek islands after departing from the Turkish coast. The research is related to the dramatic events of the European migrant crisis in a period beginning in 2015. The analysis and modeling of the refugees' time series indicates that a stochastic process as a time series generator is a complex composition of many diverse effects driven by the forces related to different factors. For the purpose of research, the framework that includes an ARIMA-intervention model was designed. The analysis of intervention events and their effects represents a typical case of the state's social irresponsibility of Turkey via presumed collaborating with smugglers' networks and manipulating with refugees to blackmail the EU. The constructed model might have also been treated as an early detection warning system, i.e. a detector of bigger discrepancies between the real measured influx and the forecasted refugees' influx.

Keywords: Social Responsibility, Migrant crisis, ARIMA-Intervention model, Short-term forecasting model, Quantification of state's social irresponsibility.

Strategije za boj proti terorizmu za potrebe obveščevalnih služb: Model zgodnjega opozarjanja na osnovi kratkoročnega napovedovanja migracijskih tokov v Evropo

Povzetek

Prispevek obravnava zasnovo sistema za zgodnje opozarjanje z zmožnostjo kratkoročnega napovedovanja prihodnjih časovnih vrst tokov migrantov v Evropo. Študija se osredotoči na opazovanje migracijskega toka v EU preko balkanske migracijske poti, ki se začne preko grških otokov po odhodu s turške obale. Raziskava je povezana z dramatičnimi dogodki evropske migrantske krize v obdobju z začetkom leta 2015. Analiza in modeliranje časovnih vrst beguncev pokažeta, da je stohastični proces kot generator časovne vrste begunskih tokov kompleksna kompozicija mnogih različnih učinkov, ki jih poganjajo sile, povezane z različnimi dejavniki. Za namene raziskave je bil zasnovan koncept, ki vključuje ARIMA-intervencijski model. Analiza intervencijskih dogodkov in njihovih učinkov predstavlja tipičen primer državne družbene neodgovornosti Turčije v obliki sodelovanja z mrežami tihotapcev in manipulacije z begunci za potrebe izsiljevanja EU. Razvit model bi se lahko obravnaval tudi kot sistem za opozarjanje z zgodnjim odkrivanjem bodočih tokov beguncev, to je kot detektor večjih neskladij med dejanskim izmerjenim pretokom in napovedanim pretokom beguncev.

Ključne besede: Družbena odgovornost, Migrantska kriza, ARIMA-intervencijski model, Model kratkoročnega napovedovanja, Kvantifikacija državne družbene neodgovornosti.

1. Introduction

In 2015 and 2016, Europe faced the first biggest wave of migrants coming from Northern Africa, Middle East, Western Asia and (in lesser extent) Eastern Europe. Europe, especially Western Europe, should have been better prepared, but instead of it one redirected one's attention to Turkey, Greece and other countries of the Western Balkans. The South-Eastern Europe became a so-called 'Tampon zone' due to different political international interests. The (Western) Europe believed that this zone would stop or at least slow down the migrant wave, if not diminished the number of migrants in total on the so-called Balkan Migrant Route. The details of the background regarding a significant discrepancy of perception of migrant crisis between the European and non-European countries (or continents) are precisely explained and can be found in our previous work (Ivanuša et al. 2018) and references therein.

Perhaps even bigger discrepancy can be identified between the countries in Europe, particularly between the Western and Balkan European states. The countries of Western Balkans are economically weaker; therefore, they are more affected by the migrant crisis. They were affected mostly because of their geographical position as a part of the before-mentioned tampon zone. Different authors outside the Balkan states consistently ignore the perception and opinions of their fellow authors from the Balkans on the migration crisis. Comparison of the literature from 'both sides' reveals a hardly understandable paradox: humanitarian versus security viewpoints. 'Western literature' irrationally connects each security action or aspect with the humanitarian viewpoint, which is at least insulting since no country on the Balkan Migrant Route, including Slovenia, denied the humanitarian aid to migrants on her soil (Ivanuša et al. 2018). Balkan countries offered humanitarian aid to the migrants in the most generous way–in spite of their economic situation–before the migrants reached their wanted/final destination in Europe (e.g. Germany). To be precise, the security viewpoints do not exclude the humanitarian viewpoint and vice versa; but the fact is that the security viewpoints and actions/reactions cannot be entirely a public matter–i.e. confidentiality of intelligence reports (Ivanuša et al. 2018).

International Center for Counter-Terrorism (ICCT) stated that very few instances of terrorists posing as refugees should be seen for what they are – exceptions. On the other hand, the empirical analyses of unregulated immigration to the EU requires consistent and complete data on migration flow. Publicly available data, however, present an inconsistent and incomplete set of measurements obtained from a variety of national data collection systems. In order to overcome these obstacles, standardization of migration reports and data of sending and receiving countries in the EU is essential. Furthermore, the ICCT probably did not consider the ambiguity or the mathematical phenomena of the accumulation. The latter can be interpreted in the sense of stochastic processes such as Poisson process, which has a property of negative exponential distribution of inter-event time between two consecutive events (e.g. terrorist attacks). Thus, if something does not occur for a very long period of time, the possibility of its occurrence increases. French authorities confirmed that the terrorists who committed terrorist attack in Paris in 2016 came to France via the Balkan Migrant Route. It is entirely obvious that logistics hubs of terrorist organizations and their cells have been a part of 'European reality' for a long time; therefore, such attacks can be explained with accumulation (Ivanuša et al. 2018). The migration flow also presents a possibility for people engaged in terrorism and human and drugs trafficking or weapons proliferation. Prevention of such and similar forms of threats to national, regional and international security is a task for state security authorities and collective international security organizations. The (probably) leading role in ensuring national security belongs to the intelligence services that are mainly responsible for data collection outside the domestic environment. Migrant crisis is one of the phenomena with substantial impact on national interests and security; therefore, the on-time data collection regarding migrant crisis is or should be one of the top priorities, not only of intelligence services but also of the whole national security system–especially of the countries along the Balkan Migration Route (Ivanuša et al. 2018).

Monitoring and analysis of the migration flow are complex tasks, which demand special capabilities and tools. It is even more difficult to predict the appearance or scale of migration flow in the future. Such prediction should include not only the statistical aspects, which are mostly used by researchers focused on humanitarian point of view, but also the social and security aspects, which cannot be statistically and unambiguously explained due to their fuzzy nature. That is why the authors of this article are offering the intelligence community a new tool, i.e. early-warning short-term forecasting model of refugees' inflow time series (TS). The applied model is called "ARIMA-intervention" model and belongs to the family of Box-Jenkins models (Box et al. 2015), where ARIMA denotes *Auto-Regressive Integrated Moving-Average* model. The intervention component has been added to the basic ARIMA model since it was noticed that the refugees' inflow is occasionally influenced and interrupted by some outer, external source (mechanism), most likely related to the complicated EU-Turkey (with USA as the biggest merchants with weapons behind the scene) relations and unexpected changes in their policies and strategies. As will be shown in results, surprisingly, the analysis of intervention events and their effects discloses a typical case of the state social irresponsibility of Turkey that has been carried out via presumed collaborating with smugglers' networks and manipulating with refugees to blackmail the EU. Namely, it is a tragedy to play with the destiny of innocent people to achieve political and merchants' goals.

2. **Arima Intervention Modeling**

Such aforementioned unexpected exogenous processes are not unusual in reality, since the time series are often disturbed by infrequent unpredictable events that generate abnormal observations. They may happen due to some errors rising in the measuring process, or due to certain unusual events (outliers) which influence the analyzed TS, such as strikes, wars, economic crisis, etc. Outliers may have a significant impact on the results of TS analysis, modeling and forecasting, therefore it is crucial to detect them and estimate their effects. For that purpose, the intervention analysis is usually applied, which can assess the effect of such exogenous intervention events on the observed TS dataset.

Detection of outliers in time series was firstly studied by Fox (1972), who applied a statistical model for series contaminated by additive outliers (AO) and innovations outliers (IO) (Choy 2001). Box and Tiao (Box and Tiao 1975) developed and introduced ARIMA-intervention models which were proved to be statistically valid to assess the significance of the exogenous intervention events on a given time series. However, their approach was suitable only for situations when the outlier's time location is known. If the time location is unknown, the problem is much more controversial. Since Fox's study of autoregressive models in 1972, studying detection of unknown outliers has been enlarged to ARMA, ARIMA and other models by numerous studies. In the latter, an iterative procedure for outliers' detection and parameter estimation have been also developed including the detection of temporary changes (TC) and level shifts (LS) (Ivanuša et al. 2018). In 1993, two influential papers by Chen and Liu have been published (Chen and Liu 1993b, 1993a), where the authors introduced widely used automatic three-stage procedure of joint outlier detection and parameter estimation with several additional improvements (Jesús Sánchez and Peña 2003). Since then, many researchers have carried out further improvements regarding the ARIMA-intervention analysis and modeling (Ivanuša et al. 2018).

With inclusion of intervention analysis and modeling, three main goals had been tried: 1. Accurate detection of outliers and analysis of their effects; 2. The construction of ARIMA-intervention model of refugees' inflow time series; 3. Short term forecasting of future refugees' inflow with model's additional ability to predict the dimensions of effects of future intervention events. As will be later shown in results, the presented model provides quite promising prediction results. Besides offering the intelligence community a new instrument to support the decision-making process, we believe that the main contribution of research reported about in this paper might also be the quantitatively based intervention modeling approach, focused to the refugees' inflow via the Balkan route. To our best knowledge, such kind of modeling is not very frequent in the field of security and counter-terrorism research, with only several similar studies detected (for instance the research by (Wilson, Wilson, and Olwell 2006; Morakabati and Beavis 2017)).

3. Background and Problem Statement

Our study is focused on observing the refugees' inflow entering the EU borders via the Balkan route passing the Greece Islands after departing from the Turkish coast. Therefore, the traveling processes of shipping will be shortly introduced here. The authors of studies (Georgiou 2016; Georgiou, Kapodistrian, and Nkua 2016) did an excellent job describing these processes. The influx data analyzed in this paper was collected based on open-access database (UNHCR 2016) and was composed of partial data mostly collected from six Greek Islands: Lesvos, Chios, Kos, Samos, Leros, and Rhodes (see figure 1) (Leadbeater 2016; Georgiou 2016).

Figure 1: The map of observed area in Aegean Sea where the data were collected.

As can be seen in Figure 1, there are several passages across the sea borders between Turkey and Greece with very small distances, in some cases even smaller than 8 n.m. Since these distances are pretty short, the departing and arriving points of interest from both sides are quite attractive not only for the smuggling networks which organize the refugees' transport, but also for the coast guard patrol. Despite these short routes represent relatively dangerous passages, desperate refugees are prepared to risk everything just to get to the supposedly safe havens in Greece. According to the UNHCR, 1,000,573 migrants and refugees arrived in Europe from the North Africa and Middle East during 2015 (Leadbeater 2016; Georgiou 2016). Most of them (app. 850,000) landed on the Greek islands, from which 49% were Syrian, 21% Afghani and 8% Iraqi refugees. Figure 2 shows the refugees' inflow daily time series, based on the historical data measurements obtained from the UNHCR official database (UNHCR 2016), where the time horizon after the starting day of the EU-Turkey agreement (on March 20th 2016) is shadowed.

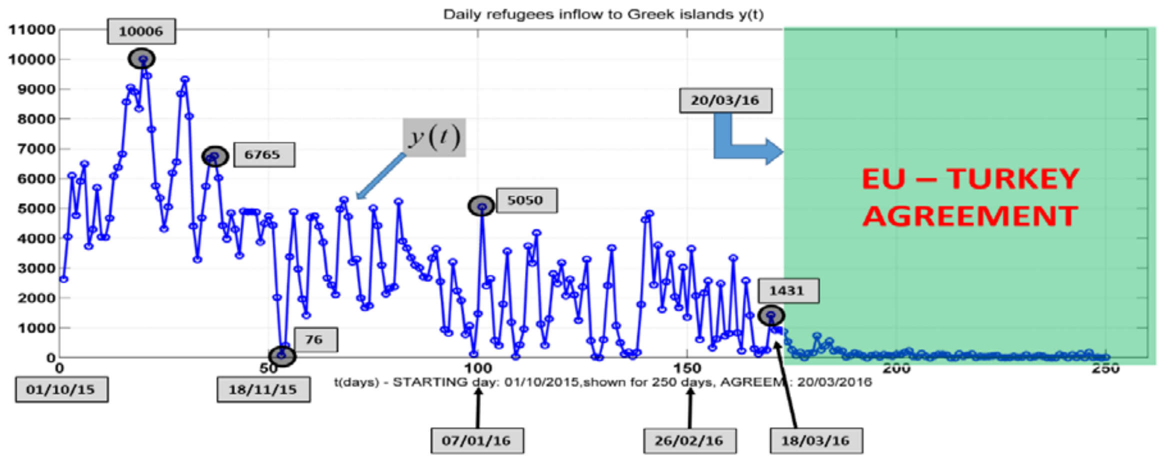

Figure 2: 250 refugees' inflow time series daily measurements shown from October 1st 2015 to June 5th 2016 (173th measurement corresponds to the March 20th 2016) (source: UNHCR)

From Figure 2 it can be seen that the stochastic mechanism behind the generated time series caused several significant abrupt dynamic changes in its trend, which were detected before the beginning of the EU-Turkey agreement. Besides the obvious change in time series dynamics, which happened after the beginning of the agreement (as the consequence of changed policy i.e. intervention event), we suspected that also other "hidden" interventions might have occurred before the agreement initiation. Namely, we were aware of several sudden changes in both the European and Turkish policy, as well as some other unexpected events (e.g. on the Syrian battlefields) before the March 20th 2016. Thus, we decided to investigate whether these external events could have also affected the observed time series $y(t)$ via the additional unrevealed outliers.

4. The Conceptual Framework of Intervention Modeling with Cl Procedure

The conceptual framework of intervention modeling with CL procedure is shown in Figure 3, where $y(t)$ denotes the observed time series, $\hat{y}(t)$ the model's output, while the jth intervention variable $u_j(t) = L_j(B) \cdot I_t(t_j)$ stands for a possibly detected outlier of certain type, i.e. AO, IO, TC, or LS type of outlier (Ivanuša et al. 2018).

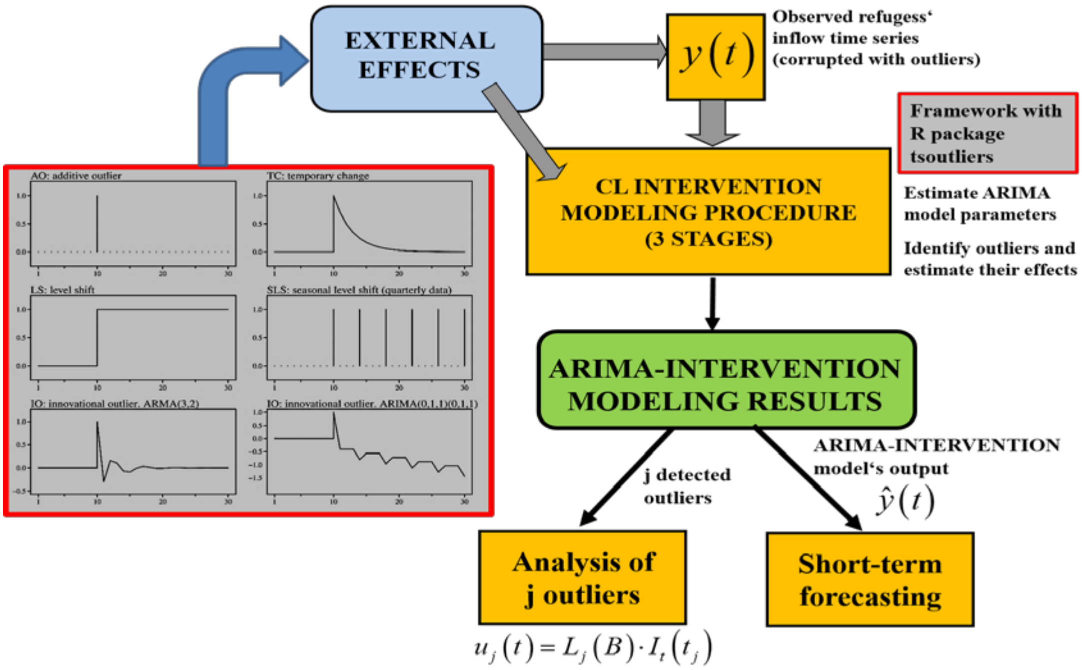

Figure 3: The conceptual framework of intervention modeling with CL procedure (external effects i.e. outlier types adopted and modified from (López-de-Lacalle 2015)).

The CL procedure is composed of three main stages (López-de-Lacalle 2015; Chen and Liu 1993b):

1. *Initial model's parameters estimation and significant outliers' detection,*
2. *Joint estimation of outlier effects and model's parameters, and finally*
3. *Detection of final outliers based on final model's parameters' estimates.*

When the intervention modeling process is finished, the main result is the derived ARIMA-INTERVENTION (AI) model on one hand, and the detected outliers' types, magnitudes and shapes of their effects, and outliers' time locations (time windows) on the other hand. Afterward, it is possible to analyze the detected outliers and investigate whether they correspond to some important events (i.e. terrorist attacks, changes in policies, etc.), which happened at the time of outliers' presence. This way, it is maybe possible to make a reconstruction of possible causal inter-dependence between series of external events on one hand, and consequential influx' changes reflected via outliers on the other hand. More importantly, it is possible to apply a derived model to make short-term forecasts useful in the sense of an early-warning mechanism representing the future refugees' inflow predictions.

5. Applied Methodology and Modeling Design

It can be shown that pure ARIMA(p,d,q) time series $y_0(t)$ corrupted with *m* intervention effects (outliers) $u_j(t)$ can be written in the following form of the AI time series $y(t)$ (Ivanuša et al. 2018):

$$y(t) = \underbrace{y_0(t)}_{\substack{ARIMA\\PART}} + \underbrace{\sum_{j=1}^{m} w_j \cdot u_j(t)}_{\substack{INTERVENTION\\PART}} = \frac{\theta(B)}{\alpha(B)\cdot\phi(B)} \cdot a(t) + \sum_{j=1}^{m} \underbrace{w_j}_{weights} \cdot \underbrace{L_j(B)\cdot I_t(t_j)}_{u_j(t)-outliers}, \quad where:$$

$$\phi(B) = \left[1 - \sum_{i=1}^{p} \alpha_i \cdot B^i\right]; \quad \theta(B) = \left[1 + \sum_{i=1}^{q} \theta_i \cdot B^i\right]; \quad B - lag\ operator; \quad a(t) \sim NID(0, \sigma_a^2); \quad (1)$$

$\alpha(B) = (1-B)^d$; d : number of differentiations to obtain the stationary time series

In general, the outliers $u_j(t)$ can be given by the product $L_j(B)\cdot I_t(t_j)$, where $L_j(B)$ is a polynomial of lag operators for the j^th outlier, while $I_t(t_j)$ is an indicator (dummy) variable that takes the value 1 when the j^th outlier erupts and the value 0 elsewhere (López-de-Lacalle 2015). The polynomial $L_j(B)$ for each type of outlier is defined in the following form (López-de-Lacalle 2015; Chen and Liu 1993b):

$$\textbf{IO}: L_j(B)=\frac{\theta(B)}{\alpha(B)\cdot\phi(B)};\quad \textbf{LS}: L_j(B)=\frac{1}{(1-B)};\quad \textbf{SLS}: L_j(B)=\frac{1}{(1-B^S)};$$

$$\textbf{AO}: L_j(B)=1;\qquad \textbf{TC}: L_j(B)=\frac{1}{(1-\delta\cdot B)} \tag{2}$$

where S is the possible periodicity of the data, while δ is usually set to 0.7

5.1. Identification of the Model Structure, Parameter Estimation, and Model Validation

Figure 4 (and Table 1) illustrates the results of the process of identification of the best AI model's structure, its parameters' estimation, and model validation (diagnostic checking). It turned out that ARIMA(1,1,2)-INTERVENTION model (see block A) with estimated ARIMA orders $p = 1$, $d = 1$, $q = 2$ was the most adequate in the modeling process, in which eight significant outliers $\hat{L}_j(B)$ were detected (see Table 1 referring the estimated parameters, weights $\hat{w}_j$, and outliers $\hat{L}_j(B)$). In the next step, after successful diagnostic checking of the most adequate AI model, we can further analyze eight identified outliers in $y(t)$ (block B) and investigate possible relationships between the detected intervention effects and known external events as their triggers. Moreover, the developed AI model can be used for short-term forecasting purposes (block C).

ARIMA (1,1,2)-INTERVENTION MODEL	Parameter	Parameter/ Weight Estimate	Standard error	Time index	t value	Outlier type
AR1	$\hat{\alpha}_1$	0.2794	0.1094			
MA1	$\hat{\theta}_1$	-0.5621	0.1043			
MA2	$\hat{\theta}_2$	-0.3468	0.0899			
$\hat{L}_{LS1}(B)$	$\hat{w}_1$	3003.5011	891.7599	3	3.368	Level shift
$\hat{L}_{TC1}(B)$	$\hat{w}_2$	-2947.4957	905.0998	7	-3.257	Temporary change
$\hat{L}_{LS2}(B)$	$\hat{w}_3$	-2359.3545	588.6966	32	-4.008	Level shift
$\hat{L}_{LS3}(B)$	$\hat{w}_4$	-2055.8508	582.2464	52	-3.531	Level shift
$\hat{L}_{TC2}(B)$	$\hat{w}_5$	2714.4080	880.6263	67	3.082	Temporary change
$\hat{L}_{TC3}(B)$	$\hat{w}_6$	2944.2182	876.9576	81	3.357	Temporary change
$\hat{L}_{AO}(B)$	$\hat{w}_7$	2981.9511	725.4007	101	4.111	Additive
$\hat{L}_{IO}(B)$	$\hat{w}_8$	810.8793	329.1023	155	2.4639	Innovation

Table 1: Estimated parameters of the derived model and the most important test statistics (AO, IO, TC, LS – outliers' types); time horizon: (01/10/15 to 05/06/16) – see also figure 4.

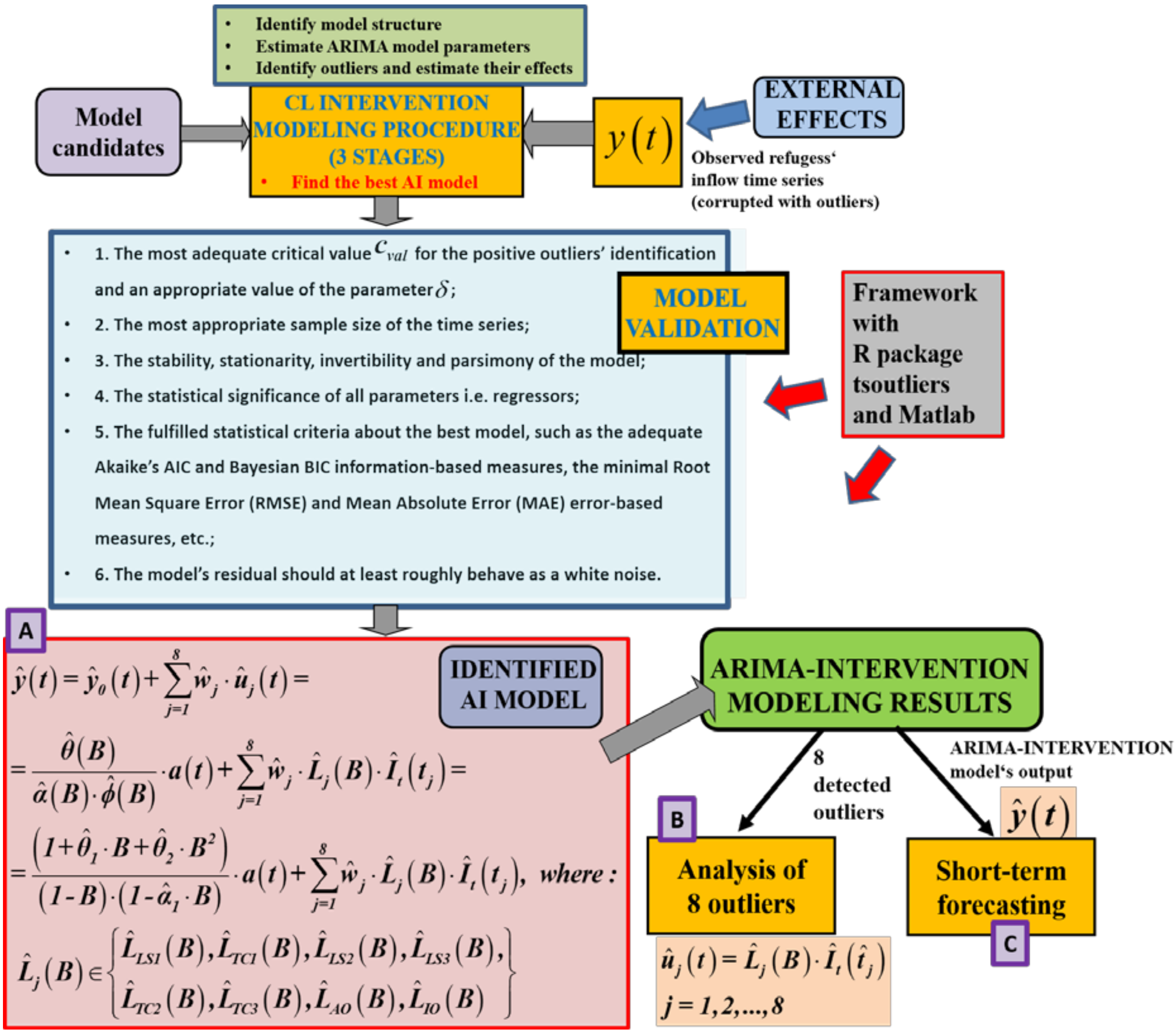

Figure 4: The process of identification of the best AI model's structure, its parameters' estimation, and model validation (see also table 1).

6. Analysis of possible relations between important political events and inflow changes via detected outliers

Figure 5 shows a time-dependent cumulative (aggregated) sequence $u^*(t)$ of detected outliers (intervention effects) in $y(t)$ representing the chronological path of all detected revealed external disturbances and their remaining effects that push refugees' flow up ($u^*(t)>0$) or down ($u^*(t)<0$). From Figure 5 it is possible to reconstruct the type and shape of these outliers, as well as the time windows of their influence (see also estimates for $\hat{w}_i$ in Table 1). On October 3rd, 2015 (time index 3), the positive level shift LS1 is firstly detected near value 3003.5011, which is after four time samples followed by temporary change TC1 (drop for value 2947.4957, then $u^*(t)$ is gradually rising back to the value 3002.9). Afterwards, two consecutive negative level shifts (LS2, LS3) happen, which decrease the signal $u^*(t)$ from the value 3002.9 to the value (3002.9 - 2359.3545 - 2055.8508 = - 1411.7). The same logic continues for the rest of the signal $u^*(t)$, which means four additional consecutive outliers in the following order: Two temporary changes (TC2, TC3), then additional outlier

(AO), and finally the innovational outlier (IO). The final position of the signal $u^*(t)$ is fixed to the negative value (- 1411.7) and will remain here until the next influential outlier.

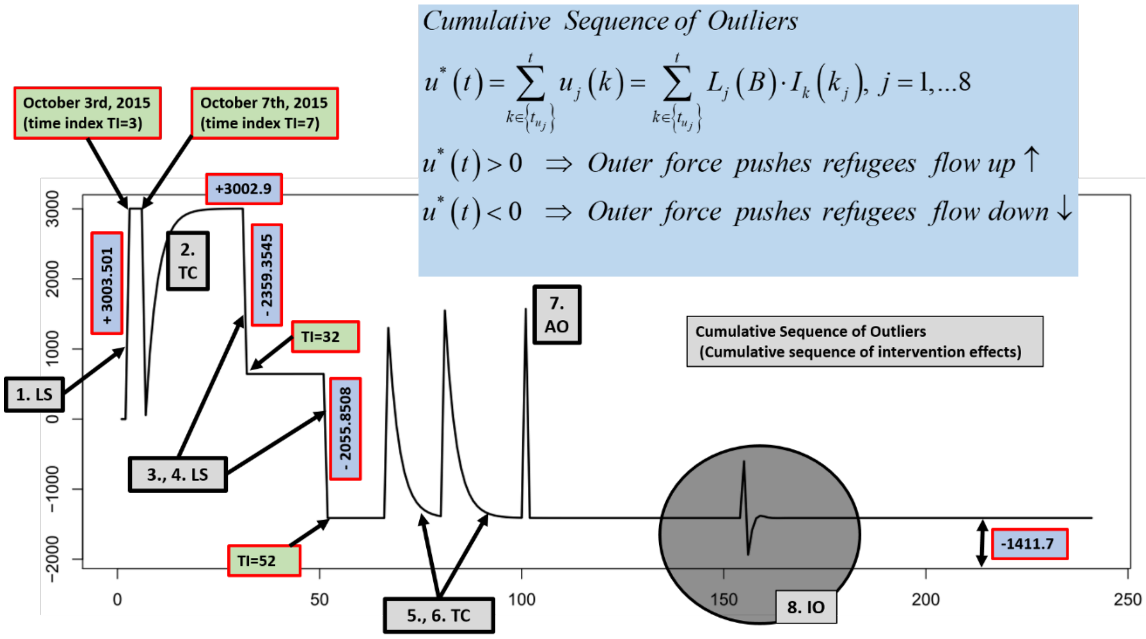

Figure 5: A time-dependent cumulative sequence $u^*(t)$ of detected outliers (intervention effects); (AO, IO, TC, LS – types of outliers); Observed time horizon: (01/10/15 to 05/06/16).

We might also be interested in investigating possible (causal) inter-dependence between some important external (political) events on one hand, and consequential influx' changes reflected via individual outliers $u_j(t)=L_j(B)\cdot I_t(t_j),\ j=1,\dots 8$ on the other hand. For this purpose, we have included 13 important (known) events $E_i(t),\ i=1,\dots 13$ in our analysis, which happened at the time of outliers' presence (see Table 2).

Event	Meaning	Date	Time index
$E_1(t)$	**Erdogan goes to negotiations (Brussels).**	**05/10/2015**	**5**
$E_2(t)$	**Tusk's warning to Turkey.**	**13/10/2015**	**13**
$E_3(t)$	**Turkey's elections, Erdogan will fight against smugglers.**	**01/11/2015**	**32**
$E_4(t)$	**Terrorist attack in Paris.**	**13/11/2015**	**44**
$E_5(t)$	**Meeting Patriarch – Juncker.**	**16/11/2015**	**47**
$E_6(t)$	**Meeting Tsipras and Davutoglu.**	**17/11/2015**	**48**
$E_7(t)$	**Greece-Germany-Turkey meeting.**	**21/11/2015**	**52**
$E_8(t)$	**Signature of the EU-Turkey agreement, the EU gives 3 billion EUR to Turkey.**	**29/11/2015**	**60**
$E_9(t)$	**Meeting of the EU leaders about migrations.**	**17/12/2015**	**78**
$E_{10}(t)$	**Tsipras angry because of Turkey being inactive in fight against the smugglers.**	**18/12/2015**	**79**
$E_{11}(t)$	**Turkey applies a new visa regime for the Syrians.**	**08/01/2016**	**100**
$E_{12}(t)$	**Two days before the start of agreement.**	**18/03/2016**	**170**
$E_{13}(t)$	**Agreement's start.**	**20/03/2016**	**172**

Table 2: 13 important events $E_i(t),\ i=1,\dots 13$, happened at the time of outliers' presence.

Figure 6 shows the individual outliers $u_j(t)$ detected in $y(t)$ and 13 important events $E_i(t)$ introduced in Table 2 (see also Figure 5). Since these events happened at the time of outliers' presence, we can investigate whether the events $E_i(t)$ and outliers $u_j(t)=L_j(B)\cdot I_t(t_j)$ are somehow logically related (in the spirit $\underbrace{E_i(t)}_{cause} \Rightarrow \underbrace{u_j(t)}_{consequence}$). Moreover, we should be aware that some outliers might have also had an additional origin from some other, unknown source (e.g. smugglers activities).

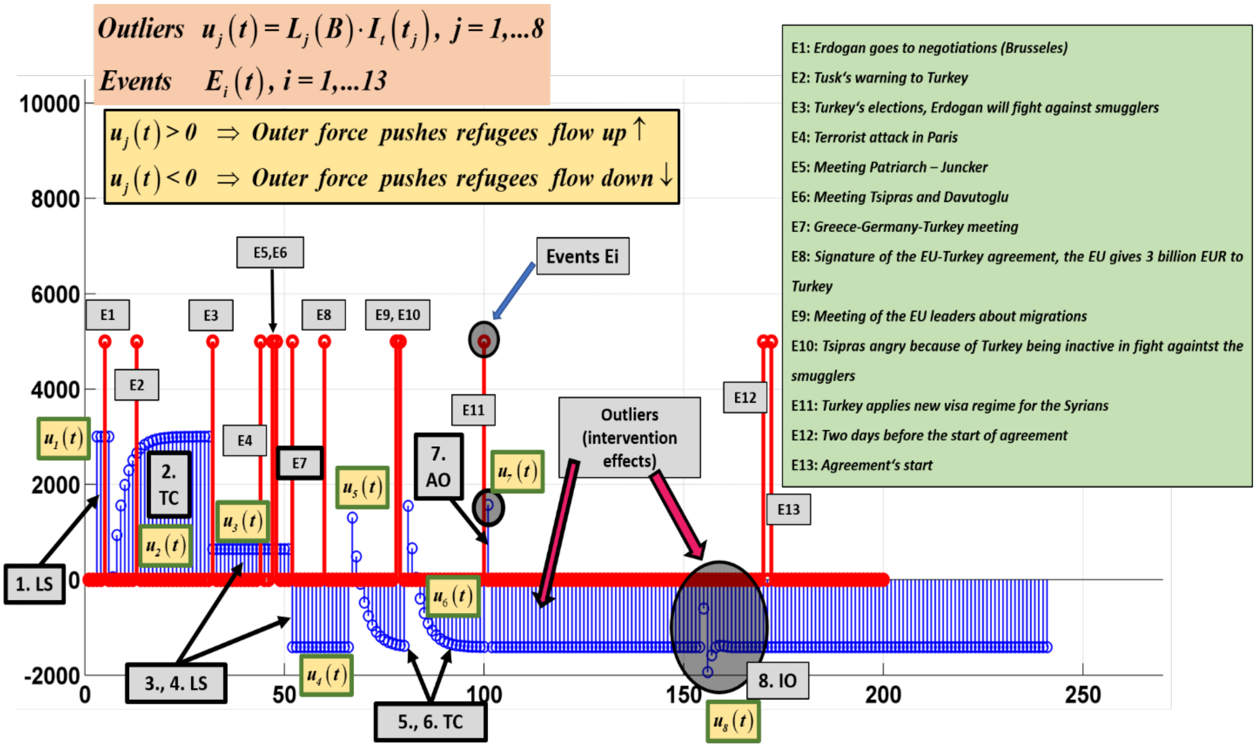

Figure 6: Important events $E_i(t)$, $i=1,...13$ and detected outliers $u_j(t)=L_j(B)\cdot I_t(t_j)$, $j=1,...8$ in time series $y(t)$; Observed time horizon: (01/10/15 to 05/06/16).

From Figure 6 we can make certain conclusions (see also Figures 2, 5 and Tables 1, 2). At the beginning of October 2016, the refugees' influx $y(t)$ erupted and was significantly amplified by smugglers' increased activity during the presence of the first outlier $u_1(t)$ (LS). After a while, during these first days, the EU detected a jeopardy of serious migration crisis. On October 5th, Turkish President Erdogan visited Brussels to discuss the frightening migration crisis with EU officials (event $E_1(t)$). Meanwhile, the migration flow was still enforced for couple of days, and soon the second outlier $u_2(t)$ (TC) occurred meaning a temporary down-change of influx. The reason for this variation might be in the change of smugglers' timetable. However, since new migrants were still massively entering into the Greece Islands, the persisting influx caused the Tusk's reaction (event $E_2(t)$). Tusk, as the President of Council of Europe, warned the Turkey to cut the refugee flow if Turkey wanted to receive the promised favors. Despite Tusk's warning, the migrant daily flow remained in a high, although fluctuating state. On one side, the detected outlier $u_2(t)$ was still gradually rising causing the increased influx (which reached the maximal daily value 10006 on October 19th, c.f. Figure 1), while on the other hand some other, unknown events (perhaps first Turkish antismugglers reaction, and/or variations in smugglers' timetable, etc.) occasionally decreased the daily influx $y(t)$. Nevertheless, the flow was gradually diminished in the days following the November 1st, when elections took place in Turkey (event $E_3(t)$). Then, Erdogan took the opportunity and addressed Turkish voters; in his speech, he promised stricter actions against migrant trafficking. At the same day, during elections, the third outlier $u_3(t)$ (LS) started meaning a negative level shift in signal $u^*(t)$ from Figure 5. From this one can conclude that after the elections' day, Turkish security forces started to take more determined campaign against the smugglers' networks. A big decline of incoming migrants occurred soon after November 21st, 2016, when Greece, Turkey and Germany discussed the migrant crisis and possible future actions (event $E_7(t)$). The consequence was the fourth outlier $u_4(t)$ (significant negative level shift), which reflected the startup of even more aggressive actions against the smugglers. On November 29th, Turkey and EU signed the agreement to stop illegal migrations to EU. Additionally, Turkey received 3 billion euros for this cause (events $E_8(t)$). Since then, the migrant flow was kept on relatively low numbers with occasional increases for short periods. However, despite the benefits that the Turkey achieved during the events $E_8(t)$, its policy changed when the time index reached the value of 67. At that time, the fourth outlier $u_4(t)$ from Figure 6 evolved into the positive temporary change-based outlier $u_5(t)$, which implies the relaxing of pressure of Turkish security forces on smugglers. Consequently, the fluctuating influx started to increase again and reached two significant spikes (5287, 5005) at time indexes (69, 76) (see Figure 1). When information about this influx's increase reached the EU leaders, two new important events $E_9(t)$ and $E_{10}(t)$ happened. The first one occurred around December 17th and December 18th when European leaders held a meeting regarding migrant crisis and EU Commission took actions to prevent the migrant crisis. At the same time, Greek premier Tsipras expressed his angriness because of Turkey being inactive in fight against the smugglers. Despite events $E_9(t)$ and $E_{10}(t)$, another positive temporary change-based outlier $u_6(t)$ occurred at time index 81 and was persisting for 20 days. Afterwards, on January 8th, Erdogan announced a change of asylum policy for Syrians (event $E_{11}(t)$, time index 100). This triggered another raise of numbers of migrants coming to EU from Turkey (see spike 5050 in figure 1, time index 103), which was a consequence of the one of the last smugglers' attempt to push as many refugees as possible towards the Greek islands (AO outlier $u_7(t)$, time index 101). Subsequently, the Turkish authorities started to strictly keep smugglers under control and prevent any of their actions. Regarding the outliers, the signal $u^*(t)$ from Figure 5 persisted to be fixed to the final position (-1411.7) in the remaining monitored time horizon, which confirms the unchanged Turkish policy to aggressively fight against the smugglers. After the application of the EU agreement on March 20th, 2017, the migrants' inflow was almost totally diminished and never raised upon the value of 900 in the observed time horizon again.

7. Short-Term Forecasting Performance of ARIMA-Intervention Model

The derived forecasting model can be rewritten into the following predictive form (c.f. Table 1 and Figure 4):

$$\hat{y}(t)=\frac{a(t)-0.5621\cdot a(t-1)-0.3468\cdot a(t-2)}{(1-B)\cdot(1-0.2794\cdot B)}+\sum_{j=1}^{8}\hat{w}_j\cdot\hat{L}_j(B)\cdot\hat{I}_t(t_j),\ \ where:$$
$$\hat{L}_j(B)\in\left\{\hat{L}_{LS1}(B),\hat{L}_{TC1}(B),\hat{L}_{LS2}(B),\hat{L}_{LS3}(B),\hat{L}_{TC2}(B),\hat{L}_{TC3}(B),\hat{L}_{AO}(B),\hat{L}_{IO}(B)\right\}, \tag{3}$$
$$\hat{w}_j\in\{3003.50, -2947.49, -2359.35, -2055.85, 2714.40, 2944.21, 2981.95, 810.87\},\ and$$
$$t_j\in\{3,7,32,52,67,81,101,155\}.$$

In its current form, it is suitable for a short-term forecasting only to support the early-warning mechanism used by decision-makers. The forecasting performance of model (3) is shown in Figure 7, from where it can be seen that the employed model provides quite promising prediction results. Namely, the forecasting performance of the model ensures a relatively good fit to the real influx data.

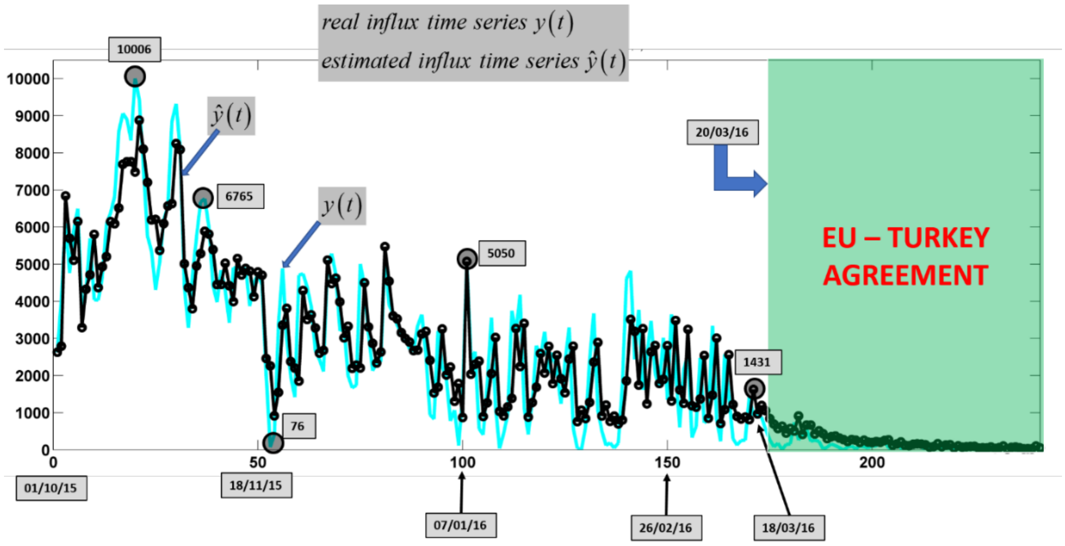

Figure 7: The forecasting performance of ARIMA-INTERVENTION model: $\hat{y}(t)$ - the predicted influx; $y(t)$ - the measured migrants' influx time series.

8. Conclusion

In this research, the design of an early warning predictive system with the capability of short-term forecasting of a future migrant flow time series was introduced. The study was focused on observing the migrant flow to the EU via the Balkan migration route passing the Greek islands after departing the Turkish coast. The research was related to the tragic events of the recent European migrant crisis. For the purpose of research, the ARIMA-intervention model was designed. The analysis of intervention events and their effects has revealed a typical case of the state social irresponsibility of the Turkey via presumed collaborating with smugglers' networks and manipulating with refugees to blackmail the EU.

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