

Road Freight Transport Forecasting: A Fuzzy Monte-Carlo Simulation-Based Model Selection Approach

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Abstract: As important as the classical approaches such as Akaike's AIC information and Bayesian BIC criterion in model-selection mechanism are, they have limitations. As an alternative, a novel modeling design encompasses a two-stage approach that integrates Fuzzy logic and Monte Carlo simulations (MCSs). In the first stage, an entire family of ARIMA model candidates with the corresponding information-based, residual-based, and statistical criteria is identified. In the second stage, the Mamdani fuzzy model (FM) is used to uncover interrelationships hidden among previously obtained models criteria. To access the best forecasting model, the MCSs are also used for different settings of weights loaded on the fuzzy rules. The obtained model is developed to predict the road freight transport in Slovenia in the context of choosing the most appropriate electronic toll system. Results show that the mechanism works well when searching for the best model that provides a well-fit to the real data.

Keywords: ARIMA models; forecasting road transport; Mamdani fuzzy inference model; Monte Carlo simulations; time series model selection

1 INTRODUCTION

Technological forecasting as a dominant force to create social change is a new gate to the future. This is because it arises from the interplay of public policy, strategic policy, and scientific methods to incorporate possible future technological development in management decision making. The ability to accurately predict the future is essential for decision processes in many scientific areas and real applications, let it be the planning, organizing, strategy formulation, policy-making, and so on [1, 2]. Thus, particularly in the last few decades, time series (TS) forecasting has become a stimulating research matter with mounting attention to various areas [3-6]

The capability to provide accurate forecasts is also significant in the field of broader planning of any essential road transport projects and investments. In this context, the planning of potential strategies must also take into consideration the accurate forecasting of future trends in freight transport. Such kind of forecasting is crucial in the case of developing any of future strategic policies on the state level, such as, for example, a design of a suitable tolling system on highways, where the freight traffic is usually prevailing, especially the transit one.

The study in this paper represents a continuation of the previous research of the authors of this paper (see [7]). There, the research was recognised as one of the essential studies conducted to select the most appropriate technology for the Electronic Tolling System (ETS) based on providing accurate forecasts of long-term future trends of Slovenian Highways' freight transport. Nevertheless, contrary to the previous research, this paper is more methodological than the applicative one. Also, the main focus is more dedicated to a model selection than long-term forecasting. In the modelling process, the model selection step is one of the essential steps conducted during the model identification, which includes the determination of the model's structure and estimation of its parameters [8].

The main aim of the paper is to present a novel two-stage fuzzy-based model selection procedure, which is combined with the Monte-Carlo simulations. The proposed mechanism represents an alternative to the commonly used model selection approaches, where the best model is chosen based on observing, e.g., the Akaike's AIC

information criterion or Bayesian BIC criterion [9, 10]. In some cases, these criteria do not identify the most parsimonious model, thus they have certain deficiencies that our approach strives to overcome.

In the first stage, for different combinations of orders p and q , the whole family of $i = 1, \dots, N$ plausible ARIMA model candidates is generated with different levels of fit to the given freight transport historical data $y(t), t = 1, \dots, T$. For each of these N candidates, the J various information, statistical, and residual-based criteria $X(i, j), j = 1, \dots, J$ are also calculated.

Afterward, in the second stage, the fuzzy model (FM) of type Mamdani (Mamdani Fuzzy inference system (MFIS) [11] is employed and implanted into a wider Monte Carlo Simulations (MCS) framework. While designing the FM, $X(i, j), j = 1, \dots, J-1$ are injected as inputs into the fuzzy model, while one criteria $Y(i) = X(i, J)$ represents its output.

The primary assumption is that the best ARIMA model is "hidden" behind that index i^* , for which the inputs $X(i^*, j), j = 1, \dots, J-1$ induce the closest fit of the FM's output $\hat{Y}(i^*)$ to the real one, i.e., the $Y(i^*)$. In order to verify this assumption, the $k = 1, \dots, M$ MCS iterations are executed that produce M different random sets of weights $w_k(s), k = 1, \dots, M, s = 1, \dots, S$ loaded on S fuzzy rules $FR(s)$. This way, a sequence of M fuzzy models and their belonging errors $e_{FM}(i, k) = \hat{Y}(i, k) - Y(i)$ is generated for each i -th ARIMA model candidate. From these errors, a further analysis clearly isolates the "optimal" index i^* that belongs to the best ARIMA model. The designed FM-MCS model selection mechanism was first tested for the simulation example and then used in the real case of freight transport data. Prediction results show that the developed forecasting model can provide a well-fit to the real data.

2 LITERATURE REVIEW

2.1 Forecasting the Road Freight Transport

When it comes to the forecasting of traffic flow, the methods can be, in general, divided into two main groups. The first group includes short-term forecasting (STF) methods. They are mainly used for advanced traffic management in the sphere of intelligent transportation systems at the level of urban metropolitan areas. These methods can be further divided into the classical methods (e.g., the ARIMA and other Box-Jenkins models, Kalman filters, etc. [7]) and the artificial intelligence/machine learning/data mining methods (e.g., the neural networks, support vector machines, etc.[7]).

The second group includes the methods for long-term forecasting (LTF) and is mostly used for forecasting the goods' movements on the state level. Some of these methods detected in the literature are [7]: The Dynamic Factor models, ARIMA models, ARMA-GARCH models, neural or neuro-fuzzy models, support vector regression models, etc. A more in-depth review of the methods developed for the road freight transport forecasting can be investigated in the literature (e.g., see [7]).

2.2 Forecasting, Regression and Fuzzy Logic

The classical linear regression models often suffer from a modelling error and measurement noise in the addressed data, which induces a sort of fuzziness around the precise exact data [12]. Moreover, the linear regression models often cannot deal with different nonlinearities, complex uncertainties, and chaotic behaviour of observed stochastic processes effectively enough.

To be able to deal with highly nonlinear patterns in the observed data, it is often recommended to use hybrid models or to combine several different models [13-15]. Furthermore, to deal with the modelling error and measurement noise in the data that are "captured" in the fuzzy environment, Tanaka and his colleagues [16, 17] have recommended a fuzzy regression approach in their pioneer works in the Eighties, where an interval prediction model has been conducted. Since the contributions [16, 17] occurred, the great body of literature followed dealing with the fuzzy logic (FL) applied to the time series regression, analysis, and forecasting (see [12] for contributions in the previous century).

In this century, Tseng and his colleagues [12] have combined the ARIMA model and fuzzy regression model into the FARIMA model for forecasting the exchange rate between the NT dollars and US dollars. This model was based on the triangular fuzzification of crisp ARIMA parameters and has achieved noticeably better forecasts than the competitive classical ARIMA model. The extension of the Tseng's work was done by [18], where the combining of the SARIMA (p, d, q) (P, D, Q) model with the fuzzy regression model was carried out resulting in the FSARIMA model. The model was used for forecasting the production value of Taiwan's machinery industry and the sale of soft drinks. Last but not least, the contribution [19]

has employed the Neural networks and fuzzy logic to model the nonlinear patterns of residuals of the ARIMA model to forecast various exchange rates and the gold price. Some other essential works from the field can be found in the literature (e.g., see [20-22]). To summarize, the fuzzy logic has been extensively used to improve the deficiencies of the classical forecasting models. On the other hand, there can be practically no study found that would involve the FL for the model selection purposes in the way as it was done in this paper.

2.3 Model Selection Criteria and Procedures

A lot of the single criteria for time series model selection have been developed besides the aforementioned AIC and BIC, such as, for example, the AICc (for small sample size), the Hannan and Quinn's HQ, the minimum description length (MDL), the Kullback's information criterion (KIC) and its corrected version (KICc), to mention some of them (see [23, 24] for details). However, when we are dealing with more complex TS models, such as ARMA models, it is in most cases relatively difficult to choose the appropriate order of AR and MA parts.

The monograph work by [23] reveals a wide-ranging review regarding the TS model identification and selection, including the ARMAX, ARIMAX, and other transfer function models. Here, the linear innovation regression-based estimation methods, such as the HR method, and the KP method, are discussed. These methods can determine the model's order as well as its parameter estimates, while some of them can also be applied to the Transfer function models [23]. Choi in his work also introduces the pattern identification methods, such as the SCAN¹ method, the R and S array method, the GPAC method, the Corner method, the ESACF² method, and other. Another important class of model selection and identification methods are Subspace identification regression-based methods, which are specially designed for ARMAX models' state-space representations. The main protagonists of these methods are the CCA³ method and the CVA⁴ method, proposed by [25], as well as the N4SID⁵ method [26], and the MOESP⁶ method [27].

Besides, Gomez and Maravall have proposed an algorithmic automatic procedure, which has been later also implemented in programs TRAMO and SEATS [28]. More recently, [29] proposed a state space framework for automatic model selection and forecasting based on exponential smoothing methods. On the other hand, authors [30] outlined the so-called RETINA⁷ automatic model selection procedure consisting of four main stages (data building and sorting, isolation of candidate models, the search strategy, and a selection of the most appropriate model). There also exist several other model selection strategies and approaches, such as the strategies with Genetic and Evolutionary algorithms (e.g., [31, 32]), or Branch and Bound strategies, to remark some of them. Contrariwise to all these approaches, our approach is quite different since it is grounded on the aforementioned FM-MCS based mechanism.

¹SCAN - Smallest canonical correlation method

²ESACF – Extended sample autocorrelation function

³CCA - Canonical correlation analysis

⁴CVA - Canonical variate analysis

⁵N4SID - numerical methods for subspace state space identification

⁶MOESP - multivariate output error state space method

⁷RETINA - Relevant Transformation of the Inputs Network Approach

3 METHODOLOGY

3.1 ARIMA Models

ARIMA(p, d, q) models represent an important group of Box Jenkins models, where p is the order of the AR component, q is the order of the MA component, and d is the order of differencing operator $\Delta = 1 - B$ (B is the backshift (lag) operator). The structure of the ARIMA(p, d, q) models can be characterized by the following transfer function Eq. (1), [8]:

$$\phi(B) \cdot (1 - B)^d \cdot y(t) = \varphi(B) \cdot y(t) = \theta(B) \cdot \varepsilon(t) \quad (1)$$

where $\varepsilon(t)$ is the disturbing random noise, while stationary autoregressive (AR) polynomial $\phi(B)$ and invertible moving average (MA) polynomial $\theta(B)$ have the form:

$$\begin{aligned} \phi(B) &= 1 - \phi_1 \cdot B - \phi_2 \cdot B^2 - \dots - \phi_p \cdot B^p \\ \theta(B) &= 1 + \theta_1 \cdot B + \theta_2 \cdot B^2 + \dots + \theta_q \cdot B^q \end{aligned} \quad (2)$$

When dealing with the ARIMA(p, d, q) models, the requirements of stationarity, stability, and invertibility must always be fulfilled according to the rigorous requirements of the Box-Jenkins modelling approach [8]. The invertibility implies that when a modelled time series is expressed in the form of the function of past observations, their weights should decline as one moves further into the past (i.e., the more recent observations should be taken into account more heavily than those from the more distant past).

3.2 Fuzzy Logic and Mamdani FIS Systems

Fuzzy logic offers tools to incorporate uncertainty and the human way of reasoning, thinking, and perception [11]. In fuzzy logic systems, the values of variables are articulated by linguistic terms such as for example, "large", "medium", "small", etc. Here, the relationships are expressed in a form of "if-then" rules (if - antecedent, else - consequent), while the fuzzified outputs and can be converted to "crisp" values by using the defuzzification methods [11].

When doing fuzzy modelling, the fuzzification is a process for defining the degree of the membership of a specific value being a particular fuzzy set. This can be done by evaluating the so-called membership functions (MF) belonging to the given fuzzy sets. The membership functions determine the degree of the membership of an individual element in a fuzzy set. Regarding the fuzzy rules, they are the basic elements for apprehending knowledge in fuzzy models [11].

The Mamdani and Sugeno types of fuzzy systems are the most common basic systems when applying the fuzzy logic model. The Mamdani system addresses the process states by using the linguistic variables as a means to control the fuzzy rules. It contains the following basic elements: A fuzzifier to convert the values of input variables to input fuzzy sets; the knowledge base; the inference engine, and the defuzzifier to transform the output fuzzy set to the crisp

values of the output variable (c.f. Fig. 1). The main goal of the fuzzy inference engine is to make specific calculations with the fuzzy rules. Moreover, it is based on the following three foundations: aggregation, implication, and accumulation. Further details about fuzzy logic and Mamdani systems can be found in the literature (e.g., see [11, 33]). Fuzzy set can be mathematically presented as [33]:

$$A = \{x | \mu_A(x)\} \quad (3)$$

where $\mu_A(x)$ is the membership function that determines a degree of the membership of elements $x \in U$ to the fuzzy set A . The MF $\mu_A(x)$ can be expressed as follows:

$$\mu_A(x) : A \rightarrow [0, 1] \quad (4)$$

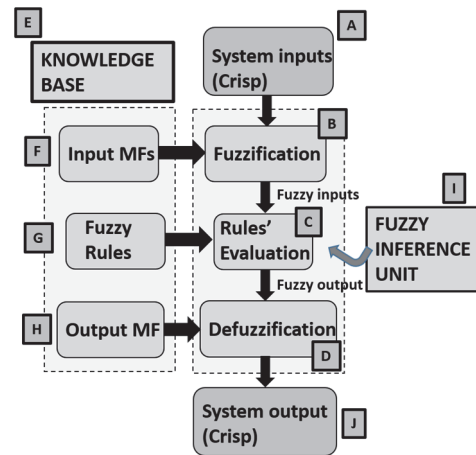


Figure 1 The fuzzy inference system

The value of the linguistic variable can be expressed by using the following triple: $[X, A(X), Rule]$, where X is the name of the variable, $A(X)$ is the set of values it can take, while the "Rule" determines the relationship between the linguistic terms and their physical meaning. According to Sivandam et al. [33], the fuzzy rules are a group of linguistic statements that define how the fuzzy system should carry out a decision considering classifying the inputs or controlling the output. Moreover, in general, the fuzzy rules can always be written in the following way (for the Multiple-Input-single-Output (MISO) systems) [11, 33]:

F Inputs and their MFs :

$$I_1, \dots, MF_1(I_1), \dots, MF_{i_1}(I_1), \dots, MF_{N_{I_1}}(I_1)$$

...

$$I_F, \dots, MF_1(I_F), \dots, MF_{i_F}(I_F), \dots, MF_{N_{I_F}}(I_F)$$

Output and its MFs :

$$O, \dots, MF_1(O), \dots, MF_{i_O}(O), \dots, MF_{N_O}(O) \quad (5)$$

Example of the s -th rule R_s :

$$\begin{aligned} R_s : & \text{if } (I_1 \text{ is } MF_{i_1}(I_1)) \text{ and } (I_2 \text{ is } MF_{i_2}(I_2)) \text{ and } \dots \\ & \text{and } (I_F \text{ is } MF_{i_F}(I_F)) \text{ then } (O \text{ is } MF_{i_O}(O)) \end{aligned}$$

4 THE DESIGNED FM-MCS MODEL SELECTION MECHANISM

Fig. 2 shows the conceptual framework with a novel two-stage FM-MCS model selection procedure (see also Fig. 1 and Eq. (1), (2) and (5)). Since the measured freight transport data $y_{ORIG}(t), t=1, \dots, T$ from 1990Q1 to 2019Q1 had contained some inconsistencies, errors, unusual spikes, abnormal and missing data, as well as

outliers, the pre-processing and data cleaning was needed in order to improve the adequacy of the data (see Fig. 2, block B). This way, a consistent and error-free time series $y(t), t=1, \dots, T$ was obtained in tonne-kilometres (Tkm). The TS was given in the cumulative and aggregated form obtained on the quarterly basis, which has given $T=117$ time samples from the first quarter of 1990 to the first quarter of 2019 (see [7] for details).

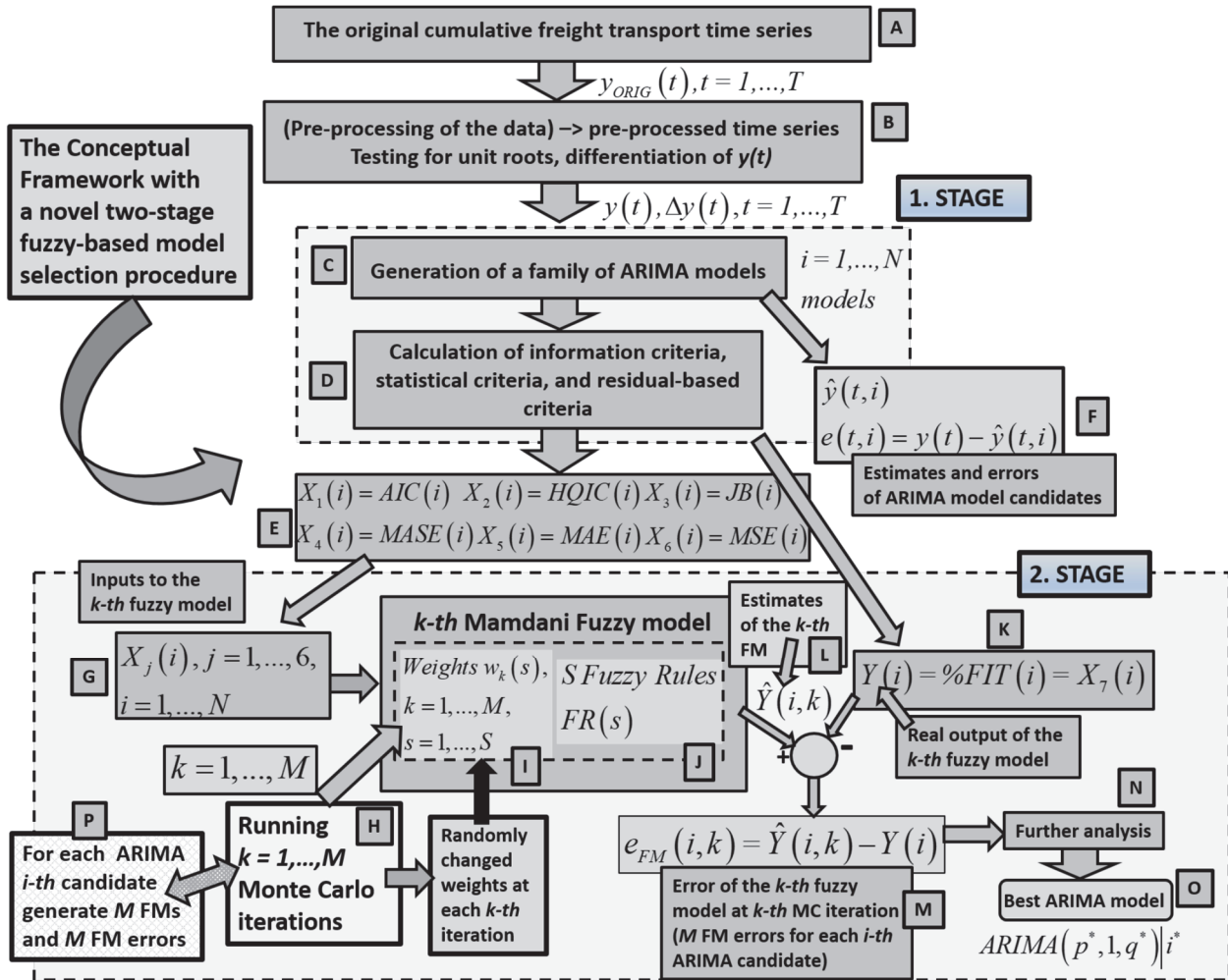


Figure 2 The Conceptual Framework with a novel two-stage fuzzy-based model selection procedure

The unit root testing was applied in the next step to examine the stationarity of the time series (c.f. Fig. 2, block B). For this purpose, two tests were accomplished, that is the KPSS (Kwiatkowski-Phillips-Schmidt-Shin) test and the ADF (Augmented Dickey-Fuller) test [8]. The tests had revealed that the ARIMA model is needed in the further modelling procedure. Also, it was discovered that the first order of differencing (i.e., $d=1$) of the TS is satisfactory to achieve its stationarity. Thus, in the further procedure, one was faced with a differentiated time series $\Delta y(t) = y(t) - y(t-1)$ and ARIMA($p, 1, q$) models [8].

4.1 The First Stage of the Algorithm

The 1. stage in Fig. 2 (see block C) started with a generation of the family of ARIMA($p, 1, q$) models for different combinations of $p, q = 1, \dots, 6$, which had given

$i = 1, \dots, N = 16$ feasible model candidates (their estimated structures and parameters) with the following orders p and q at given i :

$$ARIMA(p, 1, q) | i : \quad (p, q, i) \in \left\{ \begin{array}{l} (1, 1, 1), (1, 3, 2), (1, 4, 3), (1, 5, 4), \\ (2, 1, 5), (2, 2, 6), (2, 4, 7), (3, 1, 8), \\ (3, 2, 9), (3, 5, 10), (4, 1, 11), (4, 2, 12) \\ (4, 4, 13), (5, 1, 14), (5, 2, 15), (5, 3, 16) \end{array} \right\} \quad (6)$$

The other 20 models did not pass this modelling step due to different issues and violations regarding the Box-Jenkins methodology (the none-invertibility, the models' error had not been a white noise, etc. [8]). Because of similar reasons, the higher orders of p and q were also not

taken into consideration due to none-invertibility, ill-conditioned behaviour, and other similar issues. While processing block C, for each model candidate, besides the estimated parameters $\hat{\phi}_{i\phi}$ and $\hat{\theta}_{i\theta}$, the estimated forecasts $\hat{y}(t,i)$ and ARIMA modelling errors $e(t,i) = y(t) - \hat{y}(t,i)$ were also computed (see Fig. 2, block F).

In the next step of the 1. Stage (see blocks D, E, G, K in Fig. 2), the $J = 7$ information, statistical, and residual-based criteria $X(i,j), j = 1, \dots, J$ were calculated for each of the previously identified N model candidates. These criteria have included: 1. AIC; 2. Hannan-Quinn IC (HQIC); 3. Jarque-Berra (JB) test for testing a residual to be a white noise; 4. Mean absolute scaled error (MASE); 5. Mean absolute error (MAE); 6. Mean Square Error (MSE); and 7. Percentage of model's fit (%FIT), [24, 34, 35]. Here, the AIC and HQIC are the information criteria, while the other five measures depend on the ARIMA modelling error $e(t,i)$ (see the literature for the exact formulas of these measures, e.g., [24, 34, 35]). For the measures $X_j(i), j = 1, \dots, J-1 = 6$, it is desired that they are as small as possible (demand 1). Contrariwise, the measure $Y(i) = \%FIT(i) = X_J(i)$ should be as high as possible since it explains the level of the model's fit to the addressed data (demand 2).

4.2 The Second Stage of the Algorithm

While designing the FM of the type MFIS (see Fig. 1), $X(i,j), j = 1, \dots, J-1$ were injected as FM inputs into the fuzzy model (block G in Fig. 2), while the criteria $Y(i) = X(i,J) = \%FIT(i)$ have represented its FM output (block K in Fig. 2). Firstly, based on prior knowledge, the S fuzzy rules $FR(s), s = 1, \dots, S$ were established (c.f. Fig. 1, block G, Fig. 2, block J, and Eq. (5)), while simultaneously, the appropriate membership functions for all FM inputs and FM output were also constructed (c.f. Fig. 1, blocks F and H, and Eq. (5)). Regarding the fuzzy rules, to simultaneously satisfy demands 1 and 2, the main principle was that for low values of FM inputs, the FM output should be high and vice versa. The same logic was adapted for all the intermediate situations. Such kind of thinking has given several dozens of different fuzzy rules. Considering the MFs, for both the FM inputs and the FM output, the Gaussian membership functions were chosen with three possible classes: "low", "medium", and "high", [11].

When the fuzzy rules and MFs were constructed, the next step was to prepare the setting for weights $w_k(s), k = 1, \dots, M, s = 1, \dots, S$ (see Fig. 2, block I) that define an importance of corresponding fuzzy rules $FR(s), s = 1, \dots, S$. Since only one set of weights $w(s), s = 1, \dots, S$ (and only one fuzzy model) would not be enough to reveal hidden relationships between inputs $X(i,j), j = 1, \dots, J-1$ and output

$Y(i) = X(i,J) = \%FIT(i)$, the fuzzy model had to be incorporated into a wider framework of Monte Carlo simulations. Accordingly, after the initial setting and preparation of the key elements of the fuzzy model (FM inputs and output, MFs, rules), the $k = 1, \dots, M = 1000$ MCS iterations were executed (see block H in Fig. 2). By doing this, the M different random sets of weights $w_k(s)$ loaded on S fuzzy rules $FR(s)$ were generated. Consequently, the MCS procedure has also created an entire family of M different MFIS models and their belonging $e_{FM}(i,k) = \hat{Y}(i,k) - Y(i)$ FMs errors for each i -th ARIMA candidate (c.f. Fig. 2, blocks P, M). In this way, for each ARIMA candidate, it was possible to investigate how the FM inputs to the corresponding fuzzy models affect the FM output and FM error at different weights' combinations, and further analysis of obtained FMs errors $e_{FM}(i,k)$ finally enabled to find the best ARIMA($p^*, 1, q^*$) model (see blocks N, O in Fig. 2; p^*, q^* are the optimal orders of the AR and MA parts, while i^* is the optimal index). This manoeuvre was based on assumption that the best ARIMA model is "hidden" behind that index i^* , for which the inputs $X(i^*, j), j = 1, \dots, J-1$ induce (on average - for the majority of indexes k) the closest fit of the FM's output $\hat{Y}(i^*, k)$ (block L in Fig. 2) to the real one, i.e., the $Y(i^*)$ (block K in Fig. 2). As it turned out, this assumption was correct since the algorithm has given the minimal error $\min[e_{FM}(i^*, k)]$ (on average - for the majority of indexes k) for the best ARIMA($p^*, 1, q^*$) model.

Pseudo-code find_the_best_model():

```

1. For each ARIMA model's index i from 1 to N=16 do
    Inject the FM Inputs:  $X_j(i), j = 1, \dots, J-1 = 6$ 
    Inject the FM Output:  $Y(i) = \%FIT(i)$ 
    Create 7 Gaussian MFs and S Fuzzy Rules  $FR(s)$ 
    For each MCS iteration  $k = 1, \dots, M = 1000$  do
        Generate a random set of weights  $w_k(s)$ 
        Generate the k-th Fuzzy model for the i-th ARIMA model
        Calculate and memorise  $e_{FM}(i,k) = \hat{Y}(i,k) - Y(i)$ 
    End For index k
    End For index i
2. For each MCS iteration  $k = 1, \dots, M = 1000$  do
    Find and memorise index  $i'$  where
     $e_{FM}(i', k) = \min[e_{FM}(i, k)], i = 1, \dots, 16$ 
    Memorise  $\min[e_{FM}(i', k)]$  and corresponding k
    Memorise  $N\{\min[e_{FM}(i', k)]\} = N\{\min[e_{FM}(i, k)]\} + 1$ 
    End For index k
3. Draw a histogram  $N\{\min[e_{FM}(i', k)]\} = N(i', k)$  //  $i'$  on x-axis
4. Draw a point diagram  $\min[e_{FM}(i', k)]$  //  $i'$  on x-axis
5. Find the maximal number of occurrences
 $N_{\max}(i^*, k) = \max[N(i', k)]$ 
of the minimal FMs errors  $\min[e_{FM}(i', k)]$ , which gives the
optimal index  $i^* = i'$ .
6. Isolate the best ARIMA( $p^*, 1, q^*$ )  $i^*$  model.
    
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A further mechanism for determining the optimal ARIMA model

Figure 3 The Pseudo-code find_the_best_model() with a mechanism for determining the best ARIMA model

In other words, this can also be implicitly understood by the fact that the best ARIMA model at given weights' combinations most often has had a minimal FMs error compared to other suboptimal ARIMA models. A further mechanism for determining the optimal index i^* of the best $ARIMA(p^*, 1, q^*)|i^*$ model can be investigated by carefully observing the *Pseudo-code find_the_best_model()* in Fig. 3 (see also Fig. 2). The pseudo-code is intentionally given in the un-optimised form for easier understanding.

4.3 Some Details of Testing of Designed FM-MCS Model Selection Mechanism for a Simulation Example

In order to verify the capabilities of the developed mechanism, it was first tested for the case of simulation example. For this purpose, the simulated ARIMA(2,1,1) process was taken into consideration. In addition, the family of 36 ARIMA($p, 1, q$), $p = 1, \dots, 6, q = 1, \dots, 6$ different model candidates was generated. The output of the simulated process was intentionally corrupted with a nonlinear threshold auto-regressive (TAR) noise of the significant magnitude. Despite the substantial noise, the designed FM-MCS mechanism has undoubtedly managed to correctly estimate the exact model's orders $p^* = 2, q^* = 1$, while the parameter estimates were reasonably close to the real values of the simulated parameters. On the other side, if only the observations of the AIC measure were taken into account, the model selection mechanism has failed to estimate the exact orders and parameters of the simulated process resulting in incorrect identification results.

5 PRACTICAL NUMERICAL RESULTS

The modelling process and all other calculations were carried out in the MATLAB technical computing environment, with the additional use of the three MATLAB's toolboxes, i.e., the Fuzzy Logic Toolbox, the

Econometrics Toolbox, and the Statistics and Machine Learning toolbox.

5.1 The Results of the 1. Stage of Model Selection Process

When all steps of the 1. Stage (see blocks C, D, E, G, F, K in Fig. 2) were executed, the $J = 7$ criteria $X(i, j), j = 1, \dots, J$ were calculated for each of the previously identified N model candidates in Eq. (6) based on historical data $\Delta y(t) = y(t) - y(t-1)$. Fig. 4 shows the obtained FM inputs $X(i, j), j = 1, \dots, J-1$ and FM output $Y(i) = \%FIT(i)$. As can be seen from Fig. 4, different measures suggest a different optimal index i^* that corresponds to the best $ARIMA(p^*, 1, q^*)$ model (see shadowed circles marked with letters from A to M in Fig. 4). The residual-based measures $X(i, j), j = 3, 4, 5, 6$ would lead us to the similar conclusion suggesting that one of the models with indices $i^* \in \{10, 12, 16\}$ might have been the best model since these measures reach the lowest minimums at $X(i^*, j), i^* \in \{10, 12, 16\}, j = 3, 4, 5, 6$ (see circles D-J). Contrariwise, the AIC measure would suggest different conclusions that the best model might have been the one belonging to the index $i^* \in \{7 \vee 16\}$ (see circles A and B, where the lowest minimums are). More importantly, a very significant JB measure, which investigates whether the ARIMA model's error is the normal white noise (ideally $JB = 0$), suggests quite undoubtable conclusion that the index $i^* = 12$ corresponds to the best ARIMA model (see circle D, where JB reaches the lowest minimum). Similar guesses could be conducted for the highest maximums of the FM output $Y(i) = \%FIT(i)$. Nevertheless, instead of guessing about the actually optimal index i^* , the FM-MCS mechanism used in the second stage (see Fig. 2) is rather applied to isolate the truly best $ARIMA(p^*, 1, q^*)|i^*$ model.

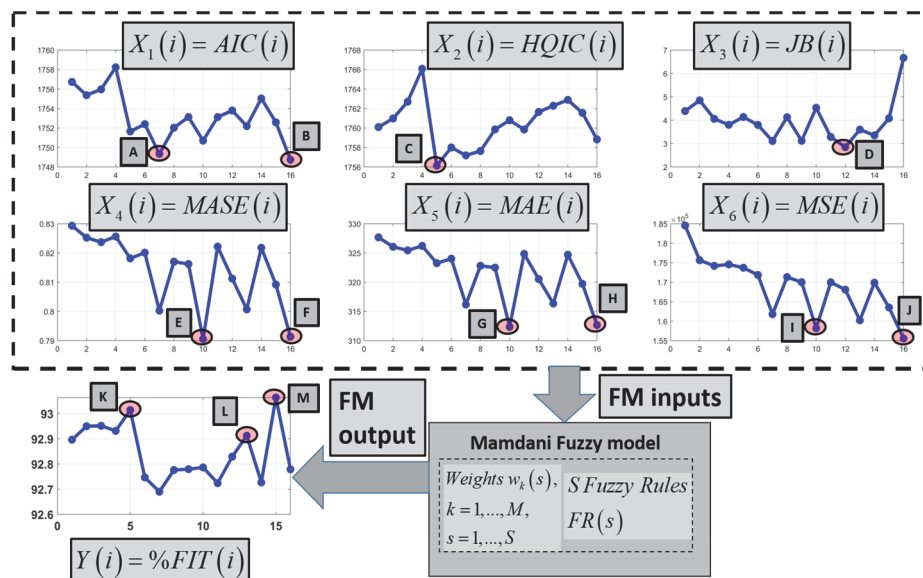


Figure 4 The obtained measures $X_j, j = 1, \dots, 6$ as FM inputs and $Y(i) = \%FIT(i)$ as FM output for 16 feasible ARIMA($p, 1, q$) models

5.2 The MFs and Fuzzy Rules Obtained by the FM-MCS Mechanism in the 2. Stage

In the 2. Stage (see Fig. 2, 2. stage), the S fuzzy rules $FR(s), s = 1, \dots, S$ were first constructed, while simultaneously, the Gaussian MFs for all FM inputs and FM output were also designed. The membership functions for the first three FM inputs $X(i, j) \in \{AIC(i), HQIC(i), JB(i)\}, j = 1, 2, 3$ are shown in Fig. 5. Due to lack of space, the MFs of the other three FM inputs ($X(i, j), j = 4, 5, 6$), as well as the MF for the fuzzy output $Y(i) = \%FIT(i)$ are not shown in this paper.

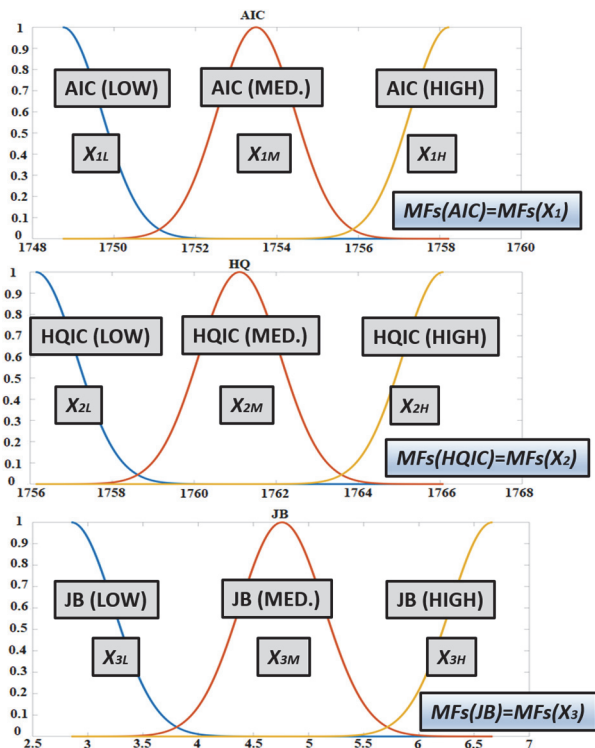


Figure 5 The MFs for the first three FM inputs $X_{j=1,2,3}(i) \in \{AIC(i), HQIC(i), JB(i)\}$ (med. = medium)

As can be seen from Fig. 5, the simpler notations for each of the three classes of individual MFs for first three FM inputs were applied, i.e., $X_{jL}, X_{jM}, X_{jH}, j = 1, 2, 3$. Similarly one can employ the notations for the other three FM inputs, i.e., $X_{jL}, X_{jM}, X_{jH}, j = 4, 5, 6$, as well as for the FM output (Y_L, Y_M, Y_H for "low", "medium", and "high" class of the output MF for the FM output Y). A simplified idea behind the setting of the $s = 1, \dots, S$ fuzzy rules can be illustrated in the following excerpt.

When observing the rules given in Eq. (7), one can see that for low values of the FM inputs (i.e., X_j is X_{jL}), the FM output Y should be high (i.e., Y is Y_H), and vice versa. The same logic holds for all the intermediate situations. As it turned out, a total of $S = 174$ rules was enough big number that the just explained logic had been satisfactorily covered.

- R_1 : if (X_1 is X_{1L}) and (X_2 is X_{2L}) and (X_3 is X_{3L}) and (X_4 is X_{4L}) and (X_5 is X_{5L}) and (X_6 is X_{6L}) then (Y is Y_H)
- R_2 : if (X_1 is X_{1M}) and (X_2 is X_{2L}) and (X_3 is X_{3L}) and (X_4 is X_{4L}) and (X_5 is X_{5L}) and (X_6 is X_{6L}) then (Y is Y_H)
- R_3 : if (X_1 is X_{1M}) and (X_2 is X_{2M}) and (X_3 is X_{3L}) and (X_4 is X_{4L}) and (X_5 is X_{5L}) and (X_6 is X_{6L}) then (Y is Y_H)...
- R_5 : if (X_1 is X_{1M}) and (X_2 is X_{2M}) and (X_3 is X_{3M}) and (X_4 is X_{4M}) and (X_5 is X_{5M}) and (X_6 is X_{6M}) then (Y is Y_M)...
- R_5 : if (X_1 is X_{1H}) and (X_2 is X_{2H}) and (X_3 is X_{3H}) and (X_4 is X_{4H}) and (X_5 is X_{5H}) and (X_6 is X_{6H}) then (Y is Y_L)

5.3 The Best ARIMA (4,1,2) Model Obtained by the FM-MCS Mechanism after the Completion of MCS Iterations (2. Stage)

The MCS procedure in Fig. 2 ($k = 1, \dots, M = 1000$ iterations) has created an entire family of M different MFIS models with corresponding $e_{FM}(i, k) = \hat{Y}(i, k) - Y(i)$ FM errors. The next step was to carry out further analysis to obtain the best $ARIMA(p^*, 1, q^*)|i^*$ model and corresponding optimal index i^* by means of mechanism **find_the_best_model()** from Fig. 3. For this index, the number of occurrences $N_{\max}(i^*, k)$ of the minimal FM errors $\min[e_{FM}(i', k)]$ should have been maximal if compared with the other $ARIMA(p, 1, q)|i$ models.

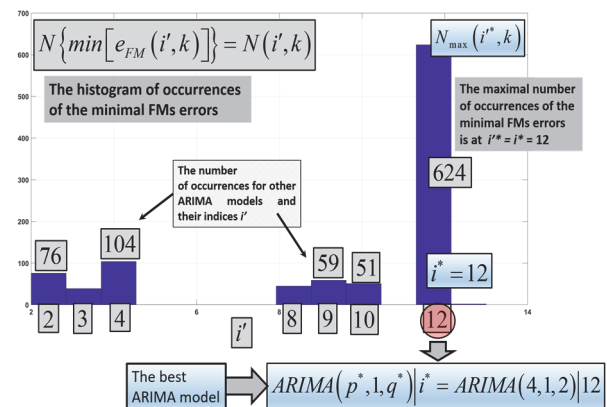


Figure 6 The histogram of occurrences of the minimal FM errors $N\{\min[e_{FM}(i', k)]\} = N(i', k)$ (see eq. (6)); $k = 1, \dots, M = 1000$

The mechanism **find_the_best_model()** from Fig. 3 has calculated the histogram of occurrences of the minimal FM errors $N\{\min[e_{FM}(i', k)]\} = N(i', k)$ shown in Fig.

6, as well as the corresponding point diagram $\min[e_{FM}(i', k)]$ shown in Fig. 7.

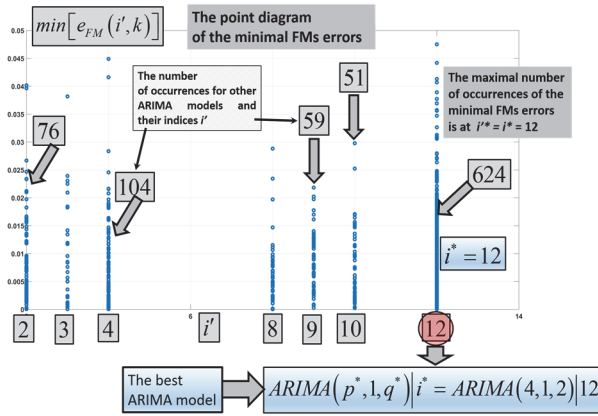


Figure 7 The point diagram $\min[e_{FM}(i', k)]$ of the minimal FMs errors for different indices i' and k (see eq. (6)); $k = 1, \dots, M = 1000$

A careful observation of Figs. 6 and 7 convinces us that for the far biggest number of MCS iterations (624 times) have happened that the maximal number of occurrences of the minimal FMs errors $N\{\min[e_{FM}(i', k)]\} = N(i', k)$ had occurred for the index $i^* = i' = 12$, which means $N_{\max}(i^*, k) = N_{\max}(12, k) = 624$. On the other side, the frequency of occurrences of the minimal FMs errors for the other indices i' was significantly lower, e.g. $N(2, k) = 76, N(4, k) = 104, N(9, k) = 59, N(10, k) = 51$, etc.

Based on these facts, by additionally considering the Eq. (6), the following best ARIMA model can be isolated with the detected optimal index $i^* = 12$:

$$ARIMA(p^*, 1, q^*)|_{i^*} = ARIMA(4, 1, 2)|_{12} \quad (8)$$

Accordingly, taking into account Eq. (1) and (2), the following form of the structure of the best model appears:

$$\hat{y}(t) = \frac{\hat{\theta}(B, q^*)}{(1-B) \cdot \hat{\phi}(B, p^*)} \cdot \varepsilon(t) = \frac{\hat{\theta}(B, 2)}{(1-B) \cdot \hat{\phi}(B, 4)} \cdot \varepsilon(t) = \frac{(1 + \hat{\theta}_1 \cdot B + \hat{\theta}_2 \cdot B^2)}{(1-B) \cdot (1 - \hat{\phi}_1 \cdot B - \hat{\phi}_2 \cdot B^2 - \hat{\phi}_3 \cdot B^3 - \hat{\phi}_4 \cdot B^4)} \cdot \varepsilon(t) \quad (9)$$

for which the estimated values of parameters, their standard errors, t values, and p values are depicted in Tab. 1 ($\hat{\phi}_i \rightarrow AR(i); \hat{\theta}_i \rightarrow MA(i)$).

Table 1 The estimated parameters and their significance

| Parameter | Estimate | Standard error | p -value | t -value |
|-----------|----------|----------------|------------|------------|
| AR(1) | 0,55484 | 0,16745 | 0,001324 | 3,3134 |
| AR(2) | 0,52508 | 0,15787 | 0,001272 | 3,3260 |
| AR(3) | -0,47366 | 0,14034 | 0,001086 | -3,3751 |
| AR(4) | 0,25811 | 0,12265 | 0,038027 | 2,1053 |
| MA(1) | 0,20872 | 0,11867 | 0,081961 | 1,7589 |
| MA(2) | -0,74033 | 0,19931 | 0,000351 | -3,7145 |

As can be seen from Tab. 1, all the parameters are statistically significant at $\alpha = 0,05$ level (t values bigger than 1,96), except the parameter MA(1) (t value is 1,7589) that is significant at $\alpha = 0,07$ level.

5.4 The Predictive Performance of the Best ARIMA Model

Fig. 8 shows the predictive performance of the obtained best ARIMA(4,1,2)|12 model. Here, the first 89 time-samples (app. 76% of all data - the estimation/in-sample interval) were used to carry out the model selection procedure and to identify the best model. The other (last) 28 time-samples were used to test the predictive power of the model (app. 24% of the data - the test/out-of-sample interval). As can be seen from Fig. 8, the model provides surprisingly good predictions $\hat{y}(t, i^*)$ of the real road freight transport time series $y(t)$ (measured in Tones km). There can be noticed some very sophisticated details of the TS dynamics, which were not entirely captured by the model. The reason is that the freight transport data dynamics likely contains a complicated nature with perhaps even a certain kind of nonlinear behaviour included. Despite this, the model generally provides an encouragingly good fit to the real data, particularly considering the key movements of the TS trend.

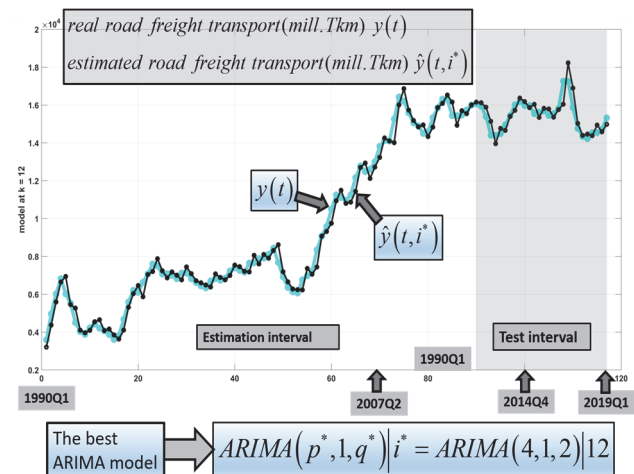


Figure 8 Prediction results for the road freight transport (Estimation interval - First 89 samples; Test interval - Last 28 samples); Tkm = Tones km

Table 2 The important measures and their requirements

| Measure | The meaning of measure | Requirement |
|---------|---|-------------|
| MAPE | Mean - Absolute - Percentage - Error / % | low! |
| sMAPE | Symmetric - Mean - Absolute - Percentage - Error / % | low! |
| MAAPE | Mean - ArcTangent - Absolute - Percentage - Error / % | low! |
| MASE | Mean - Absolute - Scaled - Error | <1! |
| GMRAE | Geometric - Mean - Relative - Absolute - Error | <1! |
| MdRAE | Median - Relative - Absolute - Error | <1! |
| MBRAE | Mean - Bounded - Relative - Absolute - Error | |
| UMBRAE | Unscaled - Mean - Bounded - Relative - Absolute - Error | <1! |

<1! → better than benchmark method (simple, usually a random walk)

The model's predictive performance should also be analytically verified by calculating the achieved measures of the quality of the derived forecasting model. Besides the

well-known classical measures (e.g., the aforementioned MAE, MSE, AIC, BIC, etc.), there have been many new measures applied in the last decade, which had become significantly attractive during the well-known Makridakis competitions [34, 35]. Tab. 2 depicts the meaning of some of these new applied measures (see [34, 35] for corresponding formulas).

Measures such as (sMAPE, MAAPE, MASE, etc.) can be treated as the most reliable and were also used to check the model's quality. Tab. 3 shows the calculated measures for the case of the best ARIMA model in order to verify its quality and performance. Some of achieved values in Tab. 3 are compared with the prescribed thresholds recommended in the literature. Computed measures confirm the adequate quality and performance of the derived model.

Table 3 Measures of the quality of the derived forecasting model

| Measure | Value |
|--------------------|--------------------------------|
| AIC | 1753,8 |
| BIC | 1773,1 |
| GMRAE* | 0,9562 < 1 |
| MdRAE* | 0,85155 < 1 |
| MBRAE* | 0,47796 |
| UMBRAE* | 0,91558 < 1 |
| UMBRAE better* / % | 8,4422% > 0% |
| MAPE* / % | 3,5944 < 10% |
| sMAPE* / % | 3,5975 < 10% |
| MAAPE* / % | 3,5873 < 10% |
| MSE* | 1,6808e ⁻⁰⁵ |
| RMSE* | 409,98 |
| MAE* | 320,53 |
| MASE* | 0,81125 < 1 |
| Stand. Deviation* | 411,72 |
| SKEWNESS* | 0,14743 |
| KURTOSIS* | 3,7056 |
| JB VALUE* | 2,8508 < 5,09 (critical value) |
| %FIT* | 92,829 (a well-fit) |

* These measures address the model' error.

(Some measures include a comparison with a simple random-walk)

5.5 Discussion and Practical Implications

Despite the fact that designed FM-MCS mechanism that gives the best ARIMA model works surprisingly well and provides a well-fit to the real road freight transport data, its prototype is currently developed for short to medium term forecasting only. Thus, similarly as in the previous research [7], it might have been appropriate to combine the FM-MCS algorithm with a Monte Carlo Scenario Playing (MCSP) mechanism for generating future scenarios about the road transport trends. The MCSP mechanism might have represented the basis for calculating the long-term interval-type forecasts, for which the corresponding probability intervals in future time-points could be computed. Besides, there are likely many other practical examples and cases not only in the infrastructure and road transport planning sphere, but also in many other theoretical and practical fields, where the designed FM-MCS mechanism might have offered an opportunity to the scholars and practitioners to facilitate the model selection procedure.

In many real applications, as much accurate forecasting as possible is of paramount importance. Namely, even slightly inaccurate forecasts can lead to wrong strategic decisions and wrong financial investments, which can have catastrophic financial consequences, such

as inappropriate investments in infrastructure, bad choice of expensive management and control systems, and the like. On the one hand, our innovative approach to modelling and choosing the best model is slightly complex, it is true. However, on the other hand, the latter is almost a fully automated generic mechanism that helps to extract the best forecasting model, which could be deployed with possible slight modifications for other similar real-world cases of forecasting in various fields as well. Since the designed algorithm helps to combine the best properties of different criteria for selecting the optimal model, statistical, information-based, residual-based, and others, it overcomes the shortcomings of other approaches, which usually unilaterally consider only one category of criteria. This way, the possibility of genuinely choosing the optimal forecasting model is increased. Consequently, the resulting predictive power leads to noticeably accurate practical results and, hence, the right decisions without too much risk of financial losses. Accordingly, it is believed that all these promising practical implications might justify the slightly higher complexity of the developed mechanism.

6 CONCLUSION AND FUTURE RESEARCH

In this paper, the new two-stage approach for the ARIMA model selection has been proposed and tested for the real case study of forecasting the road freight transport. In the first stage, the entire family of 16 feasible ARIMA models is identified. In the second stage, the novel FM-MCS mechanism has been applied, which is based on the combination of Mamdani Fuzzy modelling and Monte Carlo simulations. The Fuzzy model was used to access the "hidden" relationships between the ARIMA models' measures AIC, HQIC, JB, MASE, MAE, and MSE (Fuzzy inputs) on one side, and the measure $Y = \%FIT$ (Fuzzy output) on the other side. The 1000 Monte Carlo simulations were conducted to randomly generate different settings of the fuzzy weights, which has induced the whole cluster of different fuzzy models with different FMs errors for each ARIMA model candidate. The maximal number of 624 occurrences of the minimal FMs errors had occurred for the index $i^* = 12$, which corresponds to the best model $ARIMA(p^*, 1, q^*) \Big|_{i^*} = ARIMA(4, 1, 2) \Big|_{12}$. The detected best model provides a promisingly good fit for the real data, particularly considering the major movements of the TS trend.

In future work, it is planned to go deeper into research regarding the development of the Fuzzy-based mechanism for model selection, where the other types of the Fuzzy models (e.g., the Sugeno or ANFIS based) are also planned to be engaged. Moreover, the other methods for the optimal setting of fuzzy weights and membership functions are also intended to be deployed (e.g., by applying the Genetic Algorithms). The designed FM-MCS mechanism is also planned to be tested for more complex Box Jenkins and other time series models, e.g., the ones that include exogenous variables (i.e., ARMAX, ARIMAX, SARIMAX models, etc.). Finally, it is planned to test the designed model selection mechanism for the time series that occur in the other areas and/or industries.

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