Automatic Adviser on stationary devices status identification and anticipated change

A N Shabelnikov\textsuperscript{1,2}, N N Liabakh\textsuperscript{1,2}, Ya M Gibner\textsuperscript{1,2}, E A Pushkarev\textsuperscript{2}

\textsuperscript{1} Rostov State Transport University, Rostovskogo Strelkovogo Polka Narodnogo Opolcheniya Sq., 2, Rostov-on-Don, 344038, Russia
\textsuperscript{2} JSC «NIIAS», Rostov branch, 44/13, Lenina Str., Rostov-on-Don, 344038 Russia

E-mail: Gibner88@gmail.com

Abstract. A task is defined to synthesize an Automatic Adviser to identify the automation systems stationary devices status using an autoregressive model of changing their key parameters. An applied model type was rationalized and the research objects monitoring process algorithm was developed. A complex of mobile objects status operation simulation and prediction results analysis was proposed. Research results are commented using a specific example of a hump yard compressor station.

1. Introduction

In the last years, a large and growing group of researchers has devoted their attention to developing mathematical models and optimization approaches to tackle many of the relevant problems in the railway planning process [1]. At present, the field of knowledge associated with automata-advisers is actively developing in various fields of science and technology [2, 3, 4]. However, there is still a serious gap between theory and practice [5, 6].

Let us study the stationary objects existing on a hump yard (HY): speed indicators, retarders, compressor stations etc., unlike moving objects: locomotives, cuts, etc [7].

The task is to develop a software product: the Automatic Adviser (AA), which provides the HY service personnel with information about the facility current state and renders an advisory opinion on its further “fate”: “immediately remove from operation”, “send for maintenance within a specified period”, “keep in operation”. That is, two subtasks are solved:

- identification of the current state specified by the parameter vector:

\[ X = (x_1, x_2, ..., x_n) \] (1)

- classification into one of the three designated classes: R: remove from process, MAINT: maintenance, W: continue working process.

2. Research object description

Compressor station (CS) parameter vector (1) consists of:

\begin{itemize}
  \item The work was supported by the Russian Fundamental Research Fund, project No. 17-20-01040.
\end{itemize}
• $x_1$ - oil filter pressure drop (describes its contamination level),
• $x_2$ - oil level,
• $x_3$ - electric motor currents,
• $x_4$ - bearings state (by vibration),
• $x_5$ - water temperature and level (for water-cooled CS),
• $x_6$ - water presence of in the pit, …

Maintenance consists of the filter cleaning, bearings replacement, restoring the required levels of liquids, etc.

For the retarder:

• $x_1$ - energy height decrease,
• $x_2$ - actuation speed,
• $x_3$ - release speed, …

Maintenance consists in checking the tyres pressing, tyres width adjustment, burrs removal, etc.

3. Methods and tools

3.1. Preliminary data processing

Parameters describing the object operation have different directions: energy height, fluid levels – decrease; plays, errors - increase. For that reason, the actually received data unification is necessary. The scaling serves this purpose. It converts all data into one interval $[0, 1]$:

If $x_i$ decreases, then the scaling is carried out according to the formula:

$$u = \frac{(x-a)}{(b-a)}$$ (2)

If $x_i$ increases, then the scaling is carried out according to the formula:

$$u = \frac{(b-x)}{(b-a)}$$ (3)

where $a$ is the minimum possible, and $b$ is the maximum permissible value of variable $x_i$.

As a result of operations (2) and (3), all variables during the object operation now have the decrease tendency. Further let us consider that the stated transformations have already been made and let us use onward the initial designations of variables (1).

Area $[0, 1]$ is divided into three subintervals: from 1 to $\alpha$ is the studied variable working value; from $\alpha$ to $\beta$ - maintenance is necessary; from $\beta$ to 0 - object should be removed from the production process immediately. Values of $a$ and $b$, $\alpha$ and $\beta$ are calculated by natural constraints (specified in the user’s manual or assigned by experts) using relations (2) and (3), figure 1.
As a result of the object monitoring at the $t$ points, let us obtain time series $x_i$ for parameters $x_i$.

If parameters current coordinates are in the MAINT or R zone, then AA generates a message on these actions implementation.

3.2. Autoregression model construction

For the model analytical construction, one needs: a learning sampling and the model structure information.

Learning sampling length is obtained as a result of a compromise between the stationarity requirement and the sampling representation by volume. It is known that the larger the stationary process sampling is, the more “reliable” the corresponding model factors are. Under the statement of the problem, this process is not applied to stationary ones (the authors want to consider the equipment wear, that is, the device non-stationary operation). Therefore, the object properties change and large data sampling will contain areas described by different models [8]. Their combination is impractical, since the model parameters (factors) are averaged over the whole sampling and no longer correspond to its individual ranges.

If there is sufficient statistics for the researched object, then the learning sampling length can be determined basing on a computational experiment. Otherwise, one can use the expert commentary.

There are various models to predict the development of events [9, 10]. The forecast model structure in this problem is taken as an autocorrelation model of $m$-th order:

$$x_t = \sum_{i=1}^{m} a_i x(t - i) + \epsilon_t$$  \hspace{1cm} (4)

This expression is rationalized by the following reasoning: due to equipment wear, its parameters change in correlation with values at the previous time points. Autocorrelations consider the process prehistory, that is, its inertia (otherwise speaking, the studied process internal properties are considered).

Thus, this part of the work is to determine the model $m$ order. It will be equal to the number of the autocorrelation function significant members:
The Yule-Walker equations are used to determine the unknown factors $a_i$ of the model (4):

$$
\sum_{i=1}^{m} a_i R(i - k) = R(k), \quad = 1, m
$$

(6)

Here $R(i - k)$ and $R(k)$ are the corresponding values of $R(\tau)$. To solve (6), one can use Excel software.

Using the learning data sequence, let us estimate the models forecast power of the forecast accuracy.

4. Research object monitoring process algorithm

If parameters current values are in the W zone, then we implement the following algorithm:

- Construct the time series model basing on autocorrelation considering the process prehistory, that is, its inertia (the studied process internal properties consideration).
- Check forecast power of these particular models.
- Develop the general model, considering their contribution to the forecast.
- Use the constructed model to forecast the occurrence of states R, MAINT, W (figure 2). As a result, it is possible to obtain the time points before which one “has” to carry out maintenance, object removal from the process.

Figure 2. Geometrical illustration of monitoring process.
After “returning” the object into operation condition, let us resume the monitoring process by AA means.

5. Research and modeling results
To configure and verify the AA operation validity, it is necessary to create a complex of mobile objects status operation simulation and forecast results analysis (figure 3).

Figure 3. Automatic Adviser exhibition model diagram.

The signal generator block contains:
- Generation of autocorrelation-dependent signal according to the customer-specified formula. For example, one says “let the signal obey the dependence:
  \[ x_t = 0.7x_{t-1} + 0.1x_{t-2} \].
- Generation of \( \varepsilon_t \) noise of a given type (uniform, normal, exponential, etc.) and with the specified parameters (mathematical expectation, dispersion, kurtosis, etc.). For example: a normally distributed error with zero mathematical expectation and a constant variance with a given value.

The sum of these signals is fed to the AA. It should identify the model “unknown” for it. The original data and result are displayed on the monitor for comparison (monitor screen 1). Satisfactory match indicates the modeling process validity. The model quality is evaluated by its forecast capability.

Further AA makes a decision (remove object from work, send it to maintenance, continue the operation process in a normal mode). In the latter case, forecast time intervals are generated before the MAINT and R states occurrence.

6. Conclusion and main findings
The problem of Automatic Adviser synthesis, identifying the automation systems stationary devices status was defined and solved. The research objects key parameters change model type: an autoregression model was rationalized. Original information preliminary process methods were described and the algorithm of objects monitoring and diagnostics process was developed. The complex of operation simulation of the mobile objects status and forecast results analysis was proposed. Research results are commented using a specific example of the hump yard compressor station.
References

[1] Borndorfer R, Klug T, Lamorgese L, Mannino C, Reuther M, Schlechte T 2017 Recent success stories on integrated optimization of railway systems Transportation Research Part C: Emerging Technologies 74 196–211

[2] Haskovic D, Katalinic B, Zec I, Kukushkin I, Zavrazhina A 2016 Structure and Working Modes of the Intelligent Adviser Module Proceedings of the 27th DAAAM International Symposium ed B Katalinic 0866–0875

[3] Haskovic D, Katalinic B, Zec I, Kukushkin I, Zavrazhina A 2017 Intelligent Adviser Module: Proposals and Adaptive Learning Capabilities Proceedings of the 28th DAAAM International Symposium ed B Katalinic 1191–1196

[4] Post P 2014 Smart Systems for Intelligent Manufacturing-Industry 4.0 Plenary Lecture, 25th DAAAM International Symposium

[5] Borndörfer R, Grötschel M, Jäger U 2010 Planning problems in public transit Production Factor Mathematics 95–122

[6] Cacchiani V, Huisman D, Kidd M, Kroon L, Toth P, Velleureturf L, Wagenaar J 2014 An overview of recovery models and algorithms for real-time railway rescheduling Transportation Research Part B 63 15–37

[7] Adadurov S, Gapanovich V, Lyabakh N, Shabelnikov 2010 A Railway transport: on the way to intellectual management

[8] Fügenschuh A, Homfeld H, Schülldorf H, Vigerske S 2010 Mixed-integer nonlinear problems in transportation applications ed H Rodrigues Proceedings of the 2nd International Conference on Engineering Optimization

[9] Hsueh Y W, Yang C Y 2008 Prediction of tool breakage in face milling using support vector machine The International Journal of Advanced Manufacturing Technology 37 872–880

[10] Pavlyuk D 2017 Short-Term Traffic Forecasting Using Multivariate Autoregressive Models Procedia Engineering 178 57–66