Simulating Behavior Pattern of Key Performance Indicators to Improve Organization's Safety Performance in Maritime Transport

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Safety performance management is at the core of safety management system (SMS) in any organization. Managing an organization's safety performance in maritime transport is achieved through the identification of key performance indicators (KPIs), which are used to monitor and measure safety performance. The aim of this paper is to determine how the behavior pattern of the KPIs in an organization, can be simulated. The methods used for this research include methods of gathering, describing and analyzing the KPIs data of a sample organization, as well as statistics, causal modeling, and simulation. The results show the behavior pattern of KPIs in the organization due to the causal impact of certain KPIs. In conclusion, the simulation shows how causal modeling techniques can be useful to simulate behavior pattern of the KPIs in an organization in order to improve organization's safety performance.

KEY WORDS

~ Simulation
~ Behavior pattern
~ Key performance indicators
~ Improvement
~ Safety performance
~ Maritime transport

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1. INTRODUCTION

One of the key elements of safety management system (SMS) in any maritime organization is managing safety performance. Safety performance management ensures to the organization that all its processes are conducted in proper with the purpose of achieving organizational safety goals (Chen and Li, 2016; Patriarca et al., 2019; Di Gravio et al., 2015; O'Conner et al., 2011; Elvik and Elvebakk, 2016). This is achieved by defining the set of key performance indicators (KPIs), that represent tools to measure organization's safety performance (Kaspers et al., 2019; Sun et al., 2018). Information obtained through the identification of KPIs enables and supports informative and data-driven decision-making, including detection of necessary mitigation measures to ensure the accomplishment of organization's safety performance goals (Boström and Österman, 2017).

Every maritime transport organization has a regulatory obligation to define and monitor their KPIs (Bartulović and Steiner, 2020). Organizations usually measure indicators such as number of accidents or incidents, number of changes, number of findings related to safety, etc., in relation to a time frame (monthly or yearly data) or to conducted operations. It gives an organization a guidance to where organization has been, where it is now, and where it is heading, in relation to its safety performance (Bartulović, 2021).

There are qualitative or quantitative KPIs (Hänninen, et al., 2014). Quantitative indicators are measured by quantity, while qualitative indicators are measured by quality. Generally, the preferred indicators are those measured by quantity, due to the fact they can be easily analyzed and compared (Roelen and Klompstra, 2012). KPIs, whether they are qualitative or quantitative, require a thoughtful selection process, which can depend on the data availability and its relevance to organization's safety performance (Swuste et al., 2016; Lališ and Vittek, 2014).

The classification of organizational KPIs usually defines lagging and leading indicators (Valdez Banda and Goerlandt, 2018). Lagging KPIs or "outcome-based KPIs" monitor adverse events that have occurred in the past, i.e., those events that the organization wants to avoid in the future. Measures of implemented activities with the purpose to enhance safety performance in an organization are known as leading or "activity or process" KPIs (Leveson, 2015; Valdez Banda and Goerlandt, 2018).

The aim of the paper is to present how causal relations between the organization's key performance indicators can be detected by the use of causal modeling techniques. Another aim is to show how detected causal relations between KPIs can be used to simulate the behavior pattern of other affected KPIs in an organization.

By using causal modeling techniques, it is possible to determine the causes of past events (Qiao et al., 2021). Those same causes can be useful for mitigating adverse events, hence, provide the possibility to improve the organization's safety performance in maritime transport.

2. LITERATURE OVERVIEW

This chapter provides a chronological overview of literature regarding research of causal modeling techniques used to simulate behavior patterns.

One of the most popular causal modeling techniques related to time series analysis is Granger causality (Granger, 1969). Bivariate Granger Causality Theorem explains that by testing behavior when exchanging the roles of X and Y, the existence of a causal relation between X and Y can be determined (Granger, 1980; Granger, 1988). It indicates that X impacts Y every time the past values of X assist in forecasting Y due to its own past values.

Spirtes and others (Spirtes et al., 2000) focused on the methods that have the possibility of using observations for the purpose of determining the causes of a particular event. Also, it has been pointed out that each cause and effect are separate events; hence, planning future actions, i.e., predicting the consequences of future actions, requires knowledge about the causal relations.

In 2001, Sarasvathy determined the linkage between causation and prediction, based on business examples and realistic experiments (Sarasvathy, 2001).

In 2004, Cartwright argued that causation does not represent a single, uniform concept, and explained that various causal relations exist in various systems (Cartwright, 2004).

In 2005, Sloman presented human perception of causal relations between an activity and its outcome, with the focus on intuition and basic human cognitive functions instead of mathematical theorems. (Sloman, 2005).

Roelen (2008)was one of the pioneers in explaining how causal models could be used to manage risks related to aircraft accidents and pointed out how causation helps in predicting future system behavior based on its past and present behavior.

Shmueli (2010) stated that statistical modeling is almost exclusively used in many fields, regarding causal explanation, description, and prediction.

Buehner (2012) described temporal binding as a reduction of time between actions and their outcomes. The research showed how causes of actions result in temporal binding, i.e., it indicated causal relations between actions and their outcome.

Van De Vijver and others (2014) used heterogeneous Granger analysis, specifically Time Series Cross Section Granger causality analysis to find connections between the deployment of transport infrastructures and spatial economic development.

In 2014, Eastwell provided the definitions of causal hypothesis, prediction, rule or principle, and scientific theory, and used them to explain causal relations between different phenomena.

Peters and others (2016) explained the advantages of predicting using causal modeling, which implies more accurate and precise predictions, as opposed to predictions obtained without causal modeling.

Küçükönala and Sedefoğlu (2017) applied Granger causality analysis to detect causal factors of air transport growth, i.e., to determine causal relations between air transport, tourism, economic growth, and employment.

Pacheco and Fernandes (2017) applied Granger causality to detect impact relations among trade indicators and air passenger fluctuations in Brazil.

Peters and others (2017) stated that the fundaments of probability theory and statistics lie on the probability triple (Ω, F, P), where Ω is a set with all possible outcomes, F is a set of all events A ⊆ Ω, and P is a probability of each event.

Yarkoni and Westfall (2017) argued about crucial problem of prediction overfitting, in performance modeling, where built model usually provides less satisfactory results when using new sample (other than first one), even though it uses data from the same dataset.

In 2018, Akinyemy determined the causal relation between GDP and domestic air travel demand in Nigeria, using autoregressive distributed lag cointegration approach and Granger short-run and long-run causality tests.

Heinze-Deml and others (2018) explored prediction methods to anticipate system's response to certain interventions. The authors propose Invariant Causal Prediction (ICP) that builds a causal model from causal relations obtained by using data from different sources.

Rohrer (2018) discussed about observational data can be used to make causal inference. He presented graphical causal models which can be used to detect interrelations between variables.

Singh and others (2019) analyzed impact relations between safety management system (SMS), human factors (HF) and civil aviation safety (CAS) and used causal modeling approach to find elements that have considerable impact on CAS performance.

Laubach and others (2021) reviewed the most recent causal modeling methods that have direct applications in the field of ecology, evolution, and behavior.

3. METHODOLOGY

Methods used for this research include methods of gathering, describing, and analyzing key performance indicators data of sample organization, as well as mathematical methods, statistical methods, causal modeling techniques and simulation.

IBM SPSS Statistics is among leading softwares for solving problems, using various statistical and predictive methods (IBM, 2022; Leech et al., 2008; Kambadur et al., 2016; Baksi and Parid, 2020). IBM SPSS Statistics software was used for research in this paper.

By using the IBM SPSS Statistics software, causal modeling can be used to detect causal relations between all indicators in the observed dataset. The software also provides tools to examine relations between indicators and simulate their behavior patterns. The focus is on key performance indicators (KPIs), i.e., the causal model, which shows how organizational key performance indicators (KPIs) (Adjekum and Tous, 2020) impact each other (Bartulović and Steiner, 2022).

Monitoring and recording of key performance indicators are performed on a monthly basis at the sample organization. The organization provided collected data on key performance indicators to be used for this research. The dataset includes 60 observational points (entries) collected during the period of five years. This dataset was necessary to create causal model.

The chosen method of causal modeling is temporal causal modeling, available in the IBM SPSS software. The method requires adjusting the dataset, i.e., all the variables, and specify each set of variables as "input", "target", or "both". When the dataset is ready, the software builds an autoregressive time series model, i.e., causal model for each "target" variable and includes only those variables that have causal relations with the "target" variable.

Once the causal model is built, the simulation of the KPI behavior pattern can be conducted. The IBM SPSS function called "temporal causal model scenarios" can be applied to simulate the KPI behavior pattern by creating different scenarios using previously created temporal causal model and modifying one variable from the active dataset.

Using these techniques, it is possible to simulate increase or decrease of a certain KPI and see how it affects the behavior pattern of the other KPIs. The example of such simulation (scenario case) is presented in this paper. The results show how detecting relations between datasets, in this case key performance indicators, can help determine correlations and impacts on each other, which in turn can point to weak spots in the entire system. The example shows how increasing or decreasing values of certain KPIs can improve values of the other KPIs in the organization, i.e., it can improve overall organization's safety performance.

4. RESULTS

In this chapter, the aim is to create causal model of defined KPIs in order to present relations between them in the sample organization. Detecting relations between indicators indicates impacts (causes or effects) of indicators to one another, which in turn gives a possibility to improve planning of future actions with enhanced techniques that can improve organization's safety performance.

A dataset of actual safety performance data was used. The dataset represents the data on the KPIs of the sample organization, which requested to remain anonymous (Sample, 2022).

As a part of its safety management, the sample organization has established a set of key performance indicators (KPIs) and set accompanying performance targets (goals). The KPIs are monitored on a monthly basis, and they are all outcome-based. A dataset is composed of monthly entries for 18 KPIs. The observed period is from January 2017 to December 2021. The dataset contains 60 entries. Table 1 shows the dataset of monthly organizational key performance indicators (KPIs) of sample organization.

Date	KPI1	KPI2	KPI3	…	KPI16	KPI17	KPI18
Jan 2017	0	0	0	…	0	0	0
Feb 2017	0	0	0	…	0	0	1
Mar 2017	1	0	0	…	0	0	1
…	…	…	…	…	…	…	…
Nov 2021	0	0	0	…	0	0	0
Dec 2021	0	0	0	…	1	0	0

Table 1. Dataset of organizational key performance indicators (KPIs) (Source: Sample, 2022)

4.1. Causal Modeling of Organization's Key Performance Indicators

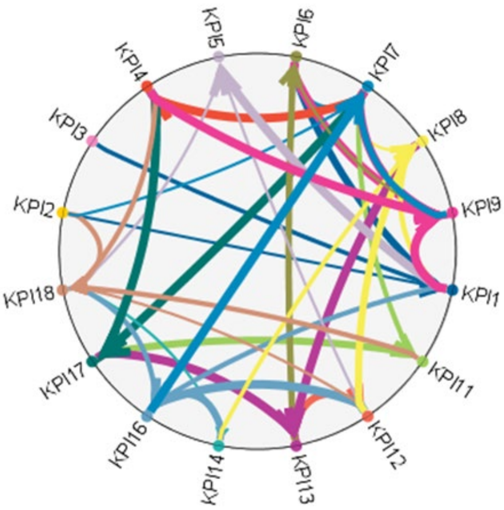
To obtain causal relations between the KPIs in the organization, IBM SPSS function Temporal Causal Modeling was used. The KPIs are considered to be dependent and independent variables in temporal causal model, i.e., KPIs are set to be "both inputs and targets". The KPI10 model was excluded due to the fact that the values are constant, i.e., equal to 0. Table 2 shows fit statistics for top causal models generated for each of the 17 KPIs of the sample organization, as well as the model quality for all the built models.

There is a variety of criteria that can be used to do the evaluation, such as Root Mean Squared Error (RMSE), Root Mean Squared Percent Error (RMSPE), Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), or R-squared. In this case, R-squared is selected, which is the default criterion for quality evaluation of causal models. R-squared is the coefficient of determination, and the larger the R-squared value, the better the model. From Table 2, the built models show very good quality because they have R-squared values in the interval [0.32, 1.00].

Target Model	Model Quality				
	RMSE	RMSPE	AIC	BIC	R-squared
KPI1	0.19	0.04	-168.67	-116.48	0.79
KPI2	0.15	0.09	-190.3	-138.11	0.32
KPI3	0.35	0.12	-98.9	-46.71	0.52
KPI4	4.58E-16	4.19E-16	-3875.49	-3853.41	1
KPI5	0.27	0.1	-127.57	-75.38	0.76
KPI6	0.69	0.19	-23.42	28.77	0.74
KPI7	0.05	0.01	-309.31	-257.12	0.92
KPI8	1.06	0.27	23.41	75.6	0.74
KPI9	0.12	0.04	-220.05	-167.86	0.97
KPI11	0.48	0.18	-63.91	-11.72	0.72
KPI12	0.18	0.07	-174.79	-122.6	0.69
KPI13	0.08	0.03	-256.4	-204.21	0.93
KPI14	1.79	0.37	81.05	133.24	0.7
KPI15	0.36	0.14	-96.93	-44.73	0.36
KPI16	0.29	0.12	-118.3	-66.11	0.86
KPI17	1.27E-15	9.01E-16	-3761.8	-3735.7	1
KPI18	0.21	0.09	-154.76	-102.57	0.76

Table 2. Fit statistics for top causal models (Source: Authors using IBM SPSS Statistics)

Figure 1 shows causal model of all causal relations between key performance indicators (KPIs) of the sample organization. It can be observed that KPI1 is in relation with KPI2, KPI3, KPI5, KPI6, KPI8, KPI9 and KPI16. KPI2 is related with KPI1, KPI7 and KPI8. KPI3 is in relation with KPI1 and KPI11. KPI4 is related with KPI7, KPI9, KPI17 and KPI18. KPI5 is related with KPI1, KPI12 and KPI18. KPI6 is related with KPI1, KPI7, KPI9 and KPI13. KPI7 is in relation with KPI2, KPI4, KPI6, KPI7, KPI8, KPI9, KPI11 and KPI16. KPI8 is related with KPI1, KPI7, KPI12, KPI13 and KPI14. KPI9 is related with KPI1, KPI4, KPI6 and KPI7. KPI11 is related with KPI3, KPI7, KPI17 and KPI18. KPI12 is related with KPI5, KPI8, KPI13, KPI14, KPI16 and KPI18. KPI13 is related with KPI6, KPI8, KPI12 and KPI17. KPI14 is related with KPI8, KPI12, KPI16 and KPI18. KPI16 is related with KPI1, KPI7, KPI12, KPI14 and KPI18. KPI17 is related with KPI4, KPI7, KPI11 and KPI13. KPI18 is related with KPI2, KPI4, KPI5, KPI11, KPI12, KPI14 and KPI16.



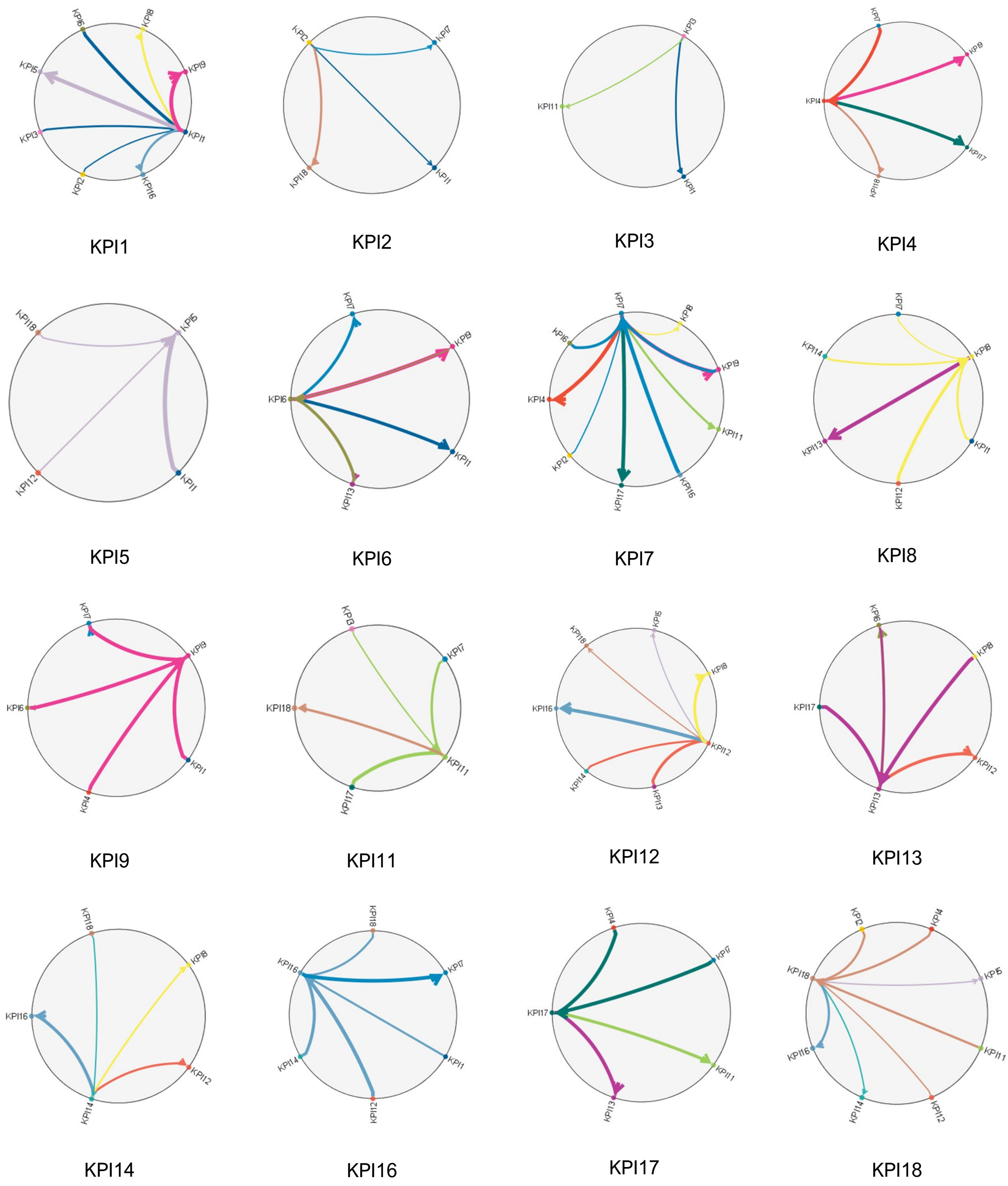


Figure 1. Causal models of key performance indicators (Source: Authors using IBM SPSS Statistics)

The next step, after creating the causal model, is to examine the relations between indicators and find impact relations between KPIs in the sample organization. Figure 2 shows impact diagrams of the detected causes and effects for each KPI.

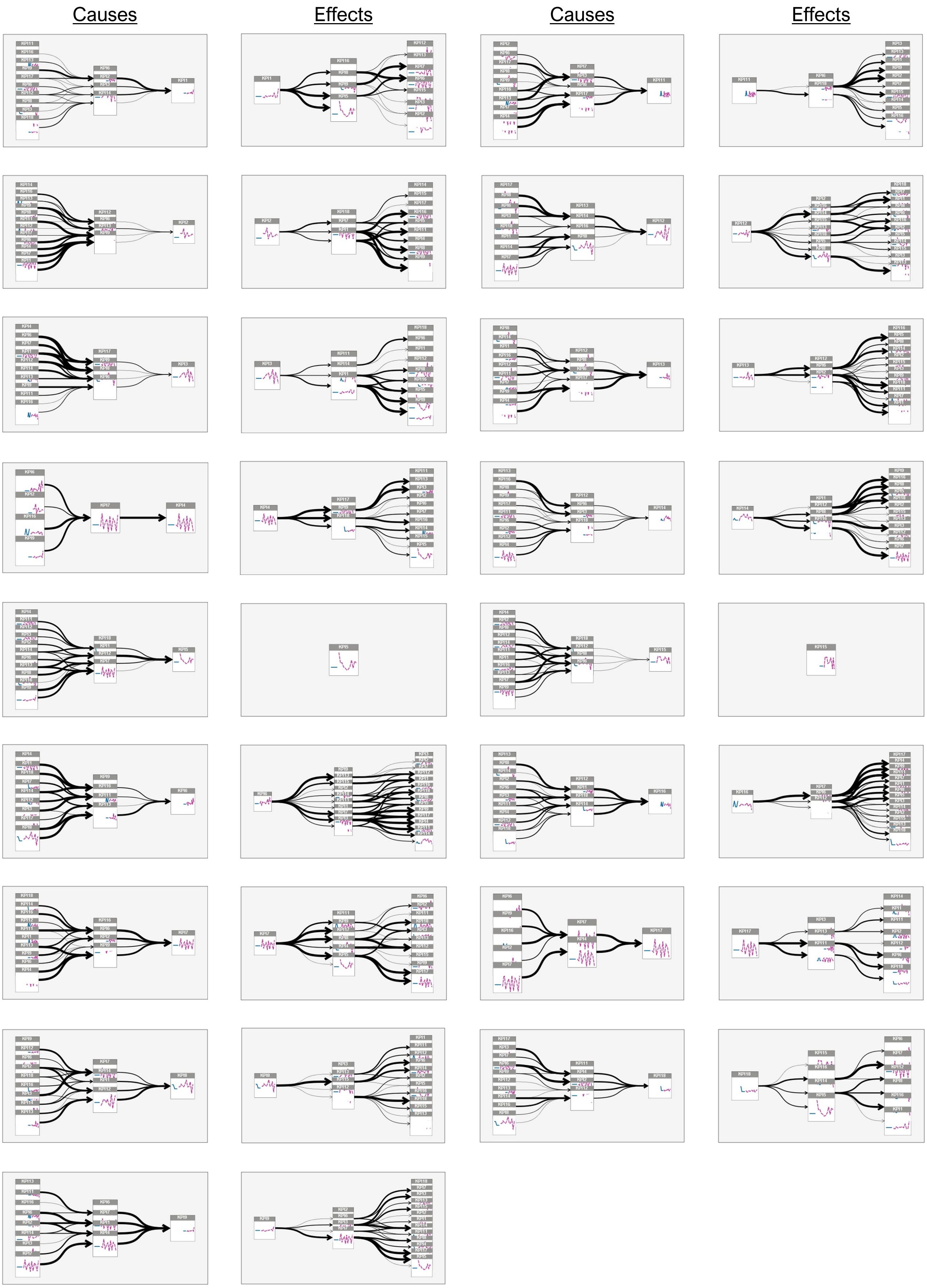


Figure 2. Impact diagrams of key performance indicators (Source: Authors using IBM SPSS Statistics).

4.2. Simulating Behavior Pattern of Organization's Key Performance Indicators

This chapter presents how the values of a specific KPI affect the behavior pattern of other KPIs using the causal model, i.e., how a specific KPI can influence other KPIs. Modifying the values of a specific KPI (lower of higher than original values), due to established causal relations, can simulate the behavior pattern of other KPIs.

Simulating the behavior pattern of KPIs includes the choice of a specific KPI and its modification to show how the values of the chosen KPI affect the other KPIs. A specific indicator in this case is KPI8. KPI8 was chosen arbitrarily, solely for the purpose of simulating behavior pattern of affected KPIs. The modification of KPI8 includes changing the values of KPI8, i.e., decreasing original values by 50%. Table 3 shows original values of the KPI8 and its decreased values by 50%, as well its diagram.

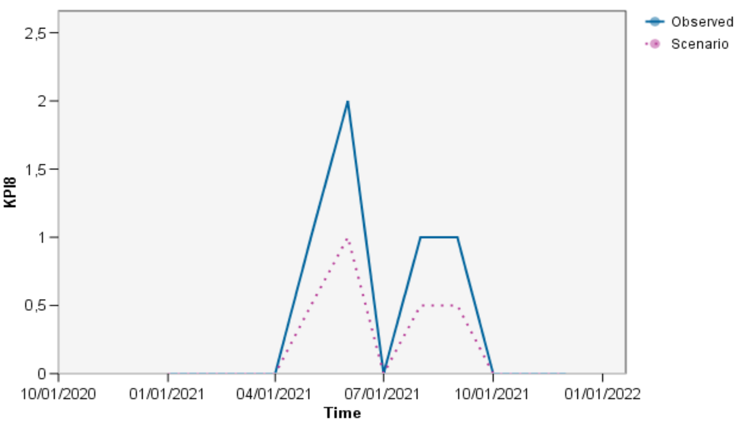
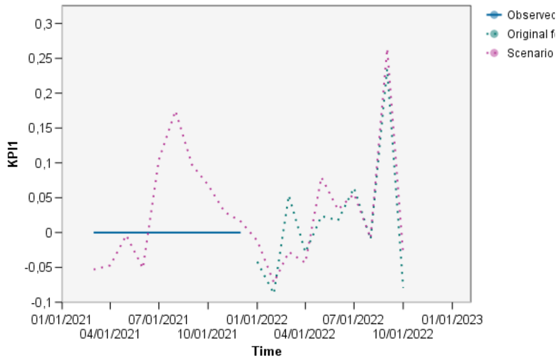
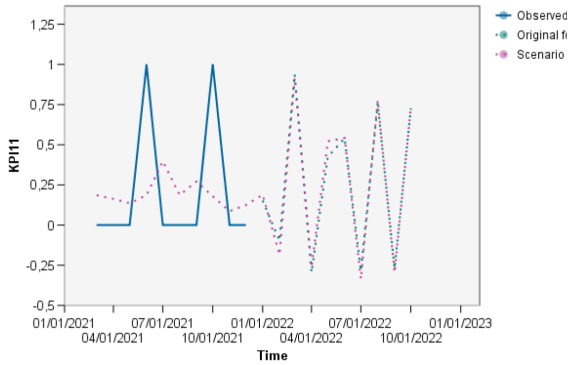
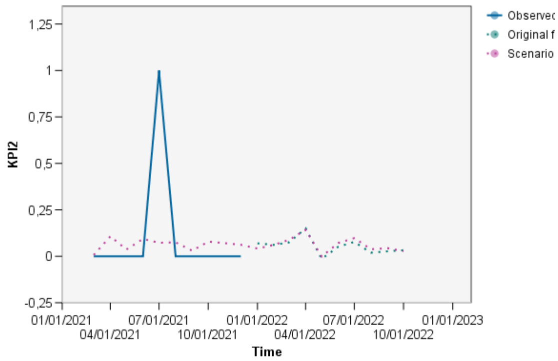
<table>
<tr><th>Time point</th><th>KPI8 original (observed)</th><th>KPI8 decreased for 50% (scenario)</th><th>Diagram</th></tr>
<tr><td>Jan 2021</td><td>0</td><td>0</td><td rowspan="12">
</td></tr>
<tr><td>Feb 2021</td><td>0</td><td>0</td></tr>
<tr><td>Mar 2021</td><td>0</td><td>0</td></tr>
<tr><td>Apr 2021</td><td>0</td><td>0</td></tr>
<tr><td>May 2021</td><td>1</td><td>0.5</td></tr>
<tr><td>Jun 2021</td><td>2</td><td>1</td></tr>
<tr><td>Jul 2021</td><td>0</td><td>0</td></tr>
<tr><td>Aug 2021</td><td>1</td><td>0.5</td></tr>
<tr><td>Sep 2021</td><td>1</td><td>0.5</td></tr>
<tr><td>Oct 2021</td><td>0</td><td>0</td></tr>
<tr><td>Nov 2021</td><td>0</td><td>0</td></tr>
<tr><td>Dec 2021</td><td>0</td><td>0</td></tr>
</table>

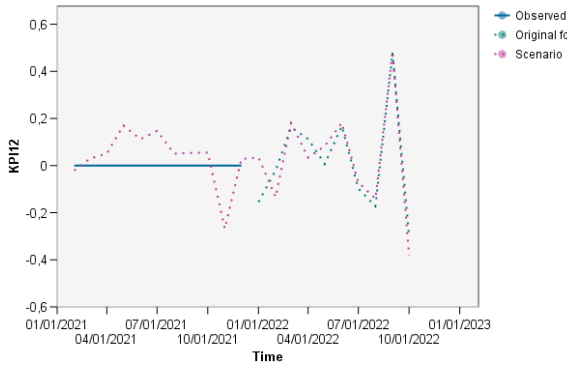
Table 3. Modifying specific key performance indicator
(Source: Authors using IBM SPSS Statistics)

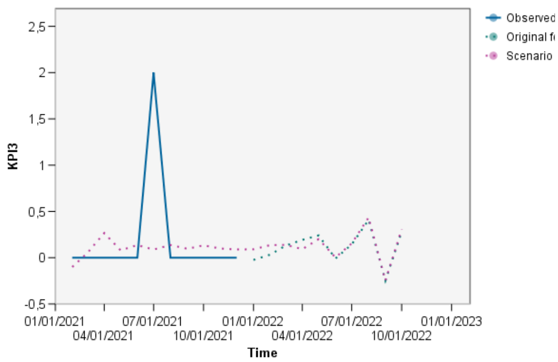
Figure 3 shows the simulated behavior pattern of the KPIs due to the influence of specific key performance indicators (KPI8). Each graph in Figure 3 presents the future behavior pattern of each KPI, due to modification made in the values of specific KPIs (KPI8). The blue line represents the original (observed) values of the KPI in the period from January 2021 to December 2021. The green line represents the initial (original) forecast calculated from the original (observed) values of KPI for the period from January 2022 to October 2022. The pink line represents the scenario case (simulation), where the modified values of KPI (due to the causal relation with the modified values in KPI8) are used to calculate the future values of each KPI. The comparison of the green and pink lines gives an insight in the future behavior pattern of each KPI, due to the causal impact of a specific KPI (KPI8).

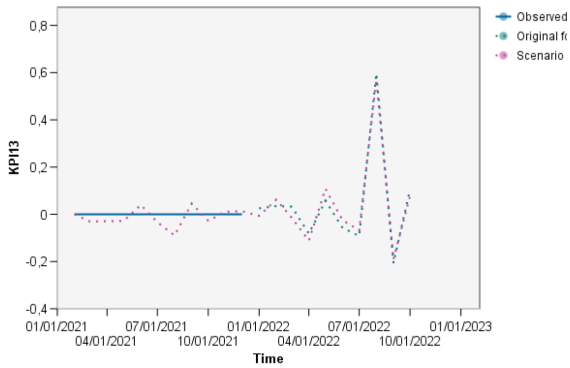

KPI1
Time
Observec
Original f
Scenario

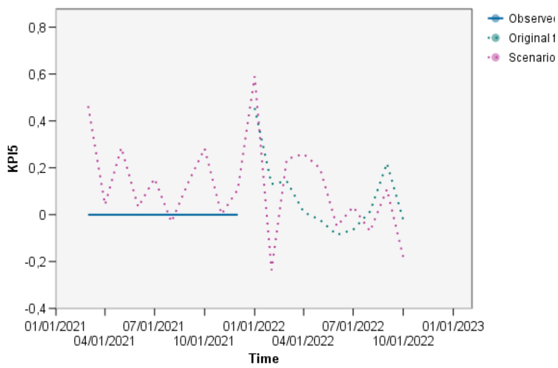

KPI11
Time
Observed
Original fc
Scenario

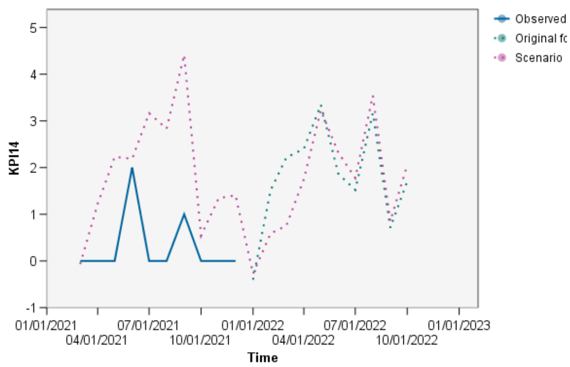

KPI2
Time
Observec
Original f
Scenario


KPI12
Time
Observed
Original fc
Scenario


KPI3
Time
Observec
Original fc
Scenario


KPI13
Time
Observed
Original fc
Scenario


KPI5
Time
Observec
Original f
Scenario


KPI14
Time
Observed
Original fc
Scenario

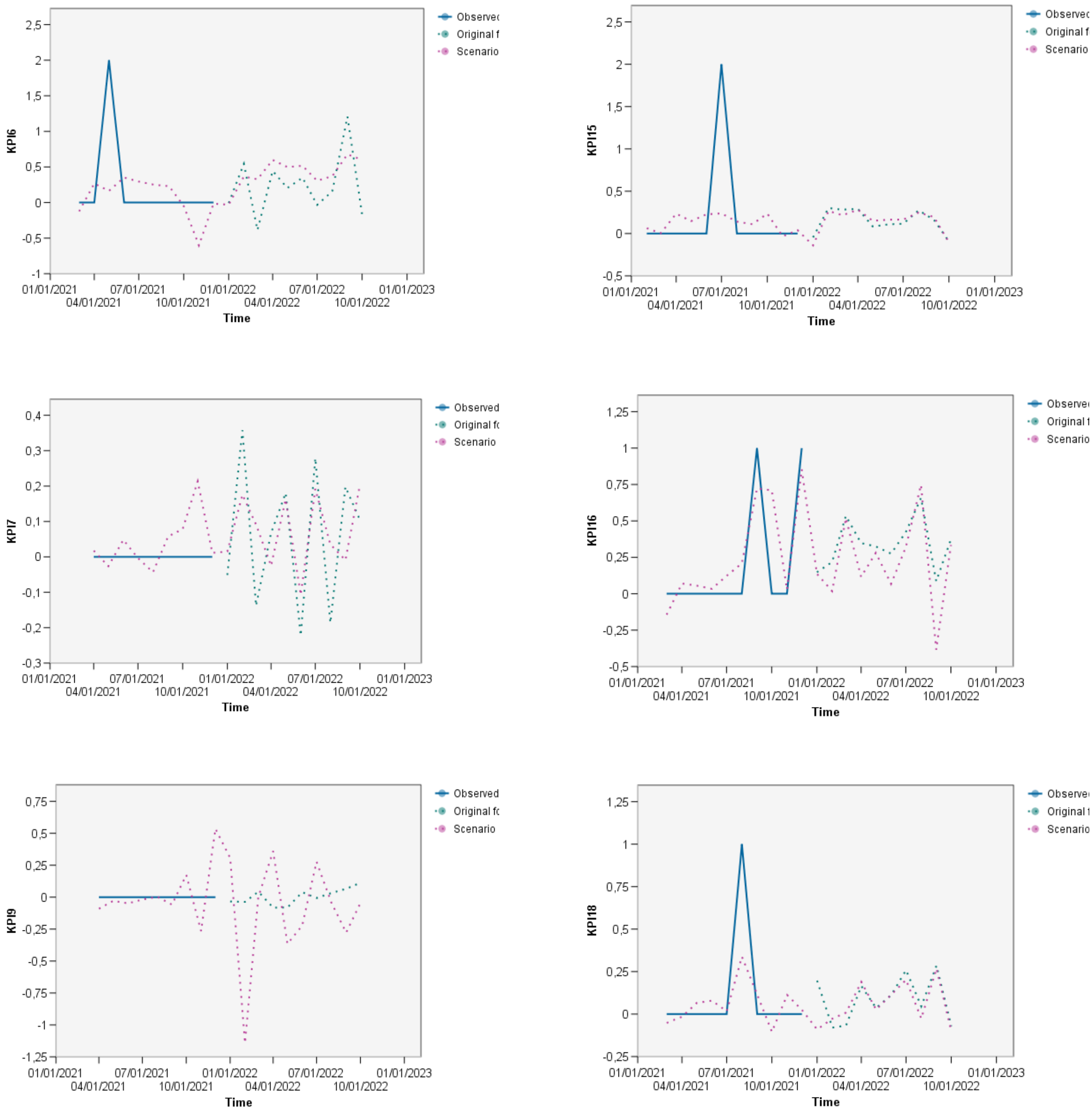


Figure 3. Simulated behavior pattern of key performance indicators

(Source: Authors using IBM SPSS Statistics).

Due to KPI8 modification, it can be observed that the behavior pattern of KPI1, KPI2, KPI3, KPI7, KPI9, KPI11, KPI12, KPI13, KPI14, KPI15 and KPI18 remains the same (no impact), the behavior pattern of KPI5 slightly increases (with no statistical significance), the behavior pattern of KPI6 decreases (statistically significant), and the behavior pattern of KPI16 slightly decreases (with no statistical significance). It can be concluded that decreasing KPI8 directly decreases, i.e., impacts the behavior pattern of KPI6; hence, KPI6 can be modified by KPI8.

5. CONCLUSION

This paper examined how the behavior pattern of the KPIs in the sample maritime transport organization can be simulated to improve the organization's safety performance. The research methods included gathering, describing, and analyzing key performance indicators' data of the sample organization, as well as statistics, causal modeling, and simulation.

A dataset of the actual safety performance data was used. As a part of its safety management, sample maritime transport organization has established a set of KPIs and set accompanying performance targets (goals). The KPIs are monitored on a monthly basis and are all outcome-based. The dataset is composed of 60 entries for the 18 KPIs in the observed period from January 2017 to December 2021.

IBM SPSS Statistics software was used, i.e., causal modeling techniques were used to detect the causal relations between all the indicators in the observed dataset. The software was also used to examine the relations between indicators and simulate their behavior patterns.

The simulation showed how the values of a certain KPI affect the behavior pattern of other KPIs using the causal model, i.e., how a specific KPI can influence other KPIs in an organization. The example showed how decreasing the KPI8 directly decreases, i.e., impacts the behavior pattern of the KPI6; hence, the KPI6 can be modified by the KPI8.

Analogously, it can be concluded that the behavior pattern of each KPI can be simulated and modified using causal modeling techniques, as presented in this paper.

Detecting the causal relations between KPIs indicates impacts (causes or effects) of the indicators on one another, which in turn gives a possibility to improve the planning of future actions, and thus improve the overall organization's safety performance in maritime transport.

CONFLICT OF INTEREST

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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