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Improving Safety and Security on Railways Using Forecasting

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Allocation of resources to improve security is crucial when we consider people's safety on transport systems. We show how a system engineering methodology can be used to link business intelligence and railway specifics toward better value for money. A model is proposed to determine a probability of a success in service management. The forecasting model is a basic Markov Chain. A use case demonstrates a way to align statistical data (crime on stations) and probability of investment into resources (people, security measures, time).

Keywords: Police; Security; Railway; Markov Chain.

1. Introduction

Railway systems that are safe and secure and that are perceived to be safe and secure by the commuter are essential to global societies and economies. Over 3,000 billion passenger-kilometers and 10,000 billion freight ton-kilometers are performed annually around the world, excluding metro systems. In the UK alone 1.69 billion passenger journeys were recorded between March 2015 and 2016 (Passenger rail usage statistical release 2015-16 Q4). The responsibility for safety and security on the British rail network falls to a number of stakeholders, including the Office of Rail and Road, individual train operating companies, Network Rail, the Rail Safety and Standards Board and the British Transport Police (BTP).

The BTP are a specialist force, that patrol Britain's railways and light rail systems. They are unlike any other police force in the UK as 95% of their funding comes from privatized train operating companies rather than the Home Office (Head Light, 2014). The BTPs current objectives by 2019

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are to reduce crime (20%), disruption to services (20%) and to increase passenger and rail staff confidence (10%), whilst providing value for money (BTP annual report 2014-15, 2015). The BTP currently deploys over 3000 officers and operates within an annual budget of £280 million. In Autumn 2015 the BTP conducted a Public Consultation to identify what matters to people travelling or working on the railway. Some of the key priorities identified were reducing antisocial behavior, greater visibility and police presence, countering terrorism, reducing violent and sexual crimes and reducing crime related disruption on the railways. These expectations are not specific to the BTP, transport police departments all over the world are challenged with expectations to deliver services at lower cost to tax payers with improved or minimum destruction of public provisions. BTP Annual Report 2012/13 stated: “We [...] reduced crime for the ninth year in a row and have done this in the context of a reduction in our budget in real terms of 14% since 2008. We think that represents exceptional value for money and we are determined to improve on this level of performance and service to rail passengers, rail stations and businesses. [...] Violent crime also rose in 2012/13, with an additional 201 crimes across the network following a slightly larger fall the previous year”. The question to be asked is “where is it most effective to allocate resources to improve security?” in light of fixed operational budgets.

There is an increasingly substantial body of research around predictive policing and fire-fighting to forecast crime and fire clustering in urban areas, location of emergency services for response time and developing resource allocation formulae. A range of mixed approaches have been used, including geographical information systems, geographical visualisation, intensity plots, Diggle’s function, cluster analysis, artificial neural networks (ANN), Chaotic Cellular Forecasting (CCF), Kernal smoothing, gamma test and chaos time theory (Ceyhan et al 2013, Corcoran et al 2003, Eckley and Curtin 2012, Gorr et al 2003, Brantingham 1993, Ackerman and Murray 2004, Brunsdon et al 2007, Murray 2013, McLafferty et al 2000). These approaches allow us to gain a deeper insight into where incidents are most likely to occur and can give us insight into how to allocate limited resources.

Information technology is seen as a resource to assist police efforts. The significant body of knowledge related to IT governance, business intelligence and project management provides some guidance to mediate the concurrent priorities through useful data insight. Police forces are already using predictive analytics to improve public safety, but must rethink traditional organisational structures and practices to maximise return on investment (Yu, 2014):

- The Los Angeles Police Department (LAPD) reported that property crime rates fell 12% within six months.
- According to police in Memphis, Tennessee, serious crime decreased by 30% between 2006 and 2010.
- In the UK, the Metropolitan Police discovered that analytics data makes it easier to prioritize and deploy limited resources.

There are a few more examples of success found in the referred literature:

- The effectiveness of predictive policing was recently tested by the LAPD, which found its effectivity to be twice that of its current practices.

- In Santa Cruz, California, the implementation of predictive policing over a 6-month period resulted in a 19 percent drop in the number of burglaries.
- In Kent, UK, 8.5 percent of all street crime occurred in locations predicted by PredPol, beating the 5 percent from police analysts.

Enterprise can be considered as a collection of organisations that have a common set of goals and/or a single bottom line (TOGAF, 2006). The architecture will provide a way to incorporate best practices in enterprise information systems management. The Rail Architecture Framework (TRAK) is a general enterprise architecture framework that sets the rules to develop systems architecture models across the airspace, defence and transport industries (Transport for NSW, 2014). The foundation of TRAK is aligned with ISO 42010 Systems & Software engineering – Architecture description requirements and the UK Ministry of Defence Architecture Framework (MODAF). The railway system is shown in context in Figure 1.

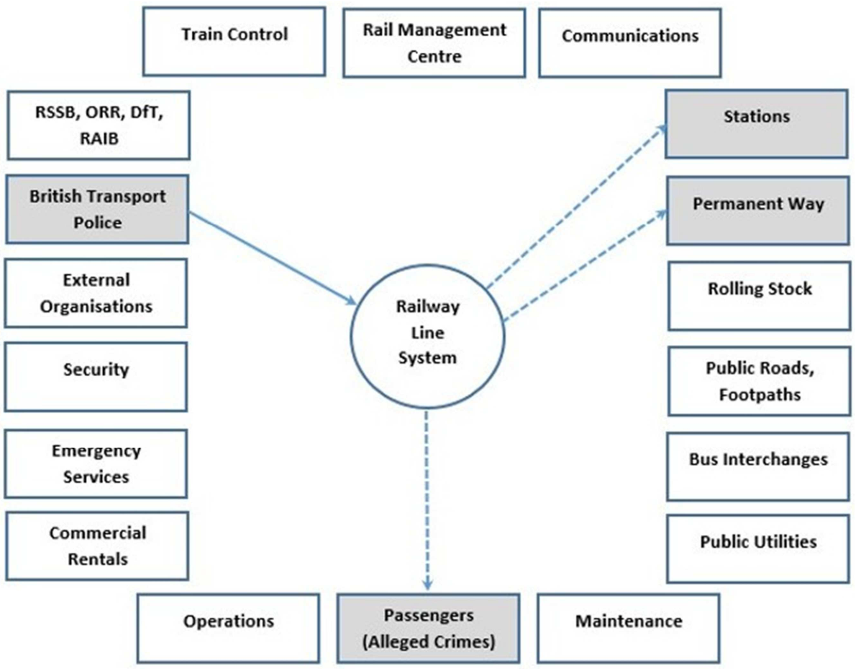

Fig. 1. System context diagram for the UK

Current literature on the modelling of security risks in railway systems is not yet mature. However, modelling techniques which are widely applied to manage risks could be effective for modelling security risks in railway systems. Such techniques include: Markov Chain and Fault Tree Handbook with Aerospace Applications (NASA, 2002), attacker - defender modelling as a game (Loukianov and Ejov, 2012), a multi-objective network security countermeasure selection (Viduto et al, 2012), Failure Mode and Effects Analysis FMEA (Goddard Space Flight Center, 1996), attack trees (Ingoldsby, 2013), attack graphs (Ou and Singhal, 2012), system anti-fragility (Vlek

2013, Bergmeister et al 2013), Supervisory Control and Data Acquisition SCADA (an overview by Cherdantseva et al, 2016).

The initiative “improving safety and security on railways using forecasting” can be abstracted by the notion of a “project”. Given a project's history and current state in terms of time, budget and value, we are going to apply a mathematical model to predict how successful a project will be finalized, according to these three parameters. The formal mathematical approach is Markov Chain which is widely used to determine system performance (Bravetti et al, 2006). The statistical analysis and stochastic modeling are exercised on data from the only found publicly available dataset by BTP (about 92000 records, 2011/12). The specific data is extracted (statistics on violent crime at Northern Rail and Mersey Rail in 2012). The case study is referred to a question of priority and better value for money when allocating resources (for example uniformed staff, CCTV or additional lighting) for improving security on “station vs. train” and reaction on passenger's trust to the future success of the mission.

The cautious approach is taken to introduce a method which was not found referred in the literature. The paper is structured as follows: in Section 1 an introduction to the problem is given that transport police departments face with regards to delivering safe environment to tax payers. Section 2 describes a problem with the need for quantitative solutions to measure service improvement followed by the case study where TRAK and MC are used to demonstrate the application to the problem BTP tries to solve on a daily basis. Then, a theoretical application of this approach to trains passing signals at danger (SPADs - Signal Passed at Danger) is given to evaluate efficacy. The fictional records are used for demonstration purpose. Section 3 will summarise the results and discuss new raised questions, followed by future research steps discussed in Section 4.

2. Methods

It is widely accepted that in order to develop a useful and valuable solution, which matches the point of view of the user and is efficient from the perspective of service provider, some quantitative measures should be defined. The context should be examined thoroughly to be able to provide a solution, including interactions between the user, service provider and third parties through time, budget, safety levels and adjust these as efficiently as possible with each other. Very often Project Managers (PM) are faced with the challenge of allocating given resources among concurrent tasks. Looking holistically for a best solution in this case would require taking into account organisational goals, capabilities, processes and its structure. Therefore, the solution should be driven not just by a project manager’s experience but also verified by some quantity.

A typical task for a transportation project manager (or a squad lead) is allocation of limited resources among concurrent tasks. For example, where uniforms should be allocated for better chance to respond to the valiant crime events? Option one is patrolling Merseyrail and Northern Rail stations. Option two is walking the route whilst trains are on the move. Another question is, what activity (a patrol on station or a patrol on train) is more promising in terms of improvement of the commuter's trust to police efforts? The intent of this example is to align statistical data (crime on stations) and probability of occurrence of undesired events into investment options of resources (security measures, time, people).

An analytical scenario by calculating the relevant performance indicators is complex. The evaluation is difficult for experts and not very helpful for non-experts and decision makers. An introduction to TRAK and finite discrete perturbed Markov Chain is a start.

The Markov property means that given the present state of the process, the future state is independent of the past. The concept of Markov dependency was published by the Russian mathematician Andrei Markov (1906). Only a few mathematical definitions to demonstrate the theoretical potential are provided.

The discrete time process $\{X_k, k = 0,1,2,\dots\}$ is called a Markov Chain if for all $i, j, \dots, m$ the following is true:

$$P[X_k = j | X_{k-1} = i, \dots X_0 = m] = P[X_k = j | X_{k-1} = i] = p_{ij}\,. \quad (1)$$

The quantity p_{ij} is called the *state transition probability* which is the conditional probability that the process will be in state j at time k immediately after the next transition, given that it is in state i at time $k-1$ (Ibe, 2009). The numbers p_{ij} can be arranged in a *transition probability matrix*

$$P = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1n} \\ p_{21} & p_{22} & \cdots & p_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ p_{n1} & p_{n2} & \cdots & p_{nn} \end{bmatrix}. \quad (2)$$

It is a *stochastic* matrix because for any row i, $\sum_j p_{ij} = 1$.

For certain types of MC, after a number of transitions the values of the transition matrix are approximately the same from transition to transition. If this is the case, the MC reached steady state. The values of the matrix are *stationary* probabilities.

A perturbed Markov chain is a dependency structure with the transition matrix

$$P(\varepsilon) = P(0) + \varepsilon C, \quad (3)$$

where $P(0) \in R^{n \times n}$ is the transition matrix of the unperturbed chain, ε is a small perturbation parameter and C represents the likely direction of the data deviation. The analytic perturbations theory and perturbed MC are discussed in detail by Avrachenkov (1999). A generic workflow of how to apply stochastic analysis in the modeling follows:

1. Define the set of system components to be transformed by a change.
2. Define what is the desired change and the transition
3. Define the meaning of a transition.
4. Define the states.

5. Define the states properties.
6. Calculate the transition probabilities.
7. Draw a transition matrix.
8. Calculate the stationary probabilities.
9. Interpret the difference between stationary and original values.
10. Specify the data deviation direction.
11. Specify the value of perturbation.
12. Calculate a transition matrix for perturbed MC.
13. Calculate the stationary probabilities.
14. Interpret the difference between stationary and original values.

2.1. A case study to support a decision on resource allocation

A scenario is that a manager is required to allocate resources aiming to reduce a number of crimes in the future. The statistic of violent crime on train platforms and on trains is known. The scenario includes open source crime data on UK railway stations and on trains. The resources include police staff to act on platforms and on trains, constrained by time and budget.

The TRAK approach was used to develop the system context diagram for a railway link (Transport for NSW, 2015). Figure 1 illustrates the linkage of the interacting systems.

A state transition model for the projects is defined with three dimensions (schedule, budget, value) and three status summaries (on, behind, ahead of) for each dimension. Hence in MC terms there are twenty-seven states, for example “on schedule, on budget, on value” and “ahead of schedule, ahead of budget, behind value” and all other combinations permissible in the set. It is assumed that an initial state and a final expected state for any project are “on schedule, on budget, on value”. The states are bound to the first day and the last day of the project.

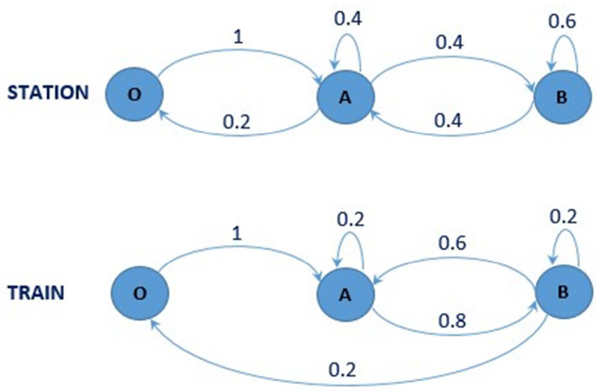

Fig. 2. Markov Chains on violent crime performance at Northern Rail, in which B, A and O stand for Behind / Ahead / On respectively.

The general statistics is 200 events of violent crime on Northern Rail stations in 2012 (the data set was extracted from BTP Crimes Recorded 2013):

- The monthly number of violent crimes is 14, 15, 11, 21, 15, 19, 23, 20, 23, 8, 17, 14 from January to December.
- 17 events per month is average.
- It means the currently invested resources has resulted in 17 crimes per month on average
- The logic of transition is tracking monthly change against average amount. For example, January is 14 which is less than the 17 average, so is interpreted as “ahead of value”.
- The data extract is in Table 1.

Table 1. Northern Rail and Mersey Rail franchises violent crime statistics for 2012

	Northern Rail		**Mersey Rail**	
	STATION	TRAIN	STATION	TRAIN
Monthly Average	**17**	**12**	**8**	**3**
January	14	7	5	6
February	15	15	7	2
March	11	5	11	4
April	21	16	6	1
May	15	12	13	5
June	19	11	6	6
July	23	9	10	4
August	20	19	13	3
September	23	11	5	2
October	8	14	6	3
November	17	15	11	2
December	14	8	5	2
Annual	**200**	**142**	**98**	**40**

Suppose, there is historical data for a team collected over 12-month assignment. The MC states are state 1 (B) “behind value”, state 2 (O) “on value”, and state 3 (A) “ahead of value” (see Figure 2). The team performance is statistically described.

For example, a transition matrix is constructed for the Station events in Northern Rail. There are 14 events in January which is less than 17 average that means state A “ahead of value”. There are 15 events in February which is less than 17 average that means state A “ahead of value”. The sequence is constructed as such AAABABBBAOA. The transitions are AA, AA, AB, BA, AB, BB, BB, BB, BA, AO, OA. There are the occasions BA (2), AB (2), BB (3), AA (2), AO (1), OA (1). For the state “behind value” is BB = 3/ (BA + BB) =3/5 and BA = 2/ (BA + BB) = 2/5 (see Table 2).

Table 2. The transition matrix for the Station events in Northern Rail.

State	B	O	A
B	0.6	0	0.4
O	0	0	1
A	0.4	0.2	0.4

For a station in Northern Rail: if the team is at state B "behind value" they used to deliver 60 percent "behind", never "on", and 40 percent "ahead" in the next time period. When the team is at state O "on" (performing on average statistical rate of violent crime) they used to deliver 100 percent "ahead". When the team is at state A "ahead value" they used to deliver 40 percent "behind", 20 percent "on", and 40 percent "ahead".

Suppose, a question is how the team will perform in a project with a 4 years' duration assuming the routine does not change. In MC terms the given team will pass 4 transitions

$$P^4 = P \times P \times P \times P = \begin{bmatrix} 0.46 & 0.09 & 0.45 \\ 0.45 & 0.10 & 0.45 \\ 0.45 & 0.09 & 0.46 \end{bmatrix}. \tag{4}$$

An answer is that the team will be better in go "ahead" (0.4 vs. 0.45) and in getting out of "behind" (0.0 vs. 0.09). Then we solve $xP = x$ and find a steady state probability distribution for a given transition matrix P which is $x = [0.45\ 0.10\ 0.45]$ for the states B, O and A respectively. The PM could expect the team to deliver on earned value a bit better in general.

Now a perturbed mathematical model is considered. Markov Chain is taken from previous section and matrix C is constructed to represent the likely direction of data deviation.

Suppose, the PM has an optimistic attitude and believes that the team can perform at 10 percent (0.1) better than usual in the discussed 4 years' period. PM's belief means that the probability to stay in state "behind" and the probability to go from state "ahead" to state "behind" will have negative dynamic. The matrix *C* will have '-1' in first row first column and '-1' in third row first column. PM also believes that the probability to go from state "behind" to state "on" and probability to go from state "ahead" to state "ahead of" will have positive dynamic. The matrix *C* will have '1' in first row second column and '1' in third row third column.

$$C = \begin{bmatrix} -1 & 1 & 0 \\ 0 & 0 & 0 \\ -1 & 0 & 1 \end{bmatrix}. \tag{5}$$

The transition matrix for the perturbed MC will look

$$P(\varepsilon) = \begin{bmatrix} 0.6 & 0.0 & 0.4 \\ 0.0 & 0.0 & 1.0 \\ 0.4 & 0.2 & 0.4 \end{bmatrix} + 0.1 \begin{bmatrix} -1 & 1 & 0 \\ 0 & 0 & 0 \\ -1 & 0 & 1 \end{bmatrix} = \begin{bmatrix} 0.5 & 0.1 & 0.4 \\ 0.0 & 0.0 & 1.0 \\ 0.3 & 0.2 & 0.5 \end{bmatrix}. \tag{6}$$

Now we do the same operation of 4 multiplications with perturbed matrix to pass 4 transitions in 4 years to have

$$P^4 = P \times P \times P \times P = \begin{bmatrix} 0.32 & 0.14 & 0.54 \\ 0.32 & 0.14 & 0.54 \\ 0.32 & 0.14 & 0.54 \end{bmatrix}. \tag{7}$$

The PM can conclude that the team will perform almost 2 times better at value “behind” (0.6 vs 0.32) if an inspirational boost takes place to do things a little bit better when the project is at “behind” value.

Table 3. Response dynamic to reduce violent crime statistics at Northern Rail

Markov Chain		STATION			TRAIN		
		behind	on	ahead	behind	on	ahead
Original	behind	**0.6**	0	0.4	**0.2**	0.2	0.6
	on	0	0	1	0	0	1
	ahead	0.4	0.2	0.4	0.8	0	0.2
Perturbed	behind	**0.32**	0.14	0.54	**0.44**	0.09	0.47
	on	0.32	0.14	0.54	0.48	0.6	0.46
	ahead	0.32	0.14	0.54	0.46	0.1	0.44

The calculus is completed for the data extract on “train” and “station” (violent crime, Northern Rail, 2012). The response dynamic is completely different. On “station” the probability to stay in poor performance at the state “behind” is decreasing (0.6 vs. 0.32). On “train” the probability to stick with disappointing “behind” is increasing (0.2 vs. 0.44). Given the question “where an extra resource could be applied to improve the violent crime statistic on Northern Rail route?” a confident answer is on “station” (see Table 3).

A specification of a resource is out of scope of the paper. There are people, technical security measure (gates, camera’s) or procedural measures (inspections). The next effort is to model Markov chains addressing these challenges.

The same calculus is applied for the data extract on Mersey Rail “train” (violent crime, 2012). On “train” the probability to stick with “behind” is almost the same (0.4 vs. 0.37). The biggest increase is in the fare optimism to keep high performance at the state “ahead” (see Table 4).

Table 4. Response dynamic to reduce violent crime statistics at Mersey Rail and Northern Rail trains

Markov Chain		**Mersey Rail**	TRAIN		**Northern Rail**	TRAIN	
		behind	on	ahead	Behind	on	ahead
Original	behind	**0.4**	0.2	0.4	**0.2**	0.2	0.6
	on	0	0	1	0	0	1
	ahead	0.5	0.25	**0.25**	0.8	0	0.2
Perturbed	behind	**0.37**	0.18	0.45	**0.44**	0.09	0.47
	on	0.37	0.18	0.45	0.48	0.6	0.46
	ahead	0.37	0.18	**0.45**	0.46	0.1	0.44

2.2. A case study to support a decision on efficacy evaluation

The same computational approach is carried on investigating a case where basic statistical analysis is not able to support a decision-making process. The dataset and tasks were used for an examination and selection process for an academic position in UK.

Suppose, a hypothetical SPAD Management Program (MP) was introduced in January or February 2012. The business intelligence task is to evaluate efficiency of the program and speculate about impact of an intervention. Table 5 shows the number of SPADs (fictional data) recorded by a railway for one year prior to, and one year after, the introduction of a SPAD management program.

Table 5. The amount of SPADs (fictional data)

Month	Number of SPADs
Feb-11	2
Mar-11	0
Apr-11	1
May-11	4
Jun-11	2
Jul-11	0
Aug-11	0
Sep-11	6
Oct-11	1
Nov-11	2
Dec-11	3
Jan-12	1
Feb-12	2
Mar-12	2
Apr-12	1
May-12	2
Jun-12	1
Jul-12	1
Aug-12	1
Sep-12	1
Oct-12	2
Nov-12	2
Dec-12	1
Jan-13	2
Feb-13	1

A discrete finite perturbed Markov Chain is suggested for further investigation. The probabilities are quantified based on frequency of the events. MP performance is defined as less amount of SPADs per calendar month.

The first block is before the program introduction (Feb 2011 to Jan 2012 called "before"):

- The states are “zero” (“zero” SPAD in a month), “one”, “two”, “three”, “four”, “six” (“six” SPADs in a month)
- The transitions are 2-0, 0-1, 1-4, 4-2, 2-0, 0-0, 0-6, 6-1, 1-2, 2-3, and 3-1.
- The number of transitions by type “zero” (3), “one” (2), “two” (2), “three” (1), “four” (1), “six” (1).

There are N states, going from 0, 1, … N-1 and conduct the numerical analysis in the future work. In principal, we could jump from state I to J (I, J = 0, …, N-1).

The second block is after the program introduction in 2012 (Feb 2012 to Jan 2013 called "after"):

- The states are 1 (“one” SPAD in a month), 2 (“two” SPADs in a month).
- The transitions are 22, 21, 12, 21, 11, 11, 11, 12, 22, 21, and 12.
- The amount of transitions per type “one” (6), “two” (5).

The basic statistical analysis appears inconclusive (see Table 6), but perturbation analysis with MC shows results.

Table 6. SPAD management program statistical analysis

SPAD MP	amount	mean	median	mode	Range	var	std
before	22	1.8	0	? (0,1,2)	6	3.24	1.8
after	18	1.5	1	? (0,1,2)	1	0.27	0.5

For example, there is a question: “Can the data support the claim that the SPAD management program has been effective and explain why?" Our answer is “Yes, it can. The data support the claim the MP has been effective.” Someone could argue that if it is statistically significant given the only 2 years of data investigated. Future research will try to answer the question (subject of data availability).

Let’s have a look at the dynamic of change in the amount of events per month before and after the program was introduced.

The first case is to consider that there *is no* program in 2011. The transition matrix is following

$$P = \begin{bmatrix} 0.33 & 0.33 & 0.00 & 0.00 & 0.00 & 0.34 \\ 0.00 & 0.00 & 0.50 & 0.00 & 0.50 & 0.00 \\ 0.66 & 0.00 & 0.00 & 0.34 & 0.00 & 0.00 \\ 0.00 & 1.00 & 0.00 & 0.00 & 0.00 & 0.00 \\ 0.00 & 0.00 & 1.00 & 0.00 & 0.00 & 0.00 \\ 0.00 & 1.00 & 0.00 & 0.00 & 0.00 & 0.00 \end{bmatrix}. \tag{8}$$

Suppose, a question is how the rail road will perform with 48-month duration. In MC terms, the rail road will pass 4 transitions:

$$P^4 = P \times P \times P \times P = \begin{bmatrix} 0.31 & 0.14 & 0.30 & 0.13 & 0.07 & 0.05 \\ 0.15 & 0.43 & 0.14 & 0.00 & 0.14 & 0.15 \\ 0.21 & 0.10 & 0.43 & 0.10 & 0.15 & 0.02 \\ 0.44 & 0.28 & 0.00 & 0.17 & 0.00 & 0.11 \\ 0.07 & 0.30 & 0.28 & 0.00 & 0.28 & 0.07 \\ 0.44 & 0.28 & 0.00 & 0.17 & 0.00 & 0.11 \end{bmatrix}. \quad (9)$$

An answer is that the risk of multiple SPAD events will increase dramatically.

The second case is to consider that there ***is*** a program in 2012**.**

$$P = \begin{bmatrix} 0.5 & 0.5 \\ 0.6 & 0.4 \end{bmatrix}. \quad (10)$$

$$P^4 = P \times P \times P \times P = \begin{bmatrix} 0.55 & 0.45 \\ 0.55 & 0.45 \end{bmatrix}. \quad (11)$$

There is no predicted risk for multiple events at all. The performance will slightly improve in the long run (0.6 for "two"- "one" decrease at the initial stage vs. 0.55 in the long run).

Another example question is that "How to estimate an impact of an intervention which might have been included in the MP?" An answer is that "The MP could provide a framework for enhancements. An engineering invention itself can hardly improve the overall picture."

Now a perturbed model is considered. Suppose, the imaginable CEO introduced a technology to improve visibility in wet conditions. He believes that the road can perform at 10 percent ($\varepsilon = 0.1$) better than usual in one year. There *is* SPAD MP in place.

CEO's belief means that the probability to go from state "one" (one SPAD per month) to state "two" (two SPADs per month) and probability to stay in state "two" will have negative dynamic. The matrix *C* will have '-1' in first row second column and '-1' in second row second column. The CEO also believes that the probability to stay in state one and the probability to go from state two to state one will have positive dynamic. The matrix *C* will have '1' in first row first column and '1' in second row first column.

$$C = \begin{bmatrix} 1 & -1 \\ 1 & -1 \end{bmatrix}. \quad (12)$$

The transition matrix for the perturbed MC will look

$$P(\varepsilon) = \begin{bmatrix} 0.5 & 0.5 \\ 0.6 & 0.4 \end{bmatrix} + 0.1 \begin{bmatrix} 1 & -1 \\ 1 & -1 \end{bmatrix} = \begin{bmatrix} 0.6 & 0.4 \\ 0.7 & 0.3 \end{bmatrix}. \quad (13)$$

The same operation is 4 multiplications with perturbed matrix to pass 4 transitions in 4 years to have

$$P^4 = P \times P \times P \times P = \begin{bmatrix} 0.64 & 0.36 \\ 0.64 & 0.36 \end{bmatrix}. \quad (14)$$

The CEO can conclude that the rail road will perform better.

Suppose the CEO made the change when there ***is no*** SPAD MP in place.

$$C = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & -1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}, \quad (15)$$

$$P(\varepsilon) = P(0) + 0.1 \times C = \begin{bmatrix} 0.33 & 0.33 & 0.00 & 0.00 & 0.00 & 0.34 \\ 0.00 & 0.00 & 0.50 & 0.00 & 0.50 & 0.00 \\ 0.76 & 0.00 & 0.00 & 0.24 & 0.00 & 0.00 \\ 0.00 & 1.00 & 0.00 & 0.00 & 0.00 & 0.00 \\ 0.00 & 0.00 & 1.00 & 0.00 & 0.00 & 0.00 \\ 0.00 & 1.00 & 0.00 & 0.00 & 0.00 & 0.00 \end{bmatrix}, \quad (16)$$

$$P^4 = \begin{bmatrix} 0.35 & 0.13 & 0.30 & 0.09 & 0.07 & 0.05 \\ 0.17 & 0.42 & 0.12 & 0.00 & 0.12 & 0.17 \\ 0.21 & 0.11 & 0.42 & 0.06 & 0.17 & 0.03 \\ 0.51 & 0.25 & 0.00 & 0.12 & 0.00 & 0.13 \\ 0.08 & 0.34 & 0.25 & 0.00 & 0.25 & 0.09 \\ 0.51 & 0.25 & 0.00 & 0.12 & 0.00 & 0.13 \end{bmatrix}. \quad (17)$$

The risk of multiple SPADs stands and an intervention was not successful.

2.3. Technological implementation

There are two software engineering technologies used to analyse the data. The Konstanz Information Mining (KNIME, 2015) platform is to build a basic analytical workflow (see Figure 3):

- read data from the file
- make standard statistical analysis
- visualise the data

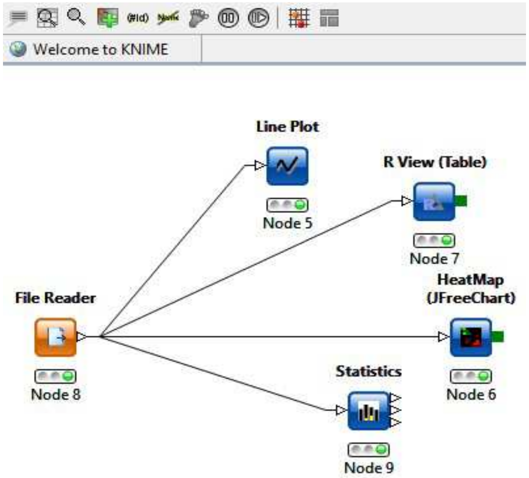

Fig. 3. Information mining and statistical analysis by KNIME

The second technology is R language (The R Foundation for Statistical Computing, 2015) and “markovchain” package (see Table 7) for a few basic steps of the analysis (e.g. construct a Markov Chain, compute the transitions and draw a Markov Chain).

Table 7. R implementation by markovchain package

```
R version 3.1.1 (2014-07-10) -- "Sock it to Me"
Copyright (C) 2014 The R Foundation for Statistical Computing
Platform: x86_64-w64-mingw32/x64 (64-bit)
> library(markovchain)
Package:  markovchain
Version:  0.4.2
Date:     2015-08-30
BugReport: http://github.com/spedygiorgio/markovchain/issues
Warning message:
package ‘markovchain’ was built under R version 3.1.3
> projectStatesNR <- c("behind", "on", "ahead")
> byRow <- TRUE
> projectMatrixNR <- matrix(data = c(0.60, 0, 0.4,
+  0, 0, 1.0,
+  0.4, 0.2, 0.4), byrow = byRow, nrow = 3,
+ dimnames = list(projectStatesNR, projectStatesNR))
> mcProjectNR <- new("markovchain", states = projectStatesNR,
+ byrow = byRow, transitionMatrix = projectMatrixNR, name = "ProjectNR")
> show(mcProjectNR)
ProjectNR
 A  3 - dimensional discrete Markov Chain with following states
 behind on ahead
 The transition matrix   (by rows)  is defined as follows
      behind  on ahead
behind    0.6 0.0   0.4
on        0.0 0.0   1.0
ahead     0.4 0.2   0.4
```

3. Discussion

Applicability of Markov processes in safety and reliability is a long-standing discussion (Birolini, 1985). There is an international standard on application of Markov techniques (IEC 61165, 2006:2009). A view is that the transition probabilities should be calculated by statistical methods only. In our opinion, any approach of predictive modeling includes a certain level of risk of being inefficient. The suggestion is to calculate the transition probabilities by observation and assume them as constant at the time of the observation. In many situations, it is also possible to use a combination of Markov analysis and fault trees (Fuqua, 2016).

The main question the model tries to answer is “What is the probability to finish a project on time, on budget whilst meeting the quality requirements?” It is a sensible question to ask a plumber or a house renovator before someone signs off for a property maintenance adventure. This is the crucial question to ask a consulting company bidding for a substantial project given the well-known statistics on unmatched expectations in IT industrial implementations. The discussed approach provides at least an educated guess in the form of statement “a degree of belief that the renovation will be finished in agreed time is *0.N*”. In that case, it is reasonable to negotiate *N* percent of total as “on-going payment” and rest of the sum paid when the “job is done”. The numerical analysis is also intended to contribute in a business case development and negotiations of terms and conditions of a service level agreement.

Another question arising from the approach introduced in this paper is “How can someone predict the termination state (schedule, budget, value) in case a project risk materialises?” Therefore, the discussion about perturbed MC is to be continued.

The safety can be viewed from the chosen industrial perspectives as a product that needs to be delivered at the highest level. When trust level in a safety product decreases, the reputation of safety providers is reduced and can have significant costly effects on business continuity. Therefore, integrated cross-modal safety management systems and models are required to allow adjustment of costing for the evaluation of the potential security and safety solutions. The proposed approach is capable to provide a project manager with the decision that predicts investment strategy in terms of resource utilisation on stations or on trains. Further work expands towards identifying main contributors and trust levels which commuters gain in police efforts.

Another case is to analyse where a violent crime occurs on a train or platform with the presence of police resources in those places. In addition to the police resources, it is interesting to consider security measures in place and their effectiveness towards reducing the probability of a crime occurring, on train and on platform.

4 Conclusion

The proposed model is based on historical data. It helps to better manage resources. In this paper, the resources are not specified (e.g. people, security measures, time). The future work is to discuss:

- specification of resources

- statistical significance
- hypothetical linkage to events or conditions
- measure of effectiveness
- further numerical analysis ($0, \ldots N-1$ states, jumps from I to J)
- software implementation of the analysis

A member of the British Police has reviewed the paper. It has been recommended consultation with BTP to obtain their views and feedback on the data itself, the benefits under consideration, the future work on analysing a case and potentially any opportunity to work with them and run this as a pilot.

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