beta	0.3	0.4	0.5	0.6	0.7	0.8
inf	0.14	0.16	0.18	0.2		
far	0.1	0.12	0.14	0.16	0.18	0.2
gamma	0.3	0.4	0.5			

Table I. Parameter space

APPENDIX

Fitting

Penalty function:

-Penalty for wrong time of infections Sum (simulated arrival – real arrival time)

-Penalty of omitting really affected poviats If poviat not infected +200

- Additional penalty for too long big or too short infection chains (Number of poviat affected – number of simulated infections)*200

We run over 50000 of simulations. As the function is highly nonlinear, we were not found single minimum od penalty function.

The most variability is explained by forest/pig influence, then infectivity coefficient, and a little by far distance infection. Gamma (human factor) does not explain variance, because it's over reporting transmission to big cities, which appeared only once in observed outbreak.

First we select range of interest in paramere space base on performence of Preliminary Landscape Model. Then suspicient parameters space has been discertized by presented values in 4 dimenstions. For each comination of presented parameters between 80 to 200i realizations were performed

The optimalization goal was to find "stable" minimas of penalty. Stable means:

- mean (median, avarege) penalty deas not differ significantly by small perturbation around selected point;

- variance of penalty within single combination of parameters is controlled;

The condictions were post because 1) penalty funtion can vary a lot for single parameters combination (with charactersictic bimodal districbutions), 2) global minimas can be surrounded by high penalty values

beta	inf	far	gamma
0.6	0.2	0.18	0.3
0.3	0.18	0.14	0.6

Table II. Stabile local minimas

par	Wald st	p-Value
beta	1023	<0.01
inf	705	<0.01
far	34	<0.01
gamma	1	0.77

Table III. Variance explanation penalty - ANOVA Test of all effects

We found 2 stabile local minimas:

An few more local non stabile minimas also mostly around beta 0.3

Nonmonotonic behavior in beta could explain, that more than one optimalization minumum can be found for this variable

With gamma parameter there also strong nonlinearity. Lower gamma, median fit is better, standard errors is growing. The reason is transmission of ASF to big metropolis, which in data occurred only once (to Warsaw)

Including elimination/recovery

We run more simulation for recovery coefficient and even for very small rates (infecious period longer than 100 years) there is no minimum of penalty function, so recovery for

par	effect	p-Value
beta	0.346	<0.01
inf	-2.07	<0.01
far	0.254	<0.01
gamma	-0.017	0.26

Table IV. Direction of gradient of penalty- Parameter estimates Regression

par	effect	p-Value
beta	-0.126	0.07
beta ^2	0.421	<0.01
inf	-2.08	<0.01
far	0.254	<0.01
gamma	-0.020	0.14

Table V. Tab. Strong nonlinearity in beta

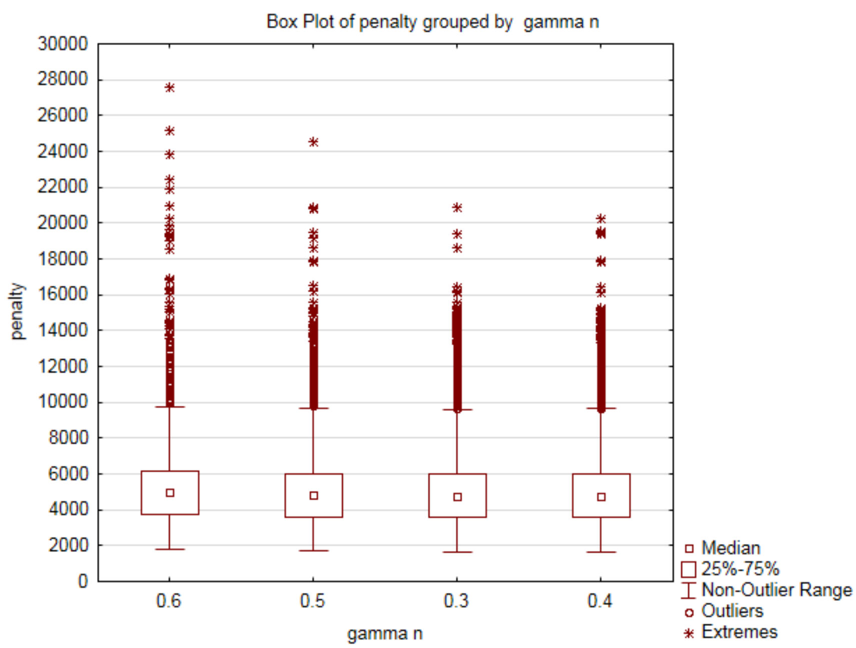

Figure 1. Box plots of penalty for various gamma..

sure will not increase the fit. One of the possible explanation of this paradox is very long stagnation stage of propagation at the beginning of the outbreak, where only on county was affected. Recovery of this county at that time would stop outbeak and big penalty would be given to this scenarios. However this is one of the goal for mitigation strategies and this is what we want to incorporate, but not to decease fit, recovery time scale must be bigger than timscale of the whole propagation.

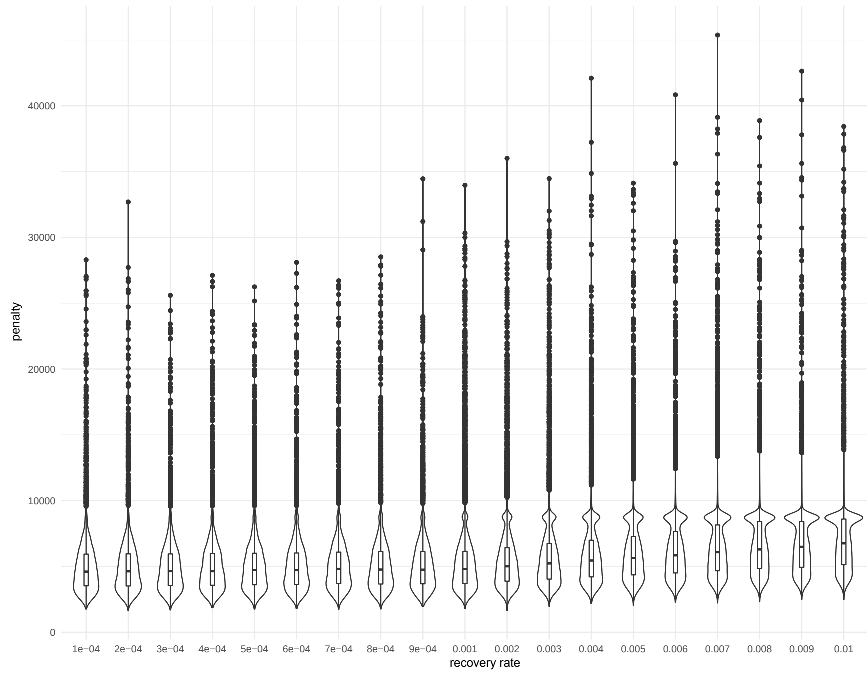

Figure 2. Box plots of penalty for various recovery rate (per week).

PROPAGATION

We run prospective simulations for next 4 years. Mean introduction time T_i for each county i has been normilized, to hadicup poviats which become infected at all many times (and punish these which were infected non to often):

$T_i =< T_i^n >_{n \subset (1,.,N_i)} \cdot \sqrt{(N_i / < N_i^k >)_{k \subset (1,.,380)}}$

where $N_i$is number of simulation where county i has been infected