Forecasting of Convective Precipitation Through NWP Models and Algorithm of Storms Prediction

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Abstract. This article focuses on contemporary possibilities of forecasting of convective storms which may cause flash floods. The first chapters are presented predictive tools such as numerical weather prediction models (NWP models) and the algorithm of convective storms prediction, which includes a storm prediction based on the principles of mathematical statistics, probability theory and artificial intelligence methods. Discussion section provides outputs from the success rate of these forecasting tools on the historical weather situation for the year 2016. The Algorithm's output may be useful for early warning of population and notification of crisis management authorities before a potential threat of flash floods in the Zlin Region.

Keywords: Weather forecast · Convective precipitation · Flash floods · Crisis management · Early warning · Artificial intelligence

1 Introduction

Incidence of storm situation that caused the flash floods, have been steadily increasing every year. In the past, floods were induced by extensive and persistent rain, especially in the years 1997, 2002 and 2006 [1]. Flash floods as a phenomenon of our time have begun to regularly occur since 2007. Although this type of flood did not cause excessive damage (in the order of several billion Czech crowns) as the first type of flood (hundreds of billions of Czech crowns), just the high frequency of occurrence has been the main impulse to the improvement of early warning of population and preventive measures against the flash floods [2].

Flash floods are caused by meteorological and hydrological factors, particularly high intensity rainfall, slow and the stationary motion of precipitation and high soil saturation [3, 4]. Meteorological factors are predicted by NWP models [5–7], nowcasting and expert meteorological systems [8–10]. Except these forecasting systems, prediction of flash flood and heavy rainfall has been also investigated by methods of artificial intelligence in the neural networks [11, 12], especially Backpropagation algorithm [13]. Hydrological factor of soil saturation is published through a Flash Flood Guidance from the Czech Hydrometeorological Institute [4]. Combination of hydrometeorological factors was investigated and implemented by the Algorithms of

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storm prediction. This algorithm has been experimentally developed in the author's dissertation. The Algorithm storms prediction is a forecasting tool the occurrence of convective precipitation and other dangerous accompanying phenomena (hail, strong wind gusts and tornadoes) induced by convective storms including forecasts of the risk of flash floods. The primary input data are data from NWP models provided in image formats PNG and JPEG. These image formats are converted with the selected image processing services to the coefficients of hydrometeorological factors specified under the proposed classification of algorithm. Secondary input data is data from historical weather situations. These data are classified by selected meteorological attributes such as temperature, humidity and wind at different levels of the atmosphere. The forecast of convective of precipitation is calculated by Backpropagation algorithm.

The main objective of this article is to compare the success rate of three methods of forecast storms for the purpose of deployment of the most successful prediction tools in experimental mode for a distribution forecast and warnings of crisis management of the Zlin Region.

2 Forecasting of Convective Storms

At present, forecasting of convective storms and their impacts is very complicated. In addition, current predictive possibilities are limited by the size of the predicted surface area (only for the regions and districts). The forecast of convective storms is focused on their symptoms, especially the interaction of significant hydrometeorological factors. The major forecasting tools are:

1. NWP models.
2. Algorithm of convective storms.
3. Prediction based on mathematical statistics and artificial intelligence.

2.1 Numerical Weather Prediction Models

Numerical weather prediction model (NWP model) is a forecasting model designated to weather forecasting. NWP models consist of a dynamic core, a set of parameterization, a model of the earth's surface and assimilated input data from ground-based meteorological stations and radiosondes [14].

NWP models contain a large number of mathematical equations describing the physical phenomena in the atmosphere. Typical ones are the equations of motion, heat exchange, parameterizations for solar radiation, continuity equation, balance equation of water vapour and the laws of energy conservation, etc. However, one of the main equations is the tools of hydrostatic equilibrium, which expresses the dependence of air pressure ρ of the vertical coordinate z:

$$\frac{\partial \rho}{\partial z} = -g\rho, \tag{1}$$

where g is the size of the gravity acceleration and ρ is the air density. The essence of this equation is the premise of an existing of the balance between the vertical force component of the pressure gradient and the force of gravity. All NWP models are based on the principle of hydrostatic equilibrium. This assumption can be used for modelling of persistent precipitation (rain, snow). Nevertheless, in reality the earth's atmosphere is compressible and hydrostatic balance can be disrupted by convection air updraft [15].

In practice, we distinguish two types of models of hydrostatic equilibrium:

- Hydrostatical models.
- Nonhydrostatical models.

Hydrostatic models are models with hydrostatic approximations based on Eq. (1). These models contain parameterization of convection eliminating a major shortcoming in predicting of convective clouds (only intense showers and weaker storms that cannot cause a flash flood are modelled). Evaluated NWP models are ALADIN model for the Czech Republic and Slovakia, EURO4 and HIRLAM (Table 1).

Nonhydrostatical models are the most local with lower resolution and detailed topography of relief. These models are specialized to forecast of convective precipitation clouds. The main representatives are models GEM, WRF ARW and WRF NMM (Table 2).

Table 1. Parameters of hydrostatical NWP models [16, 17].

Models	ALADIN CR	ALADIN SR	EURO4	HIRLAM
Country of origin	Czech Republic	Slovakia Republic	GB	DE, EST, FIN, ICE, IR, HOL, NOR, SP, SWE, LIT
Resolution (km)	5 km	5 km	11 km	10 km
Area prediction	Czech Republic	Slovakia Republic	Europe	Europe
Time step	03, 06, 12, 24 h	03, 06, 12, 24 h	00, 05, 11, 17 h	00, 06, 12, 18 h
Time advance	2,5 days	3 days	2 days	3 days

Table 2. Parameters of nonhydrostatical NWP models [16, 17].

Models	GEM	WRF ARW	WRF NMM
Country of origin	France, USA, Canada	USA	USA
Resolution (km)	11 km	4 km	3 km
Area prediction	Europe	Europe	Europe
Time step	00, 12 h	00, 12 h	00, 12 h
Time advance	10 days	3 days	1 day

2.2 Algorithm of Convective Storm Prediction

The goal of the Algorithm is to provide an advanced information and prediction of heavy convective rainfall and dangerous phenomena, which may cause flash floods.

This algorithm is based on the analysis and evaluation of the prognostic meteorological variables and parameters from numerical weather prediction models.

The main output will be a report containing an assessment of the future development of convective precipitation systems in the 3 to 24 h in advance. Other prediction outputs are:

- Place of occurrence of convective precipitation for 13 municipalities with extended powers Zlin region and its 35 regions of municipalities with extended powers.
- Time of occurrence of convective precipitation with three-hour interval and
- The time predictions for 3–12 h, or 3–24 h in advance [17].

The probability and intensity of precipitation is calculated by the following equation:

$$P = \left(\sum n / \sum m \times 3\right) \times 100(\%), \tag{2}$$

where n is the sum of the sectional predictions and m is the total number of predicted parameters.

The Algorithm of convective storm predictions are composed of these steps (Fig. 1):

The partial forecasting steps are:

1. General characteristic contains basic information about the predicted situation (date, movement direction of precipitation, warning information and synoptic forecast).
2. NWP models - seven NWP model provides a forecast of precipitation for a given time interval.

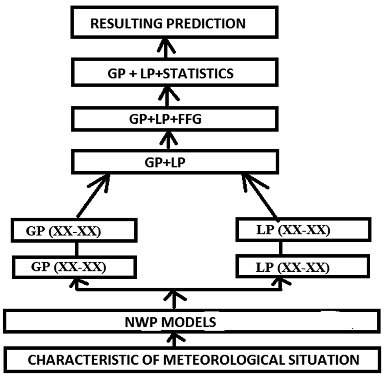

Fig. 1. The scheme of convective storm prediction

3. GP (xx-xx) is a global forecast for the three-hour interval predicted based on the second step. The data sources are ALADIN NWP models, GFS, WRF NMM and WRF ARW. The global forecast provides information on:
   - conditions of air mass above the condensation level and
   - storm (rainfall) intensity.
4. LP (xx-xx) is local forecast which gives information about conditions (potential triggers convection) of the earth's surface as the ground temperature, humidity, wind speed, cloud cover; pressure MSLP, orographic characteristics of relief). The data sources are ALADIN meteograms.
5. Statistics of historic storm situation includes a database of 100–200 weather situations. The resulting prediction is an intersection of Algorithm and selected statistic [18].

The main outputs of Algorithms of convective storm prediction:

- The probability (low/medium/high/very high) occurrence of convective precipitation computed from global and local predictions.
- The probability of occurrence of convective precipitation statistics of historical situations.
- Rainfall intensity (forecast of strong thunderstorms that may cause flash floods).
- The risk of flash floods determined by intersection of global, local predictions and soil saturation.
- The probability of occurrence of dangerous phenomena (heavy rainfall, hail, strong gusts and tornadoes).
- Type of convective storms of Global Forecasts (frontal/orographic/MCS/supercell convective storms).
- The probability of time and place the occurrence of precipitation by NWP models [18].

The probability of place of occurrence of precipitation, the risk of flash floods and more predictive outputs are classified on the calculated coefficients of convective precipitation forecast. Classification intensity of storms corresponds to the classification of dangerous phenomenon "Storm" by System of Integrated Warning Services of the Czech Hydrometeorological Institute.

2.3 Storms Prediction with the Use of Historical Data of Weather Situations

Storm prediction based on historical data meteorological situations is realized on the principle of estimation future state based on the previous state with the use a database of historical meteorological situations [19, 20].

Firstly, storm prediction is calculated from input data of NWP models. Subsequently, results are realized by artificial intelligence methods. The process of forecast creation is specified according to the below shown steps:

Table 3. Coefficients of rainfall intensity and probability occurrence of thunderstorms [17].

Coefficients	0	1	2	3
Intensity level	Weak thunderstorms	Strong thunderstorms	Very strong thunderstorms	Extremely strong thunderstorms
Rainfall intensity (mm/hours)	0–29	30–49	50–89	above 90
Probability of occurence (%)	0–24	25–49	50–74	75–100
Risk of flash flood	Low	Medium	High	Extremely high

1. Data collection.
2. Data processing and cultivation.
3. Data analysis.
4. Learning from data.
5. Development and testing of predictive models [19].

Data collection is performed from internal sources (data of 100–200 historical situations stored in MS Excel) and external sources (predictive data from NWP models) to a database of historical situations.

The specific service image of processing is the main tool for processing and cultivation data. The principle of this service is the conversion of image format into a set of parameters describing the meteorological or hydrological factors. The colour expression of the physical quantity of the factor is the converted parameter according to the scale factors (Table 3) [19].

Data analysis is addressed through statistical methods (Pearson correlation coefficient for comparison and finding dependencies between forecasted and historical weather elements and convection indices:

$$\rho_{X,Y} = \frac{E(XY) - E(X)E(Y)}{\sqrt{E(X^2) - E^2(X)}\sqrt{E(Y^2) - E^2(Y)}} \tag{3}$$

where stochastic quantities are $\mathrm{X} = \mathrm{E}\left(\mathrm{X}^2\right)$ and $\mathrm{Y} = \mathrm{E}\left(\mathrm{Y}^2\right)$. The correlation coefficient takes values in the range –1 to 1, where values approaching –1 are the least dependent and values approaching 1 increase addiction. Interval from 0.5 to 1 was experimentally chosen for the purpose of comparison [24].

Learning from data is a step where the used method of machine learning of neural networks. Used algorithm is the Backpropagation algorithm.

Input data are:

1. Meteorological elements specified conditions of air mass:
   - Temperature at altitude levels 1000, 925, 850, 700 a 500 hPa.
   - Relative humidity at altitude levels 1000, 925, 850, 700, 500 a 300 hPa.

- Wind direction at altitude levels 1000, 925, 850, 700, 500 a 300 hPa.
- Wind speed at altitude levels 1000, 925, 850, 700, 500 a 300 hPa.

2. Convection indeces (MLCAPE, MUCAPE, Lifted index, Showalter index, K-Index) (Fig. 2).

The resulting input value is determined by calculating the weighted average of these parameters. The transfer function is the logistic sigmoid. The outputs of predicted values are converted into coefficients according to Table 3.

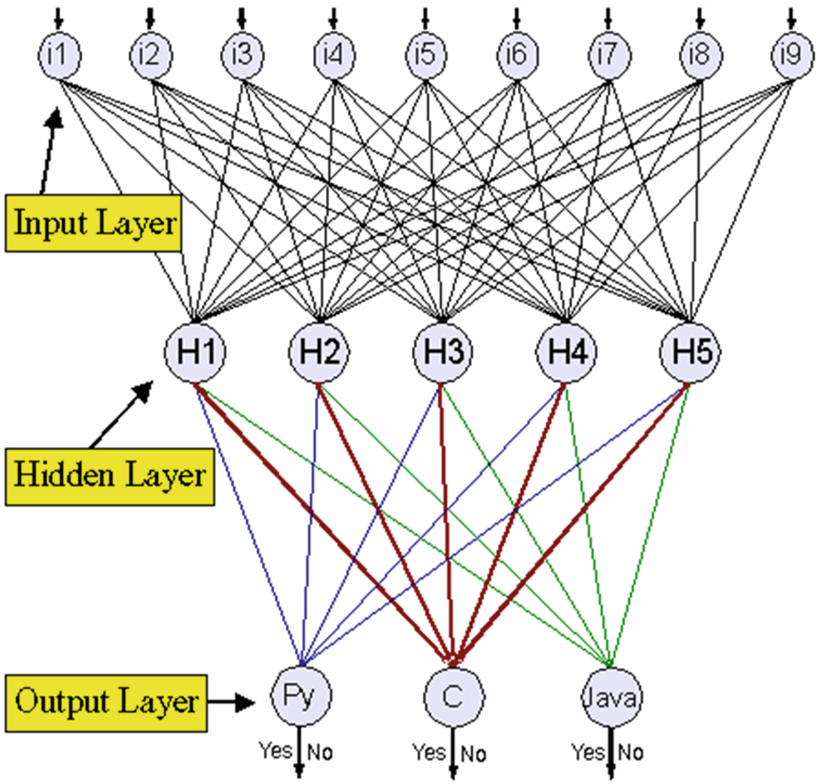

Fig. 2. Backpropagation algorithm [22].

3 Verification of Storms Prediction

Plenty of verification methods of weather forecasting are available. In practice, is often used the Skill Scores method based on the evaluation of the criteria in the pivot table. This method provides information on the number and frequency of cases where the phenomenon was or was not predicted and occurred or did not occur in all possible combinations [23]. The pivot table is adapted for calculating the percentages of success of convective precipitation forecasts:

Table 4. Contingency table for determination percentage values of success rate of forecast.

Criterion	Forecast	Reality	Result
HIT	1	1	1
MISS	0	0	1
FALSE ALARM	1	0	0
CORRECT REJECTION	0	1	0

Table 4 shows that the initial criteria represent a positive evaluation of predictions (coefficient 1, when the phenomenon occurred and was predicted). On the contrary, the last two criteria indicate bad prediction of the predicted or actual occurrence of the phenomenon (coefficient of 0, the phenomenon did not occur and was not predicted) [23]. Subsequently, the resulting percentage of the success rate of convective precipitation predictions is calculated according to the formula:

$$\bar{X} = \frac{1}{n}\sum\nolimits_{i=1}^{n} x_i \tag{4}$$

where $\sum$xi is the sum of the coefficients (0 or 1) of criteria for evaluating the success rate of convective precipitation forecasts, expressed as a percentage.

4 Discussion of Results

Percentage values of success rate of predictions were calculated for the determination of the probability of occurrence of convective precipitation:

- Algorithm of storm prediction.
- Algorithm Backpropagation.
- NWP models.

4.1 Evaluating of the Success Rate of Convective Precipitation Predictions for 13 Municipalities with Extended Powers Zlin Region

Firstly, the evaluation of the success rate of convective precipitation predictions was performed for the territory of 13 municipalities with extended powers in the Zlin Region. Success rates have been determined for the Algorithm of storms predictions, Backpropagation algorithm and NWP models. Assessed situations are historical situations in which the intensity of convective precipitation exceeded 20 mm/hr. with the probable occurrence of flash floods. The last two situations of 31.7 and 5.8 of the floods have caused considerable material damage in southwestern and southeastern part of Zlín Region.

As can be seen in Fig. 3 the lowest values predictions success rate was achieved in the first storm situation where both algorithms were deployed and tested for the first time. The success rate of forecast had a progressively upward trend where the maximum possible successful predictions has been reached in the past recent two flood

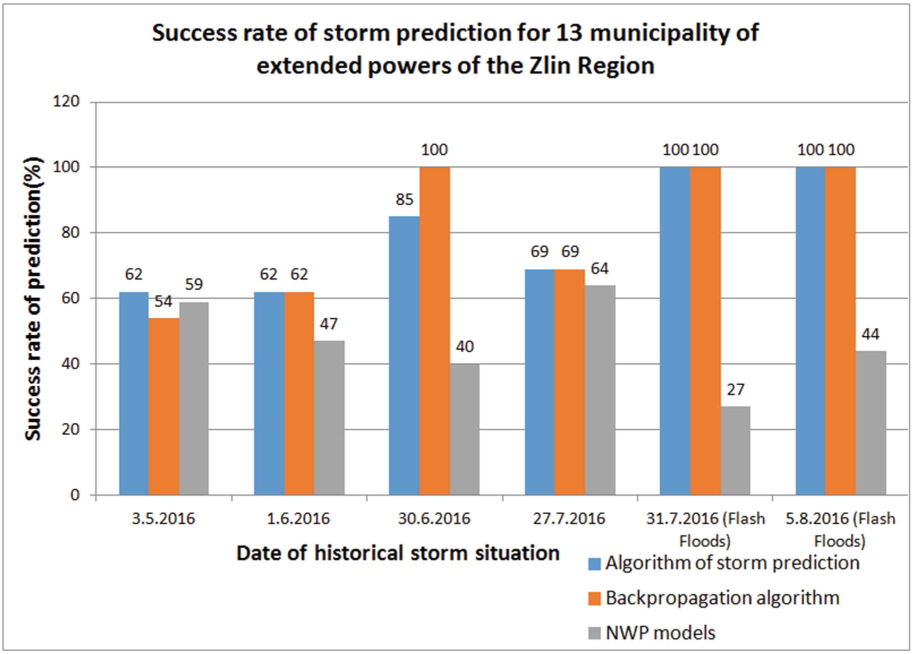

Fig. 3. Success rate of forecasting of convective precipitation for municipality with extended powers (MEP) in the Zlin region.

situation (such a high success rate was determined by the appearance of convective precipitation in the whole the Zlín Region). In contrast to both algorithms, which reached 80% of success rate, NWP models do not exceed the limit of 50% success rate predictions.

4.2 Evaluating of the Success Rate of Convective Precipitation Predictions for 35 Regions of Municipalities with Extended Powers Zlin Region

This evaluation includes the percentages success rate for only the Algorithm of storm prediction and Backpropagation algorithm. Prediction was experimentally chosen to MEP of 35 regions, wherein each MEP was divided into three regions. NWP models were not evaluated for the advanced prediction.

Figure 4 shows that the percentage of both prediction tools had an upward trend as in the first case. The success rate of forecasts reached an average from 60 to 70%, which is a relatively high value of success rate for a regionalized prediction.

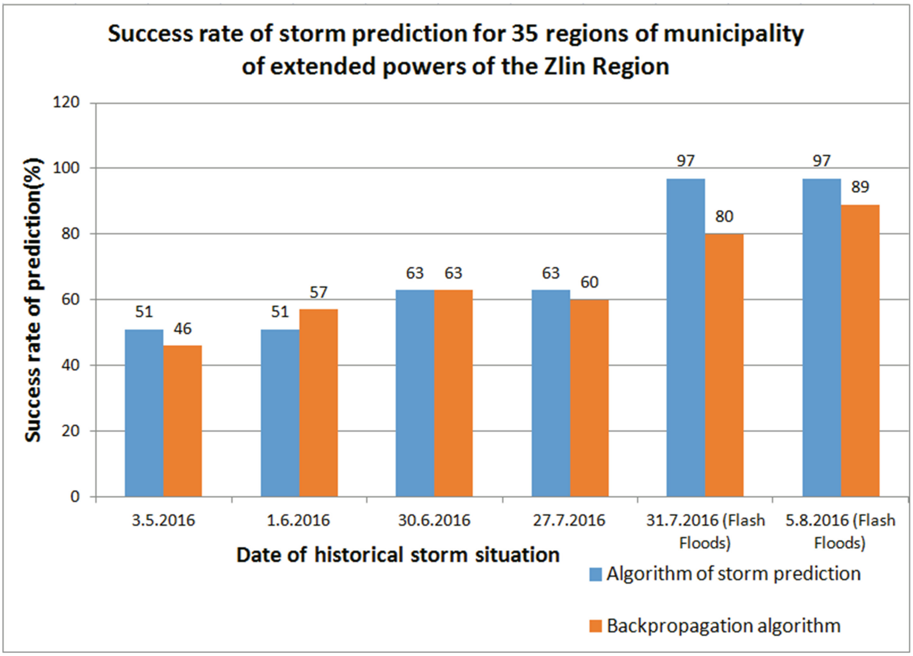

Fig. 4. Success rate of forecasting of convective precipitation for 35 regions of municipality with extended powers (MEP) in the Zlin Region.

5 Conclusion

The aim of the article was to evaluate the success forecasts storms through the NWP models, the Algorithm for the prediction of storms and the Backpropagation algorithm using an artificial intelligence. The success rate of forecasts was calculated for 35 regions including 13 municipalities with extended powers. The average success of both algorithms was around 60%, but NWP models amounted to only 47%. Consequently, the NWP models do not exceed the limit of 50%, so these predictive tools cannot be used for a qualified estimate of the probability of convective precipitation and flash floods. The algorithm storms prediction reached an average success rate of 75%, Backpropagation algorithm of 73%. Since the Backpropagation algorithm is part of the penultimate step of the prediction Algorithm so both algorithms can be used to prediction convective precipitation and the risk of flash floods.

Future research will focus on revising and optimizing forecasting parameters and their weights, including testing other algorithms of neural networks in order to achieve maximum success rate predictions about around 80% (the higher figure will not probably be achieved in terms of the quality of available data and shortcomings of NWP models). The main intention is to offer the Algorithm storms prediction at the Czech Hydrometeorological Institute for the inclusion and expansion of forecasting warnings on dangerous phenomenon “Storm” in the context of the Information Services of Warning System.

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