Using artificial intelligence in an integrated risk management program for a large alpine landslide

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ABSTRACT: This paper demonstrates the use of artificial intelligence (AI) for the forecast of sliding velocities (AILandslide) within the frame of an integrated risk management program for a large alpine landslide named Cassass (AILandslide). The slide and the forecasting of the velocity through various classic methods, have already been described in several referenced prior papers.

The Cassass Landslide is located in the NW Italy Piedmont region and impinges on the main access corridor to 2006 Winter Olympics, the international Frejus railroad line, the Frejus Tunnel Access Highway, hydro-electrical facilities as well as the village of Salbertrand. The slide underwent a paroxysm (i.e. a sudden acceleration and generalized failure) in 1957. This paper summarizes the slide's major features and the results brought in by prior studies, including a long term monitoring program implemented by the Highway Operator and financed by the Regional Government.

In recent years the area has been afflicted by rather extreme meteorological patterns. The impact of these events on the instrumentation, the evolution of the monitoring program and the risk mitigation measures undertaken are discussed. Results yielded by the probabilistic modeling of this slope are discussed in terms of the periodic risk re-evaluation, the influence on the mitigation program and decision making, and, finally the impact on future monitoring. Artificial intelligence is also used to predict velocities as a function of prior rain fall. The velocity forecasting tool (www.ailandslide.com) is integrated with the slope analysis thus leading to an integrated evaluation tool which can be maintained online (real time).

A final chapter discusses the stabilization work undertaken (drainage tunnel) as well as the latest developments of the situation and, of course, expected future developments.

1 INRODUCTION

The Cassas Landslide is located in the NW Italy Piedmont region and impinges on a corridor encompassing main transportation lines, hydro-electrical facilities and a large village. The slide, or more correctly the slide system, covers an area spanning a length of 1.4km by 0.6km and has an active sliding surface approximately 50m deep in the area of an inclinometer known as I4. Attention is focused on a subset of this system, which underwent a paroxysm (i.e. a sudden acceleration and generalized failure) in 1957 before returning to a "normal behavior", characterized by velocities ranging between 20mm/yr and 150mm/yr as a function of their location within the slide, long term meteorology.

The slide has been the object of monitoring for more than a decade by various agencies and its behavior with respect to antecedent rainfall studied in detail with classic methodologies (Oboni, 2005). The landslide impinges on an international transportation corridor (Fréjus tunnel railroad and highway), a large rest area with restaurants and gas stations, as well as on several private and public infrastructures. Models were developed to predict how a future catastrophic paroxysm would interact with the valley floor, the river and various structures/potential targets (Fig. 1), leading to the formulation of appropriate emergency plans.

1.1 *Initial Risk Assessment*

Furthermore a formal quantitative risk assessment (QRA) was performed (Roberds, 2001, Cheung et al., 2001, IUGS, 1997, Fell, 1994) and updated in several occasions over the last decade meanwhile related monitoring programs were launched (CTM, 2002-2004; Polithema & Oboni Associates, 2003).

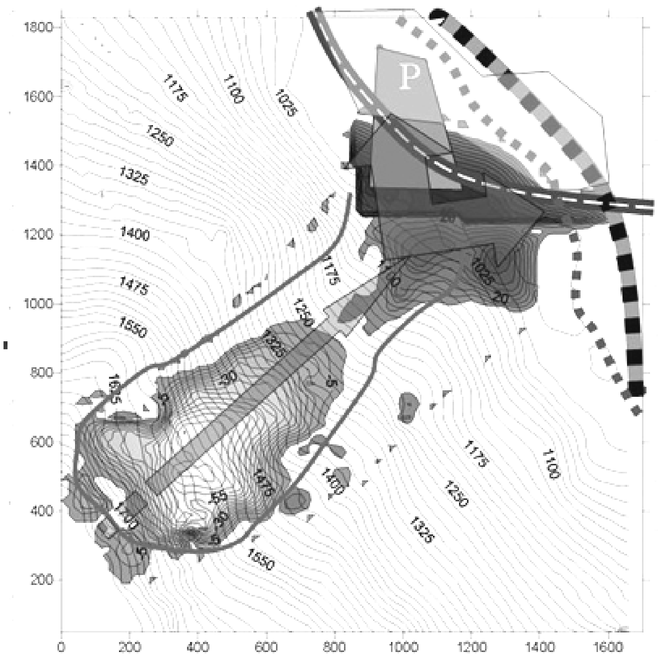

Figure 1 Study of the areas potentially invaded by a 10Mm3 potential paroxysm of the Cassass Landslide.

Within the RA the slope was modeled by using the Oboni & Bourdeau probabilistic slope stability analysis method (Oboni & Bourdeau, 1984, Oboni et al. 1984) as a tool to quantify paroxysm initiation probabilities and mobilized lengths within the active sliding body. Data for this approach were derived from preexisting studies. The initial model was developed after careful evaluation of all the available data. The main results of the Oboni & Bourdeau analyses can be summarized as follows:

- The slope would behave as a series of "independent" bodies where the uphill one would reactivate, slide down to take support on the prior, downhill one, cause its sliding, slow down and repeat the cycle unless a major heave of the water table would create the conditions for a massive reactivation.
- The slope was not prone to sudden (within days or hours) reactivations, but could feature paroxysms lasting various weeks in case of particularly unfavorable meteorological conditions.
- It was predicted that a heave of 6-8m of the water table in certain areas, monitored by piezometers, would most likely cause a significant acceleration of the sliding velocity in that area.

1.2 *Monitoring and complementary analysis/monitoring approach*

The monitoring system has undergone several reconstruction and technical evolution phases over the last decade. Beside data acquisition stations and classic inclinometers the site is nowadays also monitored with motorized optical instruments, which report via GSM (digital telecom) to a central monitoring center (CTM, 2002).

Five level velocity-alert criteria have been established for the Cassas landslide (Polithema & Oboni, 2003). These criteria drive the alert status, changes in the frequency of monitoring, and, of course, can trigger the emergency plan, which encompasses several reactivation scenario. The Regional Civil Protection Centre can trigger emergency plans specifically designed for various types of reactivation that could occur within the sliding mass, i.e. volumes going from a few hundreds of thousands of cubic meters to the largest considered potential reactivation phenomenon (Regione Piemonte, 2004).

The landslide went in a pre-alert level in the period following the year 2000 flooding which was captured by the monitoring program implemented within the risk assessment study.

The complementary analysis/monitoring approach yielded interesting predictive/ observational results, which drove stabilization actions summarized at the end of this paper. Indeed, the integration of predictive probabilistic analyses with appropriate monitoring methods, followed by an appropriate period of observation and calibration lead to a good understanding of the parameters that influence the Cassas landslide behavior. Among these the main one is the antecedent rain, net of evapotranspiration. A parametric study indicated that antecedent precipitation for periods of up to 300 days (ten months) displayed the strongest correlation with inclinometers velocity (Oboni, 2005).

The observed strong correlation made it possible to propose a simple relationship between the net antecedent rain mentioned before and the velocity at a given topographic point. Of course these results are and will remain valid within the landslide, provided global conditions do not change over time, and cannot be transferred to another landslide without a similar step-by-step, carefully designed approach. However, they constituted the formalization of a generally understood behavioral characteristic of large landslides, i.e. that these phenomena respond to long term cumulated antecedent rains rather than isolated, intense rainy events.

This paper illustrates how the research was pursued by using Artificial Intelligence systems capable of learning from past experience (measured rain-velocity data) and then predicting future behavior (we will refer to the AI system applied to landslides as AILandslide). AILandslide makes it possible to develop on-line applications to yield spot analyses to be performed on landslides that are equipped with online instruments. This will enable Civil Protection Command Centers to update their hazard evaluation as situations unfold (Regione Piemonte, 2004).

2. USING ARTIFICIAL INTELLIGENCE TO MODEL THE RAIN-VELOCITY RELATIONSHIP

The need for a predictive analysis of monitoring velocity/displacement data (inclinometers, extensometers, etc. versus pluviometric data) of landslides arises from the need to trigger alerts, organize public safety actions, civil protection in areas where accelerations of the impinging sliding movements may generate high consequences. The same need arises when alert status has to be removed, and evacuated people are to be allowed back to their residences/work places.

AI systems are capable of predicting performances in many fields and have been used in missiles guidance systems, environmental engineering, commerce and stock exchanges, mechanical and maintenance engineering. The application to natural hazards, namely landslides, which we refer to as AILandslide is an important evolution in the civil protection/geohazard field. Thus Artificial Intelligence (AI) has been used to analyze monitoring data response with respect to antecedent rain.

The AILandslide system "learns" from the past and based on its cumulated experience, makes predictions that become more and more precise as the experience on a specific landslide widens. Before the learning cycles begin, the model has to be custom tailored for any given monitoring point. AI allows reliable predictions based on past performances, significantly reducing false alerts, thus avoiding many costly errors.

AILandslide has been successfully deployed on various alpine landslides in Europe, with very significant results. The application to the Cassass landslide, object of this paper, demonstrates the outstanding predictive capabilities when using past rainfall to predict future movements/velocity.

2.1 *Customization*

Like a child, AILandslide demands a learning phase during which it analyzes the input parameters and adjustments are made. Each monitoring point needs a specific learning/ customization phase.

The predictive results are significantly influenced by the quality of the inputs. Quality of the inputs is measured by accuracy, duration, continuity.

2.2 *Data to Collect*

For a given landslide the required data are, on top of usual geological, geotechnical, geographic and climatologic data, the following:

- Rainfall Data: if possible daily precipitation, covering at least the monitoring span and continuing in the future insofar as predictions are requested.
- Temperature and Solar Radiation: if possible daily averages, to allow a precise evaluation of evapotranspiration. In case these data are not available, literature formulae can be used to yield approximation of this parameter (see Cassass analysis below).
- Movements History: Inclinometric (or other instruments) monitoring data over a sufficient time span
- History of mitigation activities/human activities on the landslide: this is important because it may lead to the preparation of two models, i.e. one before the implementation of the mitigative works, and one afterwards.

As new deformation measures and pluviometric data are inputted, AILandslide will generate new predictions. The quality of the predictions decays, of course with the range: short terms predictions are better than long term ones. The required frequency of these predictions is a "client's parameter" which will depend on the general environment (geographic, risks, prevailing meteorology) of the landslide. It is possible at any time to simulate evolution scenarios by inputting rain scenarios, thus answering questions like: what will be the deformation in the next six months if it rains, from this date on, like last year? What if the rain is double?

3. APPLICATION TO CASSASS LANDSLIDE

3.1 *Rainfall Data, Temperature and Solar Radiation*

As mentioned above these parameters constitute the basis of any AILandslide application. The first step is to evaluate the net antecedent rain, i.e. the rain minus the evapotranspiration. In the Cassass study there were no local detailed records on temperature and solar radiation, so the evapotranspiration was estimated using literature (Allen et Al., 1998).

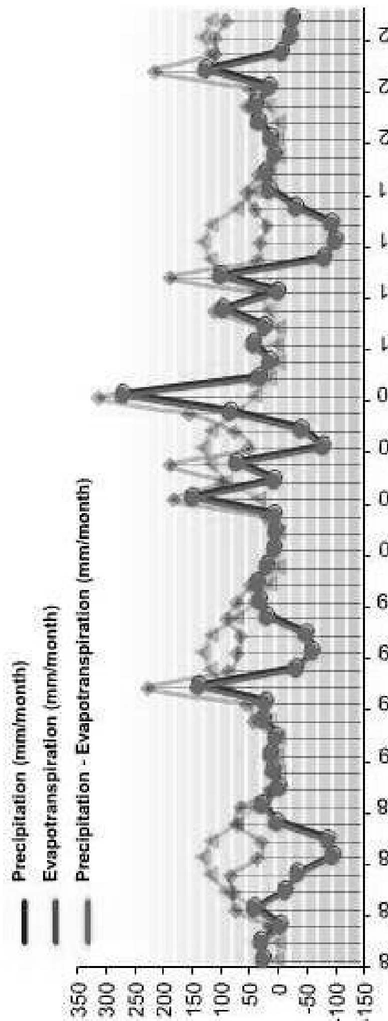

Fig 2: Precipitation, Estimated Evapotranspiration and resulting net precipitation for the period going from January 1998 to July 2002 at Cassass Landslide, based on neighboring pluviometer stations.

3.2 *Movements History*

The movement (velocity) history constitutes the other fundamental pillar of knowledge necessary to implement an AILandslide application. In this paper the inclinometer deformation readings are presented under the form of average annualized velocities (mm/yr) between measurements. As the inclinometer readings were performed discretely at a rate of 4 measures per 12 months, it was necessary to generate intermediary velocity points by interpolation (dotted points in the measured velocity in Figure 3). Modern monitoring with automatic online readings (inclinometers or surface instruments) would allow a significant increase of the accuracy of the predictions.

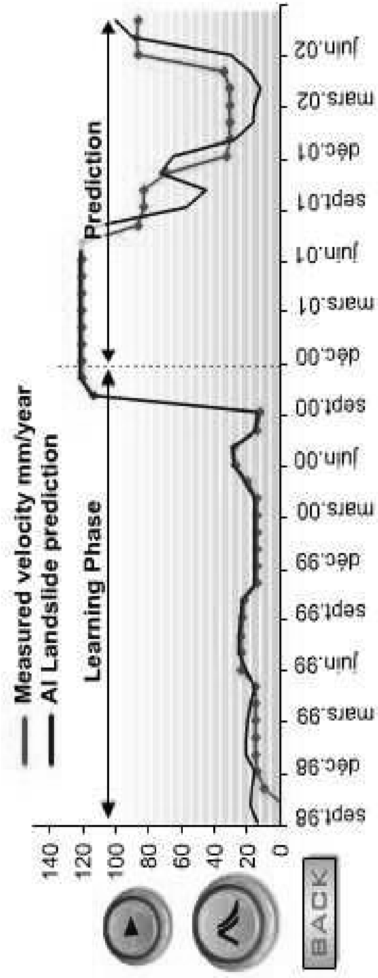

Fig. 3: Measured velocity of Inclinometer I4 at Cassass Landslide as compared with predictions during the Learning Phase and a Predictive Phase.

Figure 3 depicts the measured velocity of one specific instrument at Cassass Landslide (Inclinometer I4) together with the AILandslide prediction during the Learning Phase (September. 1998 to December 2000) and a first true Predictive Phase, from December 2000 to July 2002.

The Learning Phase was chosen to include an acceleration period resulting from a particularly severe rainy period (over a season), culminating with the October 13th -16th 2000 flooding in Regione Piemonte (Regione Piemonte, 2000). As it can be seen in Figure 3, AILandslide was then able to mimic with success the slowing down of the movements and the acceleration that ensued in late summer-fall 2002.

Figure 4 depicts another analysis that was performed using the AILandslide system. As it can be seen the Learning Phase described in Figure 3 was used to evaluate the velocities of the topographic point where Inclinometer I4 is installed during the years that actually preceded its first installation (i.e. before December 1998).

The analysis depicted in Figure 4 shows that the flooding in the region prior to the one of fall 2000 (Arpa Piemonte, 2006), i.e. November 1994, provoked, following AILandslide “back-prediction” an acceleration similar, but lower in intensity and duration, than the last one.

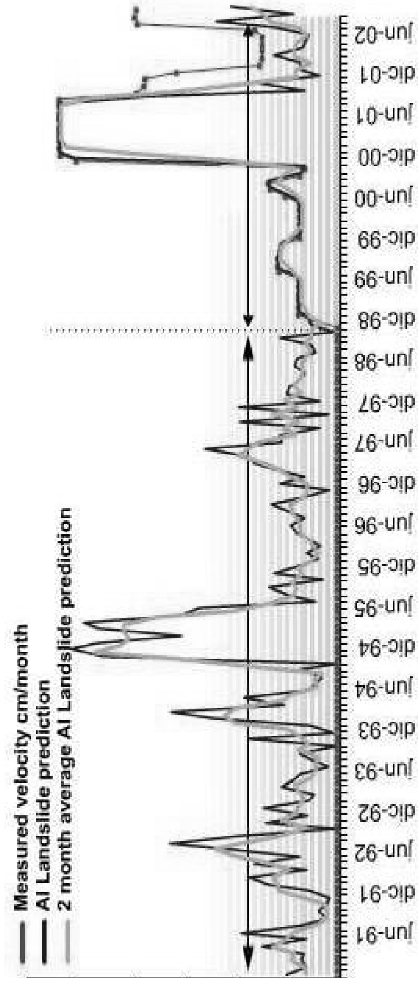

Fig. 4: Use of AILandslide to evaluate the velocities of a specific surface location (Inclinometer I4 location) during a time frame preceding the inclinometer installation (before Dec. 1998)

The integration of the velocity plot allowed the evaluation of the total displacement occurred between Dec 1990-Dec 1998 (total estimated: 21.1cm) and between Dec 1998 and Jul-Aug. 2002 (total: 20.5cm): the long term average velocities almost doubled in the second period when compared with the prior one.

4. MITIGATION

Several alternative stabilization techniques were studied, taking into account their life expectation, maintenance criteria, environmental impact (the slope is in a National Park), costs, and, of course residual risks. Risk Management has to be clearly differentiated from Hazard Management and generally leads to more sustainable choices (Oboni, 2003, IUGS, 1997, Einstein, 1988).

The main three design candidates were the ones listed below with some of their main pros/cons:

- A deep drainage by vertical shafts equipped with submerged pumps.
  - Low cost.
  - Need for regular reconstruction, at least at the beginning of the drainage action.
  - Low environmental impact
- A 600m long tunnel in "stable" ground, reaching underneath the slide from a side, equipped with ascending drainage boreholes at its end.
  - High costs,
  - Long to build,
  - High environmental impact-needs a road in stable forested areas,
  - Low maintenance
- A 150m long tunnel within the sliding mass, parallel to the movement vectors, equipped at its end with sub-horizontal drains reaching the sliding surface.
  - Intermediate cost,
  - Short building time,
  - Low impact because access runs mostly through ancient landslides devastated areas,
  - May require heavy maintenance in the future.

Finally, the 150 m long tunnel alternative was chosen and it is now almost completed. The excavation of the tunnel, 3 m x 3 m, was performed with light engines and no explosives, under an umbrella of sub-horizontal micropiles to stabilize the ceiling. At each stage an exploration drill was performed at the point of excavation to gain information on the next 30 m of terrain.

Figure 5 displays the flows drained by the semi-completed tunnel from July 2005 to August 2006. Unfortuntely the measuring station was the object of vandalism and there are no more data after August 2006. The peaks in the plot correspond to measurement errors and should be discarded.

As it can be seen the average drainage is in the order of 30 l/min, or 1300m^3 per month, with a remarkable constant flow. As the pluviometry of the last few years has been below average, the drainage acts, up to date, on the water present at proximity of the sliding surface. Only once the pluviometry would be such as to recharge the water table within the sliding mass the drainage tunnel would see the flow increase. The inclinometers display average annualized velocities in the range of 10m/yr to 20mm/yr in the last five months.

5. CONCLUSIONS

After years of attempts to define a predictive instrument for the velocity of medium to large active Alpine landslides which exhibit periodic paroxysms (acceleration and generalized failures) after particularly unfavorable meteorological cycles, the use of Artificial Intelligence has shown very promising results.

Using prior classic multiparameter correlation studies as a guide, the AILandslide application has been built linking antecedent rain (over a span of several months) to inclinometric velocities.

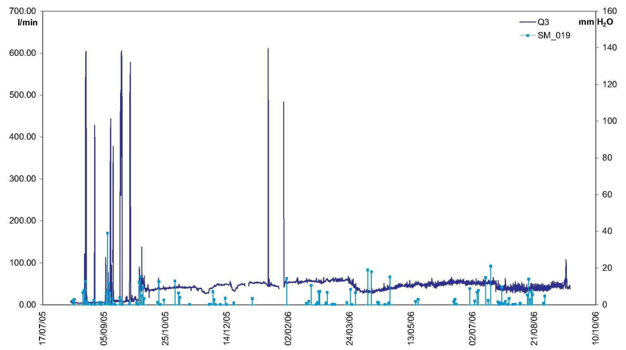

Fig 5: Outcoming flows from the semi-completed drainage tunnel between July 2005 and August 2006.

After testing the application on various landslides, the Cassass landslide was chosen as a full scale pilot application. The application was used to formulate predictions as well as to estimate cumulative displacements of the landslide in the past, when monitoring data were not present.

The AILandslide application has been integrated with success into a complex framework which includes:

- Monitoring
- Probabilistic analysis
- Quantitative risk
- Alert levels
- Catastrophy Emergency planning

In the future it is expected that AILandslide applications will allow real time prediction of velocities of large landslides under various sets of rain scenarios.

This will allow Civil Protection to deploy in a reasonable and sustainable way their assets and deliver protection to the population exposed to natural hazards.

The integration of probabilistic predictive analysis and AILandslide will bring observational approaches in landslide engineering to a new level of sophistication where, finally, all the monitoring investments will produce results that are fully used and interpreted.

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