Application of a degree-day snow depth model to a Swiss glacierised catchment to improve neural network discharge forecasts

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Abstract A trained soft artificial neural network (SANN) model was applied to the Gornera catchment (Valais Alps, Switzerland) over the melt season May to September 2001 to predict hourly discharge up to five days ahead A SANN discharge forecast for three days ahead has previously been performed on this catchment using only past discharge and past and forecast air temperature as model training inputs. In this study, present zonal snow depth was included as a model input, which was predicted for five altitudinal catchment zones using an empirical degree-day model. Hourly discharge values for up to five days ahead were reconstructed using SANN predicted daily discharge parameters along with a normalised long-term moving average model (MAHM). The efficiency criterion R^2 gives a model performance of 0.927 for a 24-hour-ahead forecast and 0.824 for a 120-hour-ahead forecast. Compared to previous work, adding the snow model to the SANN model inputs considerably increases the forecast accuracy, in particular during days of progressive discharge increase and thunderstorms. The SANN model yields excellent results on days marked by stable weather conditions, with an R^2 value between 0.913 and 0.995. However, the model is unable to reliably predict low frequency, high magnitude events, e.g. release of stored water from a glacial lake.

Keywords Artificial neural network model; degree-day model; glacial runoff forecast; HEP management; reconstructing hourly discharge curves; zonal snow depth

Introduction

Prediction of glacier runoff for hydroelectric development and operation is necessary when glaciers occupy a major portion of the catchment (Tangborn 1984). The glaciers in the Valais Alps (Switzerland) constitute a large water resource as they provide a constant source of potential stream flow during the summer months, regardless of rainfall. This reliable source of water affects the design of the hydroelectric projects of Grande Dixence SA, a Swiss hydroelectric power generation (HEP) company. The main aim of any HEP company is to pump a maximum of water as cheaply as possible into its main reservoir(s), thereby minimising cost and water loss. Successful discharge forecasting based on a profound understanding of catchment hydrology and meteorological data is necessary to achieve this aim.

Research work already carried out at Grande Dixence SA in 2002 (Meile 2002) involved a soft artificial neural network (SANN) model that was applied to the glacierised Gornera catchment in the Valais Alps over the melt season May to September 2001 to predict discharge for three days ahead. The lack of a snow melt component in Meile's work was a major limitation, given its large but temporally varying contribution to catchment runoff. So, in contrast, this research study consists of training and applying the SANN model to predict discharge for five days ahead, using not only past discharge and past and forecast air

temperature as model training inputs but also predicted zonal snow depth. The choice of an optimisation model and the respective inputs is supported by the findings of Kang and Jenson (1987), who used an ARMAX (autoregressive integrated moving average and Box–Jenkins transfer function methods) model with optimised predictor variables to predict runoff from the Z'mutt glacier drainage basin in the Valais Alps, Switzerland. They improved their results by optimising the independent model variables and found that discharge itself is the best predictor followed by precipitation and air temperature which has a strong correlation with discharge (Kang and Jenson 1987).

It was expected that the trained SANN model of this study would considerably improve the existing forecast results of the company in order to provide short-term, highly reliable predictions for more efficient water use. In other words, the innovation of this study lies in the attempt to demonstrate that artificial neural networks can be used effectively for very short-term (hourly) and reliable runoff predictions from dynamic alpine catchments. Such predictions are indispensable for the cost-effective management of water resources, such as hydroelectric power generation for example. Moreover, the highly successful reconstruction of hourly discharge values from SANN-predicted daily values contributes to the originality of this study (Meile 2002). Dayer and Rey (1984), who also applied an ARMAX prediction model to the Z'mutt glacier's meltwater discharge, state that short-term meltwater runoff has to be forecast in order to optimise pumping operations for the Grande Dixence SA power scheme. Furthermore, they argue that the need to know actual hourly values of the discharge influences the choice of the prediction method.

The number of examples in the hydrology literature referring to artificial neural network (ANN) models used to predict discharge is currently expanding (Thirumalaiah and Deo 1998, 2000; Tokar and Johnson 1999; Tokar and Markus 2000; ASCE 2000; Beven 2001; Meile 2002). The training and filtering of input data enables the model to provide, in a very short time, more reliable results than any conventional modelling technique, such as distributed hydrological models (Thirumalaiah and Deo 1998, 2000; Tokar and Johnson 1999; Tokar and Markus 2000). Hence, ANNs represent a powerful, alternative tool for cost-effective water resources management projects where quick, reliable, real-time discharge forecast is needed.

The objectives of this study are therefore to: develop a snow depth degree-day model; run several SANN model projects (runs) to link input data to runoff output; reconstruct hourly discharge values from predicted daily parameters; and finally assess model performance by comparison with previous model forecasts.

Study area

The Gornera catchment is located in SW Switzerland between the Swiss grid coordinates $622'100-633'600$ and $85'900-93'200$ at the confluence of the *Grenzgletscher* glacier and the *Gornergletscher* glacier (Figure 1). It is a typical glacierised alpine catchment which ranges from a minimum altitude of 2000 m to a maximum altitude of 4630 m a.s.l. It has an area of about $81'km^2$. The main catchment glacier, the *Gornergletscher*, is a large dendritic valley glacier ($\sim 70'km^2$) that comprises twelve different glaciers. It is characterised by a vast accumulation zone and transports an enormous ice mass to the valley. At $629'100$ and $90'300$ the glacier flows sideward into Lake Gornera, a glacial lake that empties each year at the end of June over three to four days. This natural process is of great significance not only for the water regime of the Gornera catchment but above all for Grande Dixence SA, as the glacial lake suddenly releases an enormous amount of stored water over a very short period of time.

The water captured from the river Gornera is stored in the Z'mutt compensation reservoir at an altitude of about 1950 m a.s.l., which is 450 m below the main Grande Dixence reservoir (Barrage).
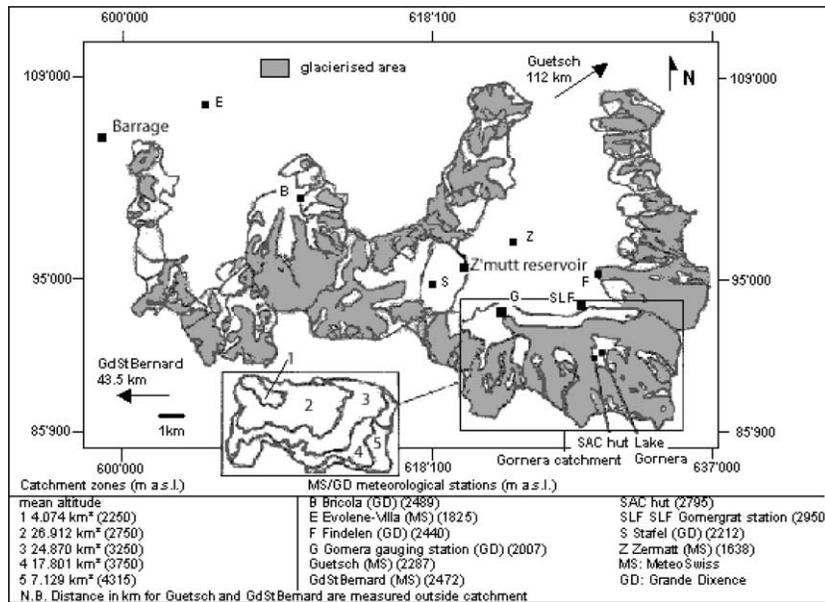
Figure 1 Map showing the main glaciers of the Valais Alps with the relative position of meteorological stations used in this study and the location of the study site (Gornera catchment)

The raw meteorological data used in this study were collected from Grande Dixence and MeteoSwiss stations. Figure 1 gives the relative position of all these stations. Guetsch station, although far outside the study area, is the only station at an adequate altitude for this study (2287 m a.s.l.) which has constantly provided daily air temperature predictions since 1990. This length of time is essential as it includes the period 1992–2001 used in this study to train the SANN model. Figure 1 also shows the five altitudinal catchment zones at a 500 m interval for which total snow depth was predicted. The SLF (Snow and Avalanche Research) station Gornergrat at 2950 m a.s.l, most representative of catchment zone 3, provided measured snow depth data for validation of the predicted snow depth values.

Methods

The methodology of this study consisted of four main steps:

1) *Air temperature calibration and precipitation averaging*

Most of the air temperature data of the Grande Dixence database had been subject to instrumental errors during most of the period 01/1988–12/2001 Errors were in the form of missing or erroneous values which had been replaced by zeros in order to have a complete, yet falsified database. Most precipitation data were prone to more or less the same errors. Moreover, there was a change from precipitation intensity (mm/h) to accumulation (mm) storage after 2000. Thus, a thorough analysis of the entire temperature and precipitation database along with detailed consultation of MeteoSwiss (MS) meteorological data of the same period was performed in order to produce a complete, more accurate database from which ANN model inputs were derived. The MS GdStBernard station was used as a reference station along with MS Evolene-Villa to calibrate raw air temperature data between 01/1988 and 12/2001 at Findelen station. Hourly values at Grande Dixence Findelen station were adjusted to the absolute difference between air temperature values (around |5|°C) of the two MS stations, which were assumed to have taken correct measurements. A new precipitation time series (*GDprecipitation*) was created for the Gornera catchment by

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averaging, differentiating and adjusting Grande Dixence stations Findelen, Bricola and Stafel in favour of MeteoSwiss station Zermatt, which was assumed to have collected reliable data. This assumption is based upon the fact that all meteorological data from MeteoSwiss showed coherent trends and no missing values. Moreover, MeteoSwiss checks and maintains the station instruments on a regular basis, as opposed to Grande Dixence SA, which does not have a long-established instrument maintenance plan.

It was expected that the calibrated temperature time series of Findelen station as well as the new precipitation time series *GDprecipitation* would provide a more reliable source of input for both the degree-day model (DDM) and the SANN model.

2) *Predicting present zonal snow depth using a DDM*

The DDM used in this study (Figure 2) is based on Martinec *et al*'s degree-day model (Martinec *et al.* 1998). They adjusted a simple DDM using both air temperature and precipitation in order to describe the present state of a snowpack, which represented an important component of their Snowmelt Runoff Model (SMR). For catchments above 500 m a.s.l. and similar to the Gornera catchment, Martinec *et al.* (1998) suggest subdivision of the area into 500 m interval zones. The mean altitude of the five catchment zones shown in Figure 1 was used to adjust air temperature, T, with a gradient of 0.65°C/100 m. Table 1 lists the precipitation correction factors for the Gornera study catchment as given by the Swiss Hydrological Atlas (SHGN 2001). The correction factors account for the change in precipitation amounts with a change in altitude. Martinec *et al.* (1998) provide monthly values of a and T_{cr} for European high mountain catchments that are similar to the Gornera catchment. Total snow depth was predicted for the SANN dataset period 1992–2001. The DDM results were validated through comparison with the measured snow depth from the SLF station. Only total snow depth predicted for zones 1, 2 and 3 was used as SANN input, as there is no significant snow melt but rather snow accumulation in zone 5 (4000–4630 m) during May and September. For zone 4 (3500–4000 m), it can be argued that most of the snow melt, which takes place mainly during August, percolates down the deep snow pack where probably most of it refreezes. Hence, it is assumed that snow melt in zone 4 only makes a minor contribution to catchment melt water runoff. These assumptions were
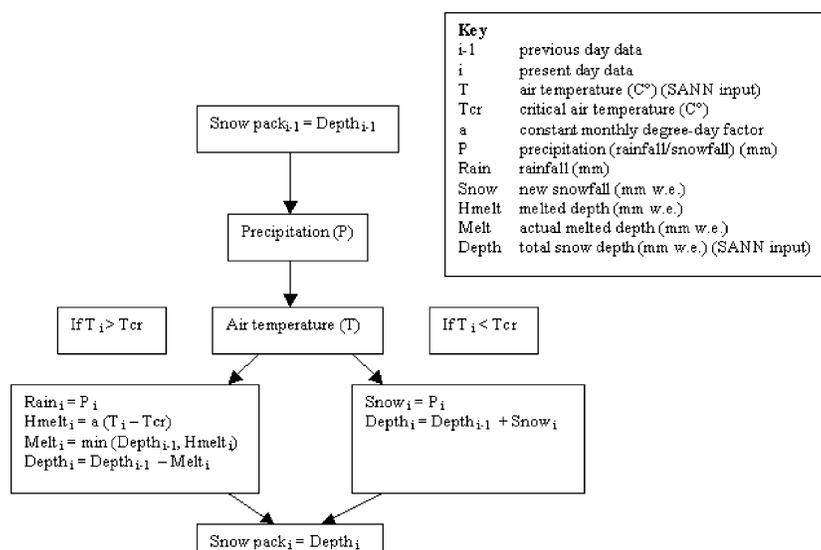
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Figure 2 Outline of the degree-day model used in this study

Table 1 Precipitation adjustment factors used for the DDM

Zone	Precipitation adjustment factor
1	× 0.9
2	× 1.1
3	× 1.3
4	× 1.5
5	× 1.7

confirmed by several SANN model runs with zones 4 and 5 that showed no significant change in forecast results when compared to model runs with only zones 1, 2 and 3.

3) *SANN predicted daily discharge parameters*

The internal functioning of neural networks is well explained in the literature (Dowla and Rogers 1995; Turban and Aronson 1998; Callan 1999; Meile 2002) The soft artificial neural network (SANN) model used in this study is a learning network model built on a multi-layer perceptron (MLP) architecture (Swingler 1996; Chatelain and Lauener 2000). The entire SANN dataset (1992–2001) was made up of numerous daily variables based on past discharge, past and forecast air temperature and predicted total snow depth. All daily model input and output variables were calculated from an hourly database. Predicting daily instead of hourly discharge mean, trend and amplitude for five days ahead and then reconstructing predicted hourly mean values is a much simpler and quicker modelling approach, as the SANN only uses 5 instead of 120 networks (Meile 2002). The time period 1992–2000 was used for network training and evolution, whereas 2001 represented the time period for final result creation, i.e. forecasting, and validation. In the 1992–2000 dataset, the period 1998–2000 was used again for the 'final error set', where the training iteration that minimises the sum of the squared errors of all data using Eq. (1) is detected and used for the process of generalisation. A large training set (1992–2000) was necessary due to the high noise content of the hydrological system assessed (Becker and Serban 1990; Swingler 1996). The objective function minimised by the SANN is given by

$$\text{MSE}_{\text{total}} = \frac{1}{T} \sum_{t=1}^{T} (y_t - f(X_t, w))^2 \rightarrow Min! \tag{1}$$

where w is the weight of connection between network units (nodes), y denotes the output and X the input to the system, and $t = 1, \ldots, T$, with T being the total number of observations.

Although the SANN was only given one year (2001) for which to forecast daily discharge parameters, it should be noted that 2001 was not part of the model training and thus represented a complete new set of data for which the trained SANN made predictions. The use of a validation dataset separate from the training period makes model validation more reliable, which is essential to demonstrate the usefulness of the SANN as an effective tool for water resources management. Moreover, as the model predicted daily values, the amount of observed data for the entire year 2001 (365 days) is large enough to validate the forecast results.

4) *Reconstructing hourly discharge values and assessing model performance*

Hourly discharge forecast values were reconstructed using Eq. (2) from predicted daily discharge mean and amplitude and calculated discharge trend (ΔQ_d), along with a normalised multi-annual hourly model (MAHM). The MAHM is a mathematical representation of the past. It is the mean over 22 years (1980–2001) of all values at the same hour and the same day as well as of x-number days before and after the date considered. Seven days (i.e. MAHM based on a 15-day period) are necessary to achieve a best

hydrographic fit of the MAHM curve (Meile 2002). In other words, the MAHM models the long-term moving average of a given variable (e.g. hourly discharge Q_i). ΔQ_d was calculated from the predicted mean, as the SANN found it very difficult to reliably predict this parameter (Meile 2002).

The performance of the reconstruction method was tested assuming a perfect SANN forecast, where $Q_{i\text{ predicted}}$ equals $Q_{i\text{ measured}}$. Over the melt season May to September 2001 the method is nearly perfect ($R^2 = 0.96$) and contributes only 10.09% to the overall error of SANN forecast results. Figure 3 shows that the algorithm performs well even during a low frequency, high magnitude event (release of stored water from Lake Gornera):

$$Q_{i\,d} = Q_{\text{mean }d} + \Delta Q_d(i - 12)/24 + Q_{i\text{ MAHMnormalised }d} \times amplitude_d \tag{2}$$

where $i = 1–24$, with $i = 1$ being the first hour of the forecast day d ($d = 1–5$), $Q_{i\,d}$ is the discharge of hour i of forecast day d, $Q_{i\text{ MAHMnormalised }d} = (Q_{i\text{ MAHM }d} - Q_{\text{mean MAHM }d})/(Q_{\text{max MAHM }d} - Q_{\text{min MAHM }d})$, $amplitude = Q_{\text{max}} - Q_{\text{min}}$ and $\Delta Q_d = (Q_{\text{mean }d+1} - Q_{\text{mean }d-1}) \times 0.5$, where d denotes the forecast day ($d = 1–5$), when d is 1, and $Q_{\text{mean }d-1}$ equals Q_{mean} of day$_{n-1}$ (previous day).

Eqs. (3)–(6) were used to assess SANN model performance and result improvements made in this study compared with previous work carried out at Grande Dixence SA:
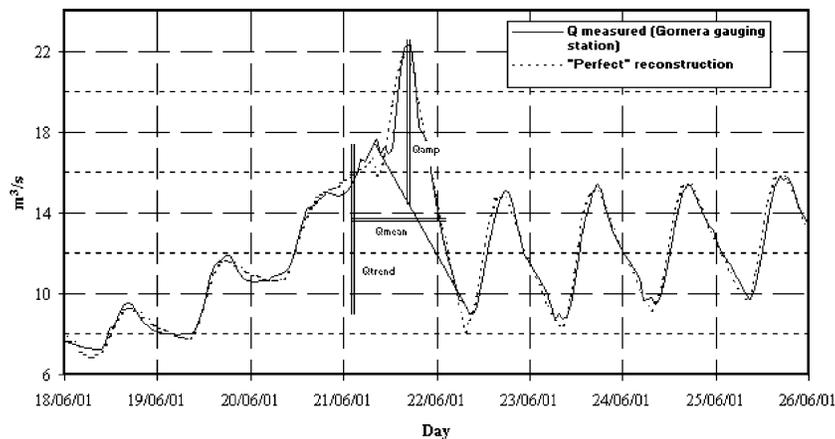
$$MRE = \sum_{i=1}^{n} (Q_p - Q_m)/n \tag{3}$$

where Q_m is the measured discharge, Q_p is the predicted discharge and n denotes number;

$$RMSE = \sqrt{\sum_{i=1}^{n} (Q_p - Q_m)^2/n} \tag{4}$$

where a result of 1.0 indicates perfect performance;

$$R^2 = 1 - \left[\sum_{i=1}^{n} (Q_p - Q_m)^2 / \sum_{i=1}^{n} (Q_m - \overline{Q_m})^2\right] \tag{5}$$

$$A_{\text{imp}}(\%) = 100/[e_{\text{palt}}/(e_{\text{palt}} - e_{\text{psann}})] \tag{6}$$

Figure 3 Performance of the reconstruction method during the three days of release of stored water, assuming perfect SANN forecast results

where A_{imp} is the improvement in accuracy, e_{palt} is the mean error in prediction when using either the MAHM or day$_{n-1}$ as an alternative to predict discharge and e_{psann} is the mean error in prediction when using the SANN model; e is given by either the RMSE or the MRE.

Results and discussion

The present zonal snow depth was predicted for five catchment zones ranging from 2000 to 4630 m a.s.l. using the DDM method illustrated in Figure 1 (Figure 4). The DDM results in mm water equivalent (w.e.) of zone 3 were validated through comparison with the measured snow depth from the SLF Gornergrat station (Figure 5). A Mann–Whitney U test was used to assess the significance in SANN performance when giving the DDM results as an additional model input. The statistical test revealed that there is a significant reduction in the root mean squared error (RMSE, Eq. (4)) of the SANN results when integrating the DDM ($p = 0.04$). Furthermore, the DDM input raises the efficiency criterion R^2 (Eq. (6)) of the SANN from 0.936 to 0.953 for one day (24 h) ahead forecast.

For the SANN model, the number of genomes within a population, the number of generations, and above all the number of training iterations determines the length of time the
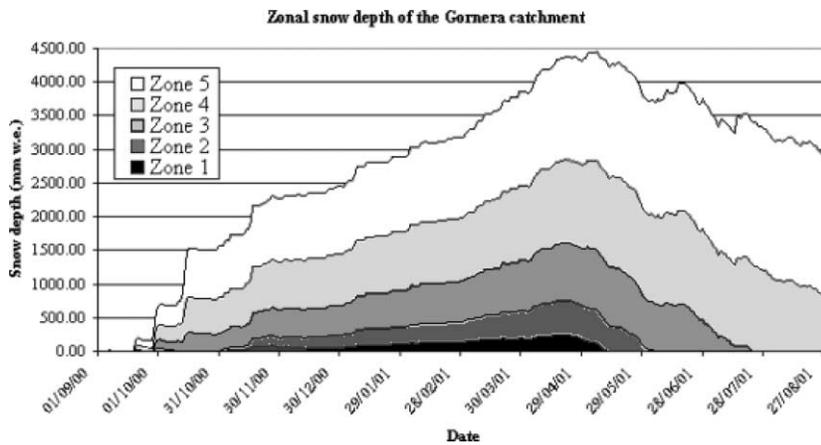
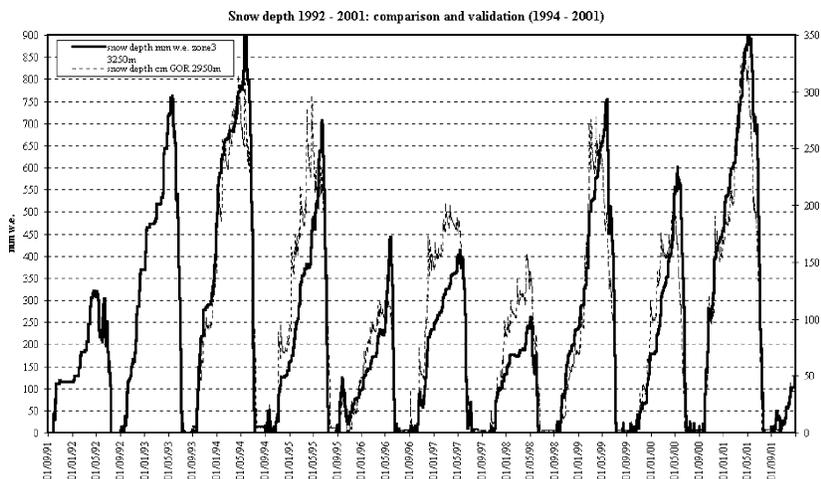**Figure 4** Predicted present snow depth of the five Gornera catchment zones

Figure 5 Validation of the predicted snow depth of zone 3 for the SANN training period 1992−2001 using measured snow depth from 1994 to 2001 (© SLF, 2002)

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SANN model takes to run a project (Meile 2002). SANN projects were first run with a small number of generations (50) in order to determine the necessary model inputs needed for reliable results in a relatively short time. By thereafter relaunching the same project with an increased number of generations (500–800), the model output error was significantly reduced. The best model configuration, i.e. where the SANN model works most efficiently, was found to have a 3-unit (node) architecture with a population of 256 genomes, 50 iterations and between 500 and 800 generations.

When assuming perfect SANN forecast of daily discharge mean, trend and amplitude, the reconstruction method (Eq. (2)) gives an RMSE value of $0.967 \, \mathrm{m^3 \, s^{-1}}$, which equals only 10.1% of the seasonal discharge of $9.584 \, \mathrm{m^3 \, s^{-1}}$. Moreover, there is no bias over the melt season 2001 and R^2 equals 0.956. For hourly discharge reconstruction of actual SANN forecast results for 24 and 48 hours ahead, ΔQ_d was calculated from the predicted daily discharge mean (Eq. (7)). Using the MAHM discharge trend ($\Delta(Q_{iMAHM})$) instead of the calculated ΔQ_d for reconstruction of 72, 96 and 120 h ahead (Eq. (8)) provided slightly better results. As far as discharge amplitude is concerned, SANN-predicted values provided a more accurate reconstruction for 24 and 48 h ahead (Eq. (7)) than using a discharge amplitude of day_{n-1} (previous day, i.e. day preceding forecasts). However, an amplitude of day_{n-1} was used to reconstruct predicted discharge values for 72, 96 and 120 h ahead (Eq. (8)). Equations (7) and (8), used for reconstruction of up to 120 h ahead forecasts, illustrate the procedure outlined above.

For 24 and 48 h ahead forecasts

$$Q_{i \, d} = Q_{\mathrm{mean} \; d} + [(Q_{mean \; d+1} - Q_{mean \; d-1}) \times 0.5] \times (i - 12)/24$$

$$+ \, Q_{i \; \mathrm{MAHMnormalised} \; d} \times amplitude_d \tag{7}$$

For 72, 96 and 120 h ahead forecasts

$$Q_{i \; d} = Q_{\mathrm{mean} \; d} + [\Delta(Q_{iMAHM})](i - 12)/24 + Q_{i \; \mathrm{MAHMnormalised} \; d} \times amplitude_{\mathrm{day} \; n-1} \tag{8}$$

where d denotes the forecast day ($d = 1$–5), when d is 1, and $Q_{\mathrm{mean} \; d-1}$ equals Q_{mean} of day_{n-1}.

Hourly discharge forecasts could be performed by using either hourly discharge values of the previous day ($Q_{i \; \mathrm{day} \; n-1}$) or MAHM discharge values ($Q_{i \; \mathrm{MAHM}}$). However, as Table 2 illustrates, predicting hourly discharge using the SANN-predicted daily values along with the hourly reconstruction (Eqs. (7) and (8)) provides much more accurate values for all ahead forecasts. If no SANN model can be used, then hourly discharge values of day_{n-1} should be used to predict 24 and 48 h ahead and the MAHM should be used for 72, 96 and 120 h ahead.

Table 2 RMSE values ($\mathrm{m^3 \, s^{-1}}$) for predictions of up to 120 h ahead using either the SANN predicted discharge, previous day (day_{n-1}) hourly discharge or the long-term average (MAHM) discharge

Hours ahead	SANN model and reconstruction method	$Q_{i \; \mathrm{day} \; n-1}$	$Q_{i\mathrm{MAHM}}$
24 (1 day)	1.64	2.20 (25.6)	3.09 (47.6)
48 (2 days)	2.13	3.03 (29.4)	3.09 (31.2)
72 (3 days)	2.46	3.54 (31.2)	3.09 (20.4)
96 (4 days)	2.56	3.93 (34.5)	3.09 (17.2)
120 (5 days)	2.76	4.26 (35.7)	3.09 (10.6)

N.B. The values in brackets indicate the % improvement in accuracy when using the SANN instead of day_{n-1} or the MAHM.

The RMSE of SANN hourly forecasts ranges from a very low $0.67\,\mathrm{m^3\,s^{-1}}$ for 24 h ahead (7% of the seasonal discharge) to a moderate $2.52\,\mathrm{m^3\,s^{-1}}$ (26%) for 120 h ahead for most of the melt season (Table 3). This explains a very high seasonal R^2 value of 0.927 for 24 h ahead and still a respectable 0.824 for 120 h ahead. Both the R^2 and the RMSE indicate that there is degradation in the model performance with an increase in hours ahead forecast, which is to be expected. Moreover, there is constant degradation in forecast accuracy in July, which reduces the overall seasonal performance. The degrading performance in July is, to a large extent, due to the error contribution of the reconstruction algorithm, which contributes as much as 21.3% to the forecast error in July. Furthermore, SANN pattern recognition, and thus accurate forecasting, is difficult on days marked by high climatic variation, i.e. instability in precipitation and air temperature, which represents a high noise level in the SANN training dataset. When such noise is predominant, as was the case for many days in July 2001, the SANN prediction accuracy decreases.

Although the RMSE values are insignificant, there is a systematic overestimation of discharge ($>15\%$) in May for all five days ahead and in June and September for 72, 96 and 120 h ahead. In these months the DDM also shows lower accuracy in predicting snow depth. This may be due to the fact that the DDM only relates T and precipitation to snow depth. In other words, it overemphasises the direct inverse relationship between T and *Depth*. During model training the SANN may recognise and overemphasise this inverse relationship. As a result, in months marked by a highly variable relationship between air temperature and total snow depth inputs and discharge output, the SANN establishes a falsified pattern. So, from late spring to the early summer months, which are marked by a moderate decrease in snow depth and so a moderate, steady increase in discharge but experience a variation in air temperatures, the SANN underestimates snow depth and thus overestimates discharge.

Apart from only moderately predicting discharge during periods of unstable and also degrading weather conditions in particular for 72, 96 and 120 h ahead (Figure 6 and Table 4), the SANN also finds it very difficult, if not impossible, to accurately predict low frequency, high magnitude events, which is to be expected because of the pattern recognition and generalisation ability of the SANN model. From 19 to 22 June in 2001, Lake Gornera released $3547\,930\,\mathrm{m^3}$ of water (i.e. $13.7\,\mathrm{m^3\,s^{-1}}$ averaged over the event period). For a 24-h ahead forecast, the SANN has a bias value of $-1.142\,\mathrm{m^3\,s^{-1}}$ which corresponds to a water loss for Grande Dixence SA of $98\,669\,\mathrm{m^3}$. As this low frequency, high magnitude event takes place each year at about the same time and the SANN cannot recognise any significant explanatory pattern for this outlier from the provided model inputs, the period 19–22 June 2001 was omitted in assessing model performance (Swingler 1996). As illustrated in Figure 6 and Table 4, the SANN performs best (R^2 equals 0.995 for 24 h ahead) on days marked by stable, sunny weather conditions. If an error margin of 15% is taken, then all RMSE values are more than acceptable for all five days ahead. It must be noted though that sunny weather

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Table 3 Monthly and seasonal RMSE values for five days ahead forecast. Model performance (R^2) for the entire melt season is also given

Hours ahead	24		48		72		96		120	
	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2
May	1.02		1.35		1.15		1.49		1.48	
June	1.31		2.12		2.61		2.82		2.95	
July	3.41		3.68		4.31		3.98		4.45	
August	1.78		2.27		2.52		2.52		3.25	
September	0.67		1.26		1.70		1.99		1.69	
Seasonal	**1.64**	**0.927**	**2.13**	**0.894**	**2.46**	**0.857**	**2.56**	**0.856**	**2.76**	**0.824**
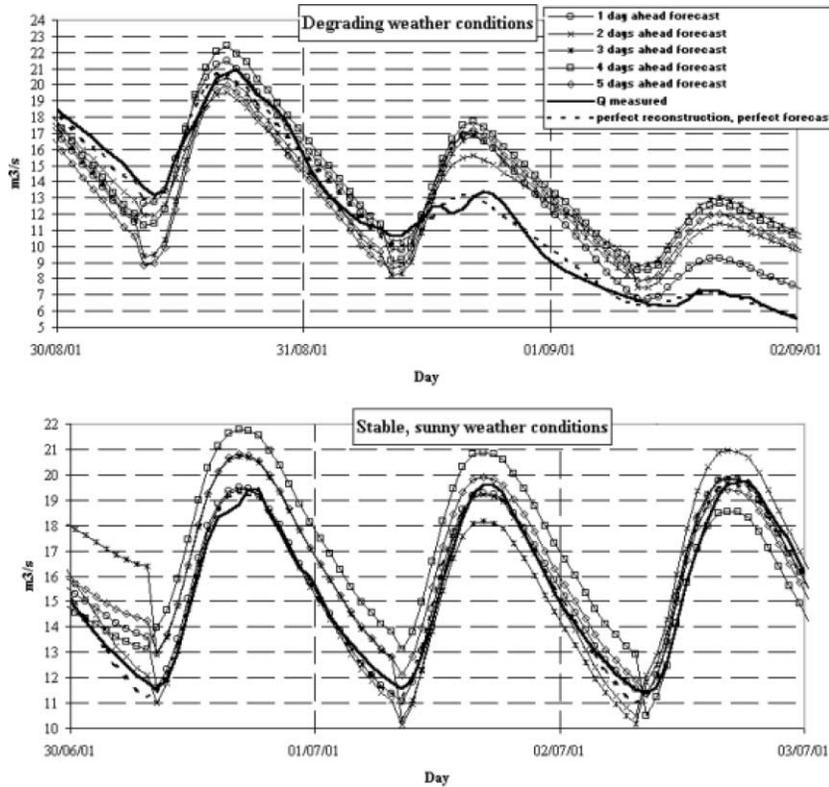
Figure 6 Hourly discharge predictions for up to 5 days ahead during unstable, degrading and stable, sunny weather conditions

conditions are predominant in the Valais region (Meile 2002) and thus the model may be 'overtrained' (Dowla and Rogers 1995) with these patterns. This could result in modelling of a 'stable, sunny' network (Meile 2002) due to an overvaluation of these weather conditions in the training dataset.

Table 5, which lists selected periods in 2001 for comparison, illustrates that the results of this research study show an overall improvement (Eq. (6)) compared to previous research (Meile 2002), in particular during periods of thunderstorms and progressive discharge increase. Although the model has difficulties in reliably predicting the release of water from Lake Gornera (MRE 31%), the prediction accuracy of previous results has been improved by 22% for this high magnitude event. Moreover, the SANN model in this study improved prediction accuracy with less inputs and training iterations than in previous work (50 as opposed to 200–250; Meile 2002), which greatly reduces the model runtime. It is assumed

Table 4 RMSE and R^2 values for a selected period of moderate and excellent model performance

Hours ahead		24	48	72	96	120
Moderate model accuracy	R^2	0.861	0.693	0.513	0.510	0.580
Degrading, unstable weather conditions (30/8–2/9) hourly Q: 10.802 $m^3 s^{-1}$	RMSE	1.807	2.683	3.378	3.389	3.138
High model accuracy	R^2	0.995	0.985	0.971	0.913	0.972
Stable, sunny weather conditions (30/6–3/7) hourly Q: 15.517 $m^3 s^{-1}$	RMSE	0.477	0.804	1.121	1.944	1.107

Table 5 MRE and % MRE of the 3 days (24, 48 and 72 h) ahead forecast results for selected periods

Period	Date	Q (m³ s⁻¹)	Meile (2002) MRE	Meile (2002) %	This study MRE	This study %	Improvement
Lake Gornera water release	19/6–22/6	13.7	5.4	39	4.2	31	**22%**
After Lake Gornera event	22/6–25/6	12.1	3.6	30	3.0	25	**17%**
High temperatures during the night and ppt	1/8–4/8	23.9	3.4	14	3.2	13	**6%**
Thunderstorms	15/8–18/8	19.1	2.6	13	1.7	9	**36%**
Progressive increase in Q	24/8–27/8	16.8	1.9	11	1.4	8	**26%**
Degrading, unstable weather conditions	30/8–2/9	10.8	3.5	32	2.9	27	**17%**

N.B. The mean relative error (MRE, Eq. (4)) was used for comparison as it was used by Meile (2002) to assess SANN model accuracy in his research

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that this is due to air temperature calibration and the creation of a more reliable precipitation time series prior to model application, to a more accurate version of the reconstruction method and, above all, to the integration of predicted zonal snow depth. Predicted zonal snow depth facilitates pattern recognition and thus the SANN can ignore certain input variables that were previously needed to reliably predict hourly discharge for up to 120 h ahead. Moreover, with a reduced number of training iterations there is a much higher chance that the SANN model minimises the mean squared errors most successfully during both the training and result creation periods (Turban and Aronson 1998).

Conclusions

This research study has considerably improved previous hourly discharge forecasts for the glacierised Gornera catchment using an algorithm to reconstruct hourly values from SANN-predicted daily discharge. The improvement was largely achieved through the integration of predicted zonal snow depth into the SANN model, even though the empirical degree-day snow depth model may have caused some overestimation of discharge. The degree-day model (DDM) results also allowed us to reduce the number of inputs and training iterations, which resulted in faster SANN processing, with no negative effect on model performance. The improvement is also due to a smaller extent to raw data calibration and correction prior to SANN training.

Model performance is poorer, although still reliable, on days marked by degrading and highly variable climatic conditions. The reconstruction algorithm also accounts for some error as does the inverse relationship between air temperature and total snow depth of the DDM. Moreover, the SANN finds it impossible to reliably predict the sudden release of water from a glacial lake. Furthermore, the SANN may be overtrained by the predominantly sunny days of the Valais region. However, due to the black-box principle of neural network models it is very difficult to identify with high confidence factors responsible for the deterioration or improvement of forecast results.

Despite the few shortcomings, the very high performance of the SANN in this study (R^2 equals 0.927 for 24 h and 0.824 for 120 h ahead) indicates that neural networks represent an inviting alternative to model dynamic hydrological systems, as they are able to filter the high level of noise and uncertainty present in such systems (Becker and Serban 1990). This potential is particularly important for water resources management (e.g. HEP) projects.

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