DOI: 10.13476/j.cnki.nsbdqk.2021.0002
黄一昕, 王钦钊, 梁忠民, 等. 洪水预报实时校正技术研究进展[J]. 南水北调与水利科技(中英文), 2021, 19(1): 12-35.
HUANG Y X, WANG Q Z, LIANG Z M, et al. Research advances on real-time correction methods for flood forecasting[J]. South-to-North Water Transfers and Water Science & Technology, 2021, 19(1): 12-35. (in Chinese)

洪水预报实时校正技术研究进展

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摘要: 回顾国内外洪水预报实时校正的产生背景, 评述其理论与方法的发展历程。在此基础上, 将实时校正方法归纳为终端误差校正和过程误差校正两类, 并梳理出各自的典型校正方法以及联合校正方法, 概述不同方法的研究成果及进展。重点介绍其中的反馈模拟技术、误差自回归算法(AR)、递推最小二乘算法(RLS)、卡尔曼滤波技术(KF)和动态系统响应曲线算法(DSRC)等 5 种代表性的实时校正技术, 阐述其计算过程, 并分析其特点与适用性。对洪水预报实时校正的未来发展方向及研究热点进行了展望。

关键词: 实时校正技术; 洪水预报; 反馈模拟; 误差自回归; 递推最小二乘; 卡尔曼滤波; 动态系统响应

中图分类号: P338; TV122 文献标志码: A 开放科学(资源服务)标志码(OSID):

洪水预报作为最重要的防洪非工程措施, 担任着防汛工作的“耳目”“参谋”与“尖兵”[1]。提前获得准确及时的预报, 可减轻甚至避免洪灾损失, 有效管理和保护水资源, 为防汛决策和水库调度提供科学依据, 具有显著的经济价值和社会效益[2]。但由于自然的复杂及人类认识的局限, 预报过程中不可避免地存在着误差。洪水预报过程包括模型输入、模型结构及参数、状态变量初值和测量等诸多环节[3-5], 产生于这些环节的误差将导致最终的预报结果与客观实际值有偏差, 从而影响洪水预报模型的预报精度。因此, 为了使结果更切合实际, 必须对洪水预报误差进行修正, 以保证预报模型的实用性和有效性。

实时洪水预报误差修正, 也称为实时校正, 是指依据洪水预报过程中不断采集的实时信息(实测信息、预报信息等), 对预报的输入、模型参数、状态变量或预报值等合理校正, 进而实时地降低洪水预报误差[6-8]。实时校正流程见图 1, $In(t-D)$ 表示 $(t-D)$ 时刻的实测模型输入, 经模型计算, 得到预见期 D 时段后 t 时刻的模型预报值或输出值 $Out(t|t-D)$, 这些输出值可以是流域出口断面的流量(水位), 也可以是模型参数、流域土壤含水量等。当获得 t 时刻的相应实际观测值 $Obs(t)$ 后, 根据模型预报值和实际观测值之间的联系, 建立校正模型, 将校正后的结果重新进行模型计算, 得到校正后的模型输出 $Out(t)$。对下一时刻 $(t+1)$, 根据该时刻的模型输入 $In(t+1-D)$ 及上一时刻 t 校正后的输出 $Out(t-1)$, 进行相同的模型计算和误差校正步骤, 得到 $(t+1)$ 时刻的校正后模型输出 $Out(t+1)$。重复上述过程, 则可实现预见期为 L 时段长, 即从 $t \sim (t+L)$ 的洪水过程实时校正预报。

收稿日期: 2020-01-10 修回日期: 2020-05-25 网络出版时间: 2020-06-01
网络出版地址: http://kns.cnki.net/kcms/detail/13.1430.TV.20200601.1411.002.html
基金项目: 国家重点研发计划(2016YFC0402709); 国家自然科学基金(41730750); 江西省水利科技项目(201921YBKT21)
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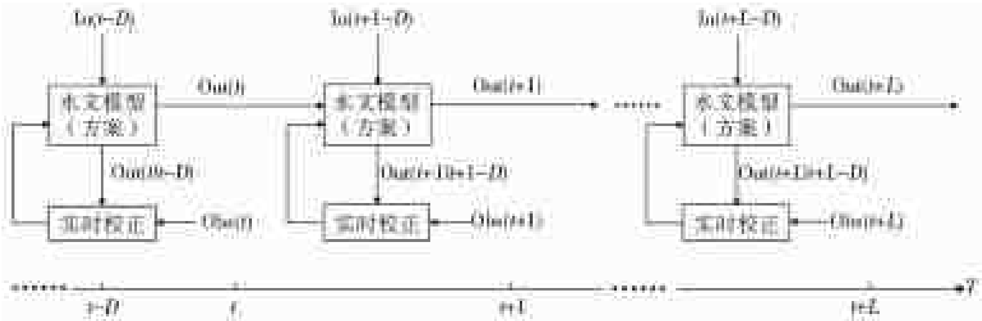

图 1　洪水预报实时校正计算流程

本文对国内外的洪水预报实时校正方法进行归纳分类和简要评述, 着重介绍其中的 5 种代表性实时校正技术, 并对未来实时校正方法的发展趋势进行展望。

1　洪水预报实时校正发展历程回顾

1.1　国内外前期研究成果

20 世纪 60 年代, 系统科学领域中的“SCI” ——系统论(systems theory, S)、控制论(cybernetics, C) 和信息论(information theory, I), 逐渐进入成熟期, 其理论与技术也迅速在自然科学、工程技术、社会经济等各个领域得到应用, 取得大量成果。1970 年, 日本学者 Hino[1,9] 首次将卡尔曼滤波(Kalman filter, KF) 技术应用于水文预报问题, 开创了这一方向研究的先河。1978 年, Wood 等[10] 完整描述了使用 KF 递推算法进行降雨径流预报的流程。至此, 以 KF 理论[11] 为代表的一批信息处理和校正技术被逐步引入到洪水预报领域中, 带动了第一次引入热潮。

基于 20 世纪 70 年代的研究热潮和大量成果, 1978 年美国地球物理学会(AGU) 召开了一次国际专题学术讨论会, 研讨成果汇编成《KF 理论和技术在水文学、水力学和水资源上的应用》论文集[1,12]。1980 年 4 月, 国际水文科学协会联合世界气象组织(WMO) 又召开了一次国际水文预报学术讨论会, 该会议论文集的 46 篇学术论文中, 有关 KF 理论的就有 16 篇[1,13]。这两本论文集中汇编的研究成果代表了当时该方向的国际最高研究水平, 例如 Ambrus[13] 引入自校正预报器算法, 在多瑙河 Budapest-Baja 河段运用 ARMA 模型(差分模型) 进行实时预报, 取得精度较高的校正效果。

我国洪水预报实时校正的研究与应用主要兴起于 20 世纪 80 年代, 相较于国外起步较晚。早期的校正技术大多是人工经验修正方法[6,14-16], 即对于一些洪水预报值误差较大的情况, 根据专家经验对洪水预报结果直接进行修正或采用回归分析手段修正, 以改善预报估计值。也有以时间序列分析为基础的统计类方法, 建立预报误差与误差之间的自回归模型, 从而根据已有的误差序列对未来的误差序列进行预测。这些校正方法基本与预报模型本身分离, 可以独立建模, 操作简便。

20 世纪 80 年代前后, 我国水文预报模型研究日新月异, 从经验模型到概念性模型再到分布式模型, 一批与水文模型集成的实时校正方法也开始涌现并发挥作用。数据同化技术便是这类实时校正方法中的代表, 能有效地提升水文模型的预报精度。数据同化主要有滤波法和变分法两种[17], 由于变分法通常假定模型误差不随时间传播, 而在水文预报中, 误差具有随时间传播的特性, 这与变分法的前提假设不相符, 因此, 在洪水预报误差修正中多采用滤波法。1984 年, 葛守西[18] 将滤波法中的 KF 技术与概念性水文模型进行耦合, 实现单独对产流预报动态实时校正, 这是实时校正在技术上的一次重要突破。此后, 各种滤波算法(包括改进的 KF 技术), 被广泛地应用于各类水文模型的实时预报误差修正, 效果显著。

1.2　国内外近期研究成果

20 世纪 80 年代后, 随着新理论的涌现和实际应用需求的提升, 洪水预报实时校正的研究亦由浅入深地向前发展, 其中一大特征是从校正数学算法的直接引用发展到适应复杂洪水预报模型和校正模型开拓性的应用研究。随之, 各种后处理技术、校正新方法应运而生。纵观这些校正技术与方法, 大体上可以归纳为两类: 一是终端误差校正方法(terminal bias correction, TBC); 二是过程误差校正方法(process bias correction, PBC)。

TBC 的实质是不直接考虑预报逐环节(子过程) 的误差以及误差在各子过程中传播, 而是直接分析处理最终流量或水位的预报误差(终端误差), 对终端误差进行校正, 以满足实时更新原预报值的目标。TBC 方法主要包括: (1) 实测流量代入法[19], 将预报流量(误差) 写成前一个或多个时刻流量(误差) 的函数形式, 在每个新的预报时间点将其前的流量

(误差)代入函数,就可达流量校正的目的。(2)水文模型流量预报实时校正法[4, 8, 20, 21],基于相关分析的基本思想,创建水文模型预报流量与实际流量之间的相关校正模型,通过实时代入实际流量,实现对模型预报流量的校正。(3)误差自回归(auto-regressive, AR)校正算法[5, 22-25],计算预报流量与实测流量之间的残差系列,基于回归分析,构建多阶自回归残差校正模型,直接对流量预报结果进行误差修正。(4)反馈模拟实时校正法(FACT 因子校正系数法)[7, 26-32],利用基于实际流量和预报流量共同构建的 FACT 因子,通过反馈模拟计算,完成对终端流量的校正。(5)基于水文相似预报误差修正方法[33, 34],认为满足相似性的两个流域其预报误差也满足相似性,则可根据相似流域不同的预见期,赋予不同的最优误差修正因子,进而构建预报误差校正模型以修正最终预报结果。(6)KNN 最邻近(K-nearest neighbor, KNN)校正法[35-40],是一种统计自动学习的方法,基于回归分析,建立实测期预报误差与预报时刻预报误差之间的校正模型,寻找出与当前预报情况最相似的 K 个历史流量过程,利用反距离加权,估计现时刻的预报误差,从而对现时刻终端流量进行校正。(7)BP(back propagation)神经网络实时校正法[41-43],是以 BP 算法的前馈神经网络来模拟预报模型的非线性,动态跟踪洪水预报误差的变化,基于回归分析,构建预报误差的非线性自回归模型,利用已有的预报误差分析出新的误差,进而修正预报流量,完成终端误差校正的目的。

PBC 的本质是先对水文预报各个子过程(如降雨、产流、汇流等)或预报模型的状态变量、参数变量等进行误差校正,校正后再重新进行模型运算得到新的预报值,通过降低预报各环节的误差,以达到降低终端误差的目的。PBC 方法主要包括:(1)递推最小二乘(recursive least squares, RLS)校正法[44-46]。以预报误差平方和最小为目标,递推估计模型参数,直至估计值达到满意的精度为止。该校正法还包括其改进算法,如基于固定遗忘因子的递推最小二乘法、基于可变遗忘因子的递推最小二乘法以及抗差递推最小二乘法等[47-50]。(2)KF 方法[18, 19, 46, 48, 51-56]。基于复杂系统的现代随机估计理论和误差协方差最小的原则,估计系统状态,赋予现时预报一定的权重比例,从而校正系统的状态变量(如预报模型参数、预报对象、预报误差等),以实现误差实时校正。KF 可应用于任何的线性系统,如马斯京根矩阵方程描述的分段河道汇流系统[29, 57]。对于非线性系统,则可基于自适应滤波(adaptive Kalman filter, AKF)、半自适应滤波(semi-adaptive Kalman filter, SAKF)、扩展卡尔曼滤波(extended Kalman filter, EKF)、无迹卡尔曼滤波(unscented Kalman filter, UKF)、集合卡尔曼滤波(ensemble Kalman filter, EnKF)以及粒子滤波(particle filter, PF)等滤波技术进行实时校正[58-62]。(3)基于 K 均值聚类分析的实时分类修正方法[63, 64]。首先对大量的历史降雨和洪水信息聚类,分类后根据各类别的特征,分析实时的降雨和洪水所属类别(水平),根据所属类别的模型参数,降低模型参数误差,进而对原始预报流量值进行校正。(4)动态系统响应曲线(dynamic system response curve, DSRC)方法[65-69]。基于最小二乘估计原理,建立洪水预报模型的输入与输出之间的动态响应系统,根据该响应系统,由输出变化量响应求得输入变化量,通过输入变化量校正输入误差,再用校正后的输入重新进行洪水预报计算得到校正后的输出。这个输入变量可以是模型中的流域面雨量、产流量、土壤含水量或自由水蓄量等任意过程变量和状态变量。对于 DSRC 方法在实际应用中会出现的“振荡”现象,可采用平稳约束项来解决这些缺陷[70-71]。最近也有相关研究应用基于 DSRC 理论的全过程联合校正方法,同时对输入误差和模型误差进行联合校正[72]。

当然,TBC 和 PBC 这两类洪水预报实时校正方法也不是截然分割的,有些实时校正技术既可以用来校正终端误差,也可以用来校正过程误差,如:(1)RLS 法可为两类实时校正方法的校正模型估计参数[44, 70, 73]。(2)交互式修正方法可根据各种参考信息,如降雨分布、气象云图、工程运用等,进行修正预报值时间序列、模型参数、交互修正信息等[3, 74, 75]。(3)贝叶斯方法可以通过综合考虑影响洪水预报精度的内外因素以实现校正,其中,外部因素是预报模型的输入及输出,内部因素是预报模型的结构、参数及状态[76-78]。还可以联合采用多种校正技术进行误差修正,如:(1)将 3 种在线识别算法(无限记忆、衰减记忆、有限记忆)与 3 种滤波器(正规、衰减记忆、自适应)组合,形成多种联合运用的校正方法[79]。(2)联合 AKF 技术和 AR 模型的实时校正方法[80]。(3)联合 RLS 算法与 AR 模型的实时校正方法[81]。(4)基于异联想技术及知识求精,模仿生物大脑神经网络的信息联想行为,将所有实时信息和历史信息与误差修正内容和修正算法联合贮存起来,构成多信息源、多修正内容和多修正技术的综合性修正方法[33, 82]。(5)结合人工神经网络技术(artificial neural network, ANN)与 AR 模型的

综合实时修正方法[82-84]。(6) 属于“后处理器”性质的实时校正模型的优选误差修正方法[29]。(7) 实时校正和组合预报一体化的校正方法[85]。

上述这些实时校正的理论与方法, 均被广泛地应用于实际洪水预报工作, 在减灾防灾和促进水文行业科技进步中发挥了重大作用。其实, 无论是属于哪类洪水预报实时校正方法, 其本质都是通过各种数学算法(实时校正技术)对预报变量或过程变量进行优化, 增强其实时更新能力, 以提高最终的预报精度。

2　代表性实时校正技术及其特点

在以上众多的实时洪水预报校正技术与方法中, 目前应用较多的有反馈模拟技术、AR 算法、RLS 算法、KF 技术和 DSRC 算法。反馈模拟技术和 AR 算法属于 TBC 方法, 前者是实用型的人工经验校正技术, 后者是基础型的处理时间序列校正技术; RLS 算法属于典型的综合校正方法, 既可为 TBC 和 PBC 方法的校正模型估计参数, 又可与其他校正技术联合进行误差修正, 可塑性强、应用范围广; KF 技术和 DSRC 算法属于 PBC 方法, 两者均代表着目前的最新进展。

2.1　反馈模拟技术

反馈模拟实时校正技术[7]基于洪水预报误差的相似性, 利用系统所能得到的各种有效信息进行洪水预报误差实时校正。其基本思路是将预报流量序列和实测流量序列在相邻时段间的特性反馈给预报系统, 重新生成校正流量序列, 使预报值更好地趋近实测值。

实测值与预报值的相关性系数 R_c 以及它们的确定性系数 D_y 计算公式为

$$D_y = R_c^2 \tag{1}$$

$$R_c = \frac{\sum_{i=1}^{N}(Q_f(i) - \bar{Q}_f)(Q_{ob}(i) - \bar{Q}_{ob})}{\sqrt{\sum_{i=1}^{N}(Q_f(i) - \bar{Q}_f)^2 \sum_{i=1}^{m}(Q_{ob}(i) - \bar{Q}_{ob})^2}} \tag{2}$$

$$\bar{Q}_{ob} = \frac{\sum_{i=1}^{m} Q_{ob}(i)}{m},\ \bar{Q}_f = \frac{\sum_{i=1}^{m} Q_f(i)}{m} \tag{3}$$

式中: $Q_{ob}(i)$ 为实测流量系列, $(i = 1, 2, \cdots, N)$; $Q_f(i)$ 为预报流量系列, $(i = 1, 2, \cdots, M)$; N 和 M 分别为实测和预报流量系列的长度, 且 $M > N$; $\bar{Q}_{ob}$ 为实测流量系列的平均流量值; $\bar{Q}_f$ 为与实测流量系列对应的预报流量系列的平均流量值。

求相邻时刻实测流量间的差值 $\Delta Q_{ob}(i)$ 和预报流量间的差值 $\Delta Q_f(i)$, 计算公式为

$$\Delta Q_{ob}(i) = \begin{cases} 0 & i = 1 \\ Q_{ob}(i) - Q_{ob}(i-1) & i = 2, 3, \cdots, N \end{cases} \tag{4}$$

$$\Delta Q_f(i) = \begin{cases} 0 & i = 1 \\ Q_f(i) - Q_f(i-1) & i = 2, 3, \cdots, N \end{cases} \tag{5}$$

计算因子

$$A_{FACT}(i) = \frac{\Delta Q_{ob}(i+1) + \Delta Q_{ob}(i)}{\Delta Q_f(i+1) + \Delta Q_f(i)}$$

$$\text{或} A_{FACT}(i) = \frac{\Delta Q_{ob}(i+1) - \Delta Q_{ob}(i)}{\Delta Q_f(i+1) - \Delta Q_f(i)} \tag{6}$$

计算

$$F(i,j) = A_{FACT}(i)^{0.75j} \qquad j = 1, 2, \cdots, 6 \tag{7}$$

依据经验, A_{FACT} 因子的取值范围一般为 $A_{FACT} \in (0.45, 2.21)$; 且当 $j = 6$ 时, $F(i,j)$ 趋近于 1.0。

基于 $\Delta Q_f(i)$　0 和 $\Delta Q_f(i) < 0$, 将洪水整个过程划分为涨水段过程和退水段过程两部分, 再分别对这两段过程进行流量校正。

(1) 涨水段过程($\Delta Q_f(i)$　0), 误差校正方程式为

$$Q_{ob}(i) = \begin{cases} Q_{ob}(i-1) + \Delta Q_f(i) \\ \qquad i - (N+6) \quad 0, i > 7 \\ Q_{ob}(i-1) + \Delta Q_f(i)c \\ \qquad i - (N+6) < 0 \end{cases} \tag{8}$$

式中: c 为实时校正系数, 计算公式为

$$c = \frac{F_{(i-6,6)} + F_{(i-5,5)} + \cdots + F_{(N, i-N)}}{7 + N - i} \tag{9}$$

若 $N = 1$, 则该过程反馈模拟实时校正的流量值为

$$Q_{ob}(i) = Q_{ob}(i-1) + (Q_f(i) - Q_f(i-1)) \tag{10}$$

式中: $i = 2, 3, \cdots, K$, K 为洪峰对应的序数。

(2) 退水段过程($\Delta Q_f(i) < 0$), 误差校正方程式为

$$Q_{ob}(i) = Q_f(i)\frac{Q_{ob}(i-1)}{Q_f(i-1)} \tag{11}$$

反馈模拟实时校正技术可以充分利用各种实测信息和预报信息, 建立经验公式, 通过反馈模拟, 重新生成预报流量, 以提升洪水作业预报的能力。反馈模拟技术与具体使用的洪水预报模型无关, 具有良好的通用性, 方法原理易懂, 且不需率定参数。因此, 该技术常被用于水文自动遥测系统, 实用性强、应用范围广[7, 26]。但其校正效果依赖于预报序列的趋势是否准确, 当预报序列不能准确把握未来流量涨跌趋势时, 校正序列也难以达到对未来流量的准确预测。此外, 反馈模拟实时校正技术在进行洪水预报和误差校正交替滚动的过程中, 预报误差会不断累积: 当预见期短时, 该方法的校正效果好; 当预见期较长时, 该方法的校正效果较差, 洪水预报精度也随之降低。

2.2　AR 算法

AR 模型校正算法[8] 假设预报误差具有前后相依联系,根据历史预报误差系列发现规律,用以对未来误差进行预测,从而实现原预报结果的修正。作业预报中,通常依据预报前几个时段的实测值与预报值之间的误差,构建基于误差的自回归模型(校正模型);然后根据该校正模型,计算出预报时刻的误差,将其加到预报值上,即为该时刻校正后的预报值。

误差自回归估计式为

$$e'_{t+L}=c_1e_t+c_2e_{t-1}+\cdots+c_pe_{t-p+1}+\xi_{t+L} \tag{12}$$

预报结果的校正式为

$$Q_C(t+L|t)=Q_C(t+L)+e'_{t+L} \tag{13}$$

式中:e'_{t+L}为$(t+L)$时刻的模型误差估计值;e_t 为 t 时刻的模型误差计算值,且 $e_t=Q(t)-Q_C(t)$;ξ_{t+L}为校正后$(t+L)$时刻的系统残差,是同时满足正态分布和时间序列独立性的白噪声;$Q_C(t+L)$代表校正前的模型计算值;$Q_C(t+L|t)$代表校正后的模型计算值;$c_1,c_2,\cdots,c_p$ 是自回归系数系列,可以是常系数,也可以是与最新反馈信息相关联的变系数;p 为模型回归阶数,一般为二阶或三阶。

AR 模型算法简单、资料需求少,因而在实际生产中得到广泛应用。其关键在于回归系数的确定,一般是根据实际资料,采用最小二乘法或递推最小二乘法、抗差递推最小二乘法等估计[47]。但 AR 模型依赖于预报误差的相依特性,当预报量变化较大时,如洪水起涨、洪峰附近(曲线拐点处)流量急变,可能引起误差规律发生变化,这时校正效果不佳。另外,AR 校正模型借助的是预报误差时序相依关系,所以在外推过程中误差会快速积累,对于较大的流域或要求预见期较长的情况不宜采用。

2.3　RLS 算法

RLS 校正算法[50] 的思想是不断地通过新的系统输入和系统输出,对模型参数的估计量加上修正量进行校正,以得到更能准确表达系统当前状态的一套新模型参数估计量。概括为

$$\theta'=\theta^s+\Delta\theta \tag{14}$$

式中:θ' 为新模型参数估计量;θ^s 为旧模型参数估计量;$\Delta\theta$ 为修正量。

根据最小二乘法,可以推导出参数在线估计

$$\theta^s_{N+1}=\theta^s_N+\boldsymbol{G}_{N+1}(\boldsymbol{y}_{N+1}-\theta^{\mathrm{T}}_{N+1}\theta^s_N) \tag{15}$$

$$\boldsymbol{G}_{N+1}=\boldsymbol{P}_N\theta_{N+1}(1+\theta^{\mathrm{T}}_{N+1}\boldsymbol{P}_N\theta_{N+1})^{-1} \tag{16}$$

$$\boldsymbol{P}_{N+1}=(1-\boldsymbol{G}_{N+1}\theta^{\mathrm{T}}_{N+1})\boldsymbol{P}_N \tag{17}$$

式中:θ^s_{N+1}为第$(N+1)$步参数估计值;θ^s_N 为第 N 步参数估计值;$\theta^{\mathrm{T}}_{N+1}$为模型新的输入量;$\boldsymbol{y}_{N+1}$为模型新的输出量;$\boldsymbol{G}_{N+1}$为第$(N+1)$步增益阵;$\boldsymbol{P}_N$ 为第 N 步误差协方差阵;$\boldsymbol{P}_{N+1}$为第$(N+1)$步误差协方差阵。

式(15)至(17)又被称为基本型的 RLS 算法。其意义就在于利用了"新息"$(\boldsymbol{y}_{N+1}-\theta^{\mathrm{T}}_{N+1}\theta^s_N)$这一预测误差,对初始的模型参数估计量 θ^s_N 修正,得出新的参数估计量 θ^s_{N+1}。

RLS 算法的特点是所有数据(历史数据和最新数据)在计算时的地位是平等的。因而,此算法适用于线性的、定常的系统,但对于水文这样一种非线性的、时变的系统,这种新旧数据一律平等的做法未必合理。对于时变系统,越新的数据越能反映当前系统的状态,越能代表当前参数的信息,也就越应该得到重视。所以,后续又提出了衰减记忆、有限记忆以及自适应衰减记忆等方法,对 RSL 的基本算法加以改进,使得改进后的 RSL 算法能更好地跟踪系统的动态特征,取得更优的校正效果[47-50]。

2.4　KF 技术

KF 校正技术[2] 通常借助 2 个方程(状态方程和量测方程)来描绘洪水的整个线性动态过程。状态方程用来描绘系统状态向量随时间的动态变化规律,而量测方程用来描绘系统状态向量与量测向量间的相互依赖关系。

状态方程

$$\boldsymbol{X}_k=\Phi_{k|k-1}\boldsymbol{X}_{k-1}+\boldsymbol{G}_{k-1}\boldsymbol{U}_{k-1}+\Gamma_{k-1}\omega_{k-1} \tag{18}$$

量测方程

$$\boldsymbol{Z}_k=\boldsymbol{H}_k\boldsymbol{X}_k+\nu_k \tag{19}$$

式中:$\boldsymbol{X}_k$ 为k 时刻的系统状态向量;$\Phi_{k|k-1}$为从(k-1)时刻到 k 时刻的系统状态转移矩阵;$\boldsymbol{X}_{k-1}$表示(k-1)时刻的系统状态向量;$\boldsymbol{G}_{k-1}$表示(k-1)时刻的输入矩阵;$\boldsymbol{U}_{k-1}$表示(k-1)时刻的输入向量;Γ_{k-1}表示(k-1)时刻的模型噪声分配矩阵;ω_{k-1}表示(k-1)时刻的模型噪声向量;$\boldsymbol{Z}_k$ 为k 时刻的观测向量;$\boldsymbol{H}_k$ 为k 时刻的观测矩阵;ν_k 为k 时刻的观测噪声向量。

设初始状态的统计特征为

$$\mathrm{E}\{\boldsymbol{X}_0\}=\boldsymbol{U}_0 \tag{20}$$

$$\mathrm{Var}\boldsymbol{X}_0=\mathrm{E}\{(\boldsymbol{X}_0-\boldsymbol{U}_0)(\boldsymbol{X}_0-\boldsymbol{U}_0)^{\mathrm{T}}\}=\boldsymbol{P}_0 \tag{21}$$

$$\mathrm{Cov}(\boldsymbol{X}_0,\omega_k)=0 \tag{22}$$

$$\mathrm{Cov}(\boldsymbol{X}_0,\nu_k)=0 \tag{23}$$

代入实际观测值 $\boldsymbol{Z}_1,\boldsymbol{Z}_2,\cdots,\boldsymbol{Z}_k$,根据线性无偏最小方差理论,计算出 $\boldsymbol{X}_{k+i}$(当 $i<0$ 时,属于内插;当 $i=0$ 时,属于滤波;当 $i>0$ 时,属于预报)。

估计误差即可通过状态向量预报误差的期望 $\boldsymbol{P}_{k|k-1}$和状态向量滤波误差的期望 $\boldsymbol{P}_{k|k}$来计算,即

$$\boldsymbol{P}_{k|k-1}=\mathrm{E}[\hat{\boldsymbol{x}}_{k|k-1}\hat{\boldsymbol{x}}^{\mathrm{T}}_{k|k-1}] \tag{24}$$

$$\hat{\boldsymbol{x}}_{k|k-1} = \boldsymbol{x}_k - \hat{\boldsymbol{x}}_{k|k-1} \tag{25}$$

$$\boldsymbol{P}_{k|k} = \mathrm{E}[\hat{\boldsymbol{x}}_{k|k}\hat{\boldsymbol{x}}^{\mathrm{T}}_{k|k}] \tag{26}$$

$$\hat{\boldsymbol{x}}_{k|k} = \boldsymbol{x}_k - \hat{\boldsymbol{x}}_{k|k} \tag{27}$$

式中:$\boldsymbol{x}_k$ 为真值;$\hat{\boldsymbol{x}}_{k|k-1}$为根据(k-1)时刻的状态量计算得到的k时刻的预报量;$\hat{\boldsymbol{x}}_{k|k}$为k时刻的滤波值。

KF突破了经典控制理论的局限,适用于平稳或非平稳、线性或非线性、集中或分布、多输入或多输出系统,因而,KF校正技术包容性强,应变灵活,应用广泛。国内外学者[18,57]将标准KF校正技术与水文模型、水动力模型相结合,均获得较好的误差校正效果。但在应用时,KF需要准确估计系统模型和噪声,由于洪水过程的复杂性,描述水文系统的模型及噪声的分布函数都是近似的,致使标准KF校正技术在实时洪水作业预报中受到一定的限制。因此,众多改进的KF校正算法被不断提出,如EKF、EnKF和UKF等[58-62]。且它们均对均值和方差的传播进行了非线性处理,使得模拟精度更高,但处理的方式和方法各有不同,例如:EKF是将非线性函数直接线性化处理而避免非线性过程;而EnKF和UKF,均是根据大量采样点(集合)近似相关的统计量[61]。因此,这些新的滤波校正技术,对洪水预报模型这类非线性系统适用性更强、应用范围更广。

2.5　DSRC算法

DSRC校正算法[67]将预报模型作为响应系统,通过计算时段的输入变量所对应的系统响应曲线来校正输入变量,校正后的输入变量重新进行洪水预报计算,即可得到校正后的流域出口断面预报流量过程。

可将洪水预报模型概化为如下非线性系统

$$Q(t) = f[X(t), \theta] \tag{28}$$

式中:$Q(t)$代表模型计算流量;$X(t)$代表预报模型输入变量或状态变量,如新安江(XAJ)模型的降雨量P、产流量R、自由水蓄量S等;θ为模型参数变量;t代表时间。

假定模型参数不随时间变化,模型计算流量仅受模型输入变量和状态变量即$X(t)$变化的影响。所以,式(28)可简化为

$$Q(t) = f[X(t)] \tag{29}$$

对式(29)右端使用泰勒展开,忽略所有高阶项,只保留一阶项,得

$$\boldsymbol{Q}(X, t) = f(\boldsymbol{X}_C, t) + \boldsymbol{U}\Delta t + \varepsilon \tag{30}$$

式中:$\boldsymbol{X}_C = [x_{c_1}, x_{c_2}, \cdots, x_{c_n}]^{\mathrm{T}}$为预报模型计算的初始被校正变量系列;$\Delta\boldsymbol{X} = [\Delta x_1, \Delta x_2, \cdots, \Delta x_n]^{\mathrm{T}}$为估计的被校正量误差;$f(X_C, t)$为初始的模型计算流量值;$\boldsymbol{Q}(X, t)$为实测流量值;$\varepsilon = [e_1, e_2, \cdots, e_n]^{\mathrm{T}}$为流量的观测误差项;$\boldsymbol{U}$为动态系统响应矩阵,可采用向后差分方法求解。

根据经典最小二乘(least squares, LS)原理,得到

$$\Delta X = (\boldsymbol{U}^{\mathrm{T}}\boldsymbol{U})^{-1}\boldsymbol{U}^{\mathrm{T}}(\boldsymbol{Q}(X,t) - f(\boldsymbol{X}_C, t)) \tag{31}$$

将估计的误差ΔX加到被校正量的初始值$\boldsymbol{X}_C$上后,重新输入模型计算,即可求出校正后的流量值。

DSRC基于系统和微分理论,逐时段对输入变量进行校正,该方法物理基础性强,且不损失预见期,校正效果明显。近十年,不少研究者[65-69]在长江、淮河、闽江等流域,借助DSRC方法对产流量、自由水蓄量、流域面雨量、以及土壤含水量等过程变量和状态变量进行校正,均取得比AR等校正模型更好的校正效果。对于实际应用中DSRC可能出现的校正效果不稳定现象(反演的不适定),可通过在计算式中增加一个罚函数,借罚函数项分担校正项的一部分变化,从而降低校正量对流量变化的敏感度,以保障DSRC修正的稳定性[70-71]。此外,应用DSRC校正时有一个前提假设,即认为终端误差只是由洪水预报各个过程(变量)中的某个(或几个)引起的,而剩余的其他过程或变量没有误差,这样将全部的终端误差归咎于一个过程或变量的误差来进行校正,与洪水预报中误差存在于各个过程的实际情况不甚相符,存在一定的局限性。因此,近期的研究[72]提出了一种DSRC的扩展方法,可对各个过程误差进行校正,可进一步提升校正效果、提高洪水预报精度。以同时校正面雨量计算误差和模型误差为例。

先在雨量站数目较多的流域,构建雨量站网密度ρ_m、面雨量误差占总误差的比例η_{P,ρ_m}($E_{P,\rho_m}/E_{T,\rho_m}$)和模型误差占总误差的比例$\eta_{M,\rho_m}$($E_{M,\rho_m}/E_{T,\rho_m}$)之间的定量关系,且$\eta_{P,\rho_m} + \eta_{M,\rho_m} = 1$。关系见表1。

表1　ρ_m与η_{P,ρ_m}、η_{M,ρ_m}之间的定量关系

雨量站密度	面雨量误差比例	模型误差比例
ρ_1	$\eta_{P,\rho_1} = 1 - \eta_{M,\rho_1}$	$\eta_{M,\rho_1} = E_{T,\rho_n}/E_{T,\rho_1}$
⋮	⋮	⋮
ρ_m	$\eta_{P,\rho_m} = 1 - \eta_{M,\rho_m}$	$\eta_{M,\rho_m} = E_{T,\rho_n}/E_{T,\rho_m}$
⋮	⋮	⋮
ρ_n	$\eta_{P,\rho_n} = 1 - \eta_{M,\rho_n} = 0$	$\eta_{M,\rho_n} = E_{T,\rho_n}/E_{T,\rho_n} = 1$

根据表1中得到的定量关系,将研究流域(雨量站密度为ρ)的洪水预报总误差$E_{T,\rho}$按照误差的分配比例,划分成面雨量误差$E_{P,\rho}$和模型误差$E_{M,\rho}$:

$$E_{P,\rho} = \eta_{P,\rho} \times E_{T,\rho} \tag{32}$$

$$E_{M,\rho} = \eta_{M,\rho} \times E_{T,\rho} \tag{33}$$

则可基于 DSRC 方法的系统响应理论, 对应用流域的面雨量误差 $E_{P,\rho}$和模型误差 $E_{M,\rho}$同时校正。得到面雨量校正量系列 $\Delta P\rho$ 和模型参数校正量系列 $\Delta\theta\rho$

$$\Delta P\rho = (\boldsymbol{A}^{\mathrm{T}}\boldsymbol{A})^{-1}\boldsymbol{A}^{\mathrm{T}}E_{\mathrm{P},\rho} = \eta_{\mathrm{P},\rho}\cdot(\boldsymbol{A}^{\mathrm{T}}\boldsymbol{A})^{-1}\boldsymbol{A}^{\mathrm{T}}E_{\mathrm{T},\rho} \tag{34}$$

$$\Delta\theta\rho = (\boldsymbol{B}^{\mathrm{T}}\boldsymbol{B})^{-1}\boldsymbol{B}^{\mathrm{T}}E_{\mathrm{M},\rho} = \eta_{\mathrm{M},\rho}\cdot(\boldsymbol{B}^{\mathrm{T}}\boldsymbol{B})^{-1}\boldsymbol{B}^{\mathrm{T}}E_{\mathrm{T},\rho} \tag{35}$$

式中: 洪水预报总误差系列 $E_{T,\rho}$是实测流量系列 $Q(P,\theta,t)$与模型预报流量系列 $f(P_{c,\rho},\theta_{c,\rho},t)$的差值; $P_{c,\rho}$是校正前的面雨量系列, $\theta_{c,\rho}$是校正前的模型参数系列; $\Delta P\rho$ 是面雨量校正量; $\boldsymbol{A}$ 是面雨量相应的动态系统响应矩阵; $\Delta\theta\rho$ 是模型参数校正量; $\boldsymbol{B}$ 是模型参数相应的动态系统响应矩阵。

校正后的面雨量系列 $P'_{c,\rho}$和校正后的模型参数系列 $\theta'_{c,\rho}$为

$$P'_{c,\rho} = P_{c,\rho} + \Delta P\rho \tag{36}$$

$$\theta'_{c,\rho} = \theta_{c,\rho} + \Delta\theta\rho \tag{37}$$

将校正后的 $P'_{c,\rho}$和 $\theta'_{c,\rho}$重新输入预报模型, 便可得到最终校正后的流量过程为

$$Q'_{c,\rho}(t) = f[P'_{c,\rho},\theta'_{c,\rho},t] \tag{38}$$

以上 5 种代表性的实时校正方法各有特点: 反馈模拟校正技术是人工经验校正方法中的典范, 计算方便、简单实用; AR 模型校正算法和 RLS 校正算法均属于回归类模型, 技术成熟, 在实际应用中易于实现、应用广泛; KF 校正技术具有理论优势, 其应变灵活、适用性强, 所以衍生出诸多改进算法, 但该类滤波方法对所需的资料条件要求较高; DSRC 方法是目前最新研究进展中的代表, 性能稳定、校正效果显著。未来水文随着计算机技术高速进步及发展, 特别是优化算法、大数据处理、人工智能等新一代科学技术的引入, 将丰富和促进这些洪水预报实时校正技术的深入发展与应用。

3　总结与展望

实时校正是洪水预报的重要组成部分。经多年发展, 从简单的 AR 模型到复杂的 KF 技术, 从专家经验修正到人工智能校正, 形成了一批研究成果。洪水预报实时校正方法大体上可以归纳为终端误差校正(TBC) 和过程误差校正(PBC) 两类, 这些方法在实时洪水预报中均发挥了各自的优势、起到了重要的校正作用。总体上看, 大数据时代的到来使得洪水预报实时校正技术的发展与数学和信息技术的进步紧密相连, 飞速发展着的人工智能和机器学习为洪水实时校正技术进步带来新的机遇, 未来可望在如下方面取得新进展。

(1) 基于 EnKF、粒子群滤波等同化技术发展的实时校正方法已展现出其优势, 是未来的一个重要研究方向。随着“天-空-地”一体化观测技术的日新月异, 对水循环过程的监测不管是在内容上还是频次、精度上, 都将取得巨大的扩展和提升。洪水的监测信息将在时间和空间尺度上更为精细, 与洪水相关的其他水文循环要素的监测信息也更为丰富, 如何将这些多元/源数据充分利用, 发展洪水预报实时校正数据同化技术, 是值得深入研究的内容。

(2) 水文物理背景分析与预报误差数学描述有机结合, 是提高 TBC 类校正方法精度的有效手段。TBC 方法直接处理终端预报误差, 简单实用、易操作性强。但现行的 TBC 方法大多仅依靠数学途径, 建立误差描述方程, 进行误差校正, 很少去探求误差背后的物理产生机制。实际应用表明, 即使对同一水文预报方案, 相同降雨量但降雨中心位置不同、涨落水不同阶段、不同洪水量级、不同季节, 其洪水预报误差的规律也会有所不同。

(3) 考虑洪水过程的 PBC 方法将是未来洪水预报实时校正的主要研究方向。本质上, 洪水预报的终端误差是由洪水预报中间过程的误差累积而成的, PBC 方法可以对中间过程进行误差修正, 从而降低最终误差, 这是其理论优势, 但目前在实际应用中因难以获得完整的中间监测数据, 限制了该方法的使用。在大数据背景下, 洪水中间过程如降雨、产流和汇流等过程的详细监测数据易获性的提升可进一步推动 PBC 方法的发展。例如: 基于系统响应理论, 根据详实的降雨径流逐过程监测信息, 可以改进或扩展 DSRC 技术方法; 若可以实时获得流域上众多水利工程的泄流数据, 则可以在卡尔曼滤波解法的马斯京根矩阵方程组中进行节点设置, 将人类活动的影响融入校正方程。

(4) 大数据预报误差修正模型可望形成新的突破方向。虽然大数据分析技术在洪水预报实时校正中尚未有实质性的进展, 但这代表了未来最有前景并产生突破的一个研究方向。基于海量的实际观测及其派生数据(包括: 前期的降水量、土湿、水库蓄水状态、河道底水; 本场降雨的暴雨中心位置、时空分布、雨量(强) , 更前期的气候背景、大气环流因子; 历史上观测的场次降雨、洪水系列; 不同模型方案的预报结果数据; 等等) , 采用各类机器学习算法, 如随机森林、支持向量机、卷积神经网络(CNN) 、循环神经网络(RNN) 、长短记忆神经网络(LSTM) 、深度神经网络(DNN) 等, 寻找终端误差或过程误差与数据之间的关联规则, 进而建立预报误差的大数据修正模型。

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• 译文(Translation) •

DOI: 10.13476/j.cnki.nsbdqk.2021.0002

Research advances on real-time correction methods for flood forecasting

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Abstract: The background of real-time correction for flood forecasting is reviewed, and the research advances in real-time correction are summarized. On this basis, real-time correction was divided into two categories such as the terminal bias correction and process bias correction. The correction methods in these two approaches were sorted out, and the research results and progress were presented. Five representative real-time correction algorithms, i.e., feedback simulation, auto-regressive (AR), recursive least squares (RLS), Kalman filtering (KF), and dynamic system response curve (DSRC), were introduced, and their characteristics and applicability were analyzed. The future development direction and research hotspots of real-time correction for flood forecasting were predicted.

Key words: real-time correction; flood forecasting; feedback simulation; auto-regressive; recursive least squares; Kalman filtering; dynamic system response

As the most important non-engineering measure for flood management, flood forecasting serves as the "eyes and ears", "advisers" and "pioneers" of flood control[1]. Acquiring accurate and timely forecasts in advance can reduce or even avoid losses by flood disasters and effectively manage and protect water resources, providing a scientific basis for flood control decisions and reservoir scheduling, which can bring significant economic and social benefits[2]. Flood forecasting includes many links such as model input, model structures and parameters, initial values of state variables and measurements[3-5]. Errors in these aspects will lead to deviations of final forecasts from the actual values, thus affecting the accuracy of flood forecasting models. Therefore, we must correct those errors to ensure the practicability and effectiveness of forecasting models, making the results more reliable.

Real-time error correction of flood forecasting, also referred to as real-time correction, indicates that forecast inputs, model parameters, state variables and forecast results are corrected based on real-time information (measurement, forecast, etc.) collected during flood forecasting, so that flood forecasting errors can be reduced in real time[6-8]. A diagram of real-time correction is shown in Fig. 1, where In($t-D$) represents the input of the measured model at moment ($t-D$). After model calculation, the forecast value or output

Received: 2020-01-10 **Revised:** 2020-05-25 **Online publishing:** 2020-06-01
Online publishing address: http://kns.cnki.net/kcms/detail/13.1430.TV.20200601.1411.002.html
Funds: National Key Research and Development Program of China (2016YFC0402709); National Natural Science Foundation of China (41730750); Jiangxi Provincial Water Conservancy Science and Technology Project (201921YBKT21)
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value Out($t|t-D$) of the model at moment t after the forecast period D can be obtained. These output values can be the flow (water level) at sections of basin outlets, model parameters, or soil moisture content of basins, etc. After the corresponding measurement Obs(t) at moment t is obtained, a correction model is established based on the relationship between the forecast values of the model and the measurements. The corrected results are re-calculated in the model, and the corrected model output Out(t) can be obtained. For the next moment ($t+1$), the same model calculation and error correction are performed according to the model input In($t+1-D$) at this moment and the corrected output Out(t) at the last moment t, so the corrected model output Out($t+1$) at the moment ($t+1$) can be acquired. Repeating the above process, we can realize the real-time corrected forecasting for the flood process with a forecast period of L, namely from moment t to moment ($t+L$).

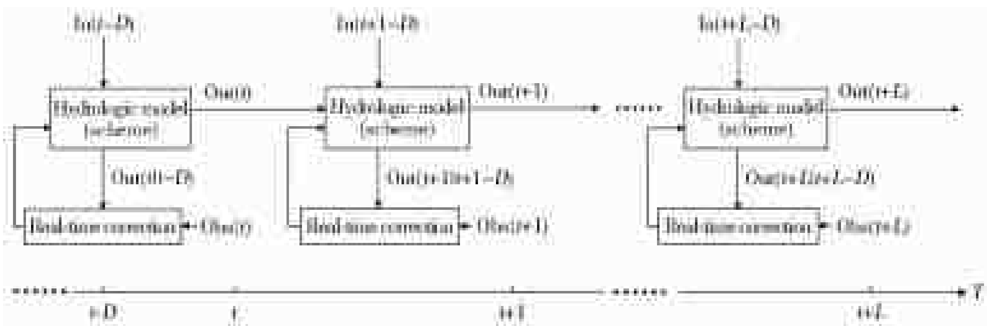

Fig. 1 Flow chart of real-time correction for flood forecasting

This paper classified and briefly reviewed the real-time correction for flood forecasting. Five representative real-time correction methods were introduced in detail, and the trend of real-time correction methods in the future was predicted.

1 Review of development of real-time correction for flood forecasting

1.1 Research results in an early stage

In the 1960s, the "SCI", systems theory (S), cybernetics (C) and information theory (I), in the systems science, gradually entered a mature stage. Its theory and techniques have been rapidly applied in fields such as natural science, engineering and social economy, achieving many fruits. In 1970, Hino[1,9], a Japanese scholar, first applied the Kalman filtering (KF) technique to the hydrologic forecasting, which pioneered the research in this direction. In 1978, Wood et al.[10] described the process of using the KF recursive algorithm to forecast rainfall runoff. Since then, a number of information processing and correction techniques, represented by KF theory[11], have been gradually introduced to flood forecasting, leading to the first boom of introduction.

Based on the research boom and a large number of achievements in the 1970s, the American Geophysical Union (AGU) held an international symposium in 1978. The results were compiled into *Proceedings of AGU Chapman Conference on Application of Kalman Filtering Theory and Techniques to Hydrology, Hydraulics, and Water Resources*[1,12]. Later, in April, 1980, the International Association of Hydrological Sciences (IAHS) together with the World Meteorological Organization (WMO) held another international symposium on hydrologic forecasting. Among the 46 papers in the proceedings of this conference, 16 were related to the KF theory[1,13]. The papers of these two proceedings represented the most advanced research on this topic at that time. For example, Ambrus[13] introduced the self-tuning predictor and applied the autoregressive-moving average (ARMA) model (a difference model) to forecast the Budapest-Baja section of the Danube in real time, achieving correction with high accuracy.

The research and applications of real-time correction for flood forecasting in China mainly emerged in the 1980s, which were later than those in other countries. Most of the early correction techniques were based on manual empirical correction[6, 14-16]. For some cases with large errors in flood forecasting, the forecast results were corrected directly based on experts' experience or by means of regression analysis, so the estimates could be improved. There were also statistical methods based on time series analysis, in which auto-regressive (AR) models between forecast errors and errors were established, thus forecasting the future error sequence based on the existing error sequence. These correction methods basically separate from forecast models, which could be modeled independently for convenience.

Around the 1980s, the research on hydrologic forecast models developed rapidly in China, from empirical models to conceptual models and then to distributed models. A number of real-time correction methods integrated with hydrologic models also began to emerge and showed effects. The data assimilation technique was a representative of such real-time correction methods, which could effectively improve the forecast accuracy of hydrologic models. The data assimilation technique mainly included filtering methods and calculus of variations[17]. However, the calculus of variations usually assumed that model errors did not propagate with time, but the errors in hydrologic models did propagate with time. Thus, the filtering methods were mostly used in error correction for flood forecasting. In 1984, Ge[18] coupled the KF technique in the filtering methods with conceptual hydrologic models to achieve independent real-time dynamic correction for runoff forecasts. This was an important technical breakthrough in the real-time correction. Since then, many filtering algorithms (including the improved KF technique) have been widely used for real-time correction of forecast errors in hydrologic models and achieved remarkable effects.

1.2 Recent research results

After the 1980s, the research on real-time correction for flood forecasting has further developed with the emergence of new theories and the increasing requirements on applications. One of the major features was the development from the direct usage of mathematical correction algorithms to pioneering studies suitable for complex flood forecasting models and correction models. As a result, many post-processing techniques and new correction methods have emerged. These methods can be classified into two categories: terminal bias correction (TBC) and process bias correction (PBC).

TBC, in essence, directly analyzes and deals with forecast errors of terminal flow or water level (terminal errors), instead of considering the errors in each link (sub-process) of forecasting and the propagation of errors in each sub-process. It corrects terminal errors to update original forecast values in real time. There are mainly the following TBC methods: (1) Substitution of measured flow[19]: It denotes the forecast flow (errors) as a function of flow (errors) at the last one moment or many moments and substitutes the previous flow (errors) into the function at each new forecast moment, thus correcting the flow. (2) Real-time correction of flow forecasting in hydrologic models[4, 8, 20-21]: Based on correlation analysis, it creates correlation correction models between the forecast flow of hydrologic models and the actual flow and corrects the forecast flow of models by substituting the actual flow in real time. (3) AR error correction[5, 22-25]: It calculates the series of residuals between the forecast flow and the measured flow. Based on regression analysis, it constructs multi-order AR residual correction models to directly correct the errors in forecast results of flow. (4) Real-time correction of feedback simulation (FACT factor correction coefficient)[7, 26-32]: It uses the FACT factor, which is established based on both actual flow and forecast flow, to correct terminal flow through feedback simulation. (5) Forecast error correction based on hydrological similarity[33-34]: It believes that the two basins satisfying similarity also have similar forecast errors. Thus, different optimal error correction factors can be assigned according to different forecast periods of similar basins, and then forecast error correction models can be constructed to correct the final forecast results. (6) K-nearest neighbor (KNN) correction[35-40]: It is a statistical automatic learning method. Based on regression analysis, this method establishes correction models between the forecast error in the measured period and that at the forecast moment, so as to find K historical flow processes that are the most similar to the current forecast. Then, it estimates the forecast error at the current moment by inverse distance weighting and thus corrects the terminal flow at the current moment. (7) Real-time correction with back propagation (BP) neural networks[41-43]: It uses the feedforward neural network of the BP algorithm to simulate the nonlinearity of forecast models, so as to dynamically track the changes in flood forecasting errors. Based on regression analysis, it constructs non-linear AR models of forecast errors. Then it uses existing forecast errors to analyze new errors and corrects forecast flow, so the terminal errors can be corrected.

PBC, in essence, first corrects errors in state variables and parameters in each sub-process (such as rainfall, runoff and confluence) or forecast models of hydrologic forecasting and then re-calculates models after correction to obtain new forecast values. It reduces terminal errors by reducing errors in each forecasting link. PBC mainly includes the following methods: (1) Correction based on recursive least squares (RLS)[44-46]. It recursively estimates model parameters with minimizing the quadratic sum of forecast errors as the objective until the estimates reach the satisfied accuracy. This correction method also has the improved algorithms, such as the RLS based on fixed forgetting factors, the RLS based on variable forgetting factors, and robust RLS[47-50]. (2) KF[18, 19, 46, 48, 51-56]. It estimates system states and assigns a certain weight to the current forecast by referring to the modern stochastic estimation theory of complex systems and the principle of minimum error covariance, so as to correct state variables of the system (such as parameters of forecast models, objects, errors, etc.), thus realizing real-time error correction. KF can be applied to any linear system, such as the confluence system of segmented river channels described by the Muskingum method[29, 57]. Nonlinear systems can be corrected in real time based on filtering techniques such as adaptive Kalman filtering (AKF), semi-adaptive Kalman filtering (SAKF), extended Kalman filtering (EKF), unscented Kalman filtering (UKF), ensemble Kalman filtering (EnKF) and particle filtering (PF)[58-62]. (3) Real-time classified correction based on the K-means clustering algorithm[63, 64]. It first clusters a large amount of information on historical rainfall and flood, and after classification, it analyzes the categories (levels) to which the real-time rainfall and flood belong according to the characteristics of each category. Then according to the model parameters of the category, it reduces errors of model parameters and thus corrects original forecast flow. (4) Correction based on the dynamic system response curve (DSRC)[65-69]. It establishes dynamic response systems between input and output of flood forecast models based on the principle of least-squares estimation. According to the response system, input variations are obtained from the responses of output variations, and input errors are corrected by the input variations. Then the corrected input is used to re-run the flood forecasting to obtain the corrected output. The input variable can be any process or state variable such as surface rainfall, runoff, soil moisture content or storage of free water. A smoothing constraint term can be used to address the "oscillations" in the applications of the DSRC method[70-71]. Some recent studies used the whole-process joint correction based on the DSRC theory to jointly correct both the input errors and the model errors[72].

The classification of the two methods of real-time correction for flood forecasting, TBC and PBC, is not absolute. Some real-time correction techniques can be used to correct both terminal errors and process errors. The followings are example: (1) the RLS method can estimate parameters for correction models of both two types of real-time correction methods[44, 70, 73]. (2) The interactive correction method can correct the time series of forecast values, model parameters and interactive correction information based on reference information such as rainfall distribution, meteorological cloud charts and engineering applications[3, 74, 75]. (3) The Bayesian method can correct errors by comprehensively considering internal and external factors that influence the accuracy of flood forecasting. The external factors are the input and output of forecast models, while the internal factors are structures, parameters and states of forecast models[76-78]. Many correction techniques can also be jointly used for error correction. The followings are example: (1) three on-line recognition algorithms (infinite memory, fading memory and finite memory) are combined with three filters (regular, fading memory and self-adaptive) to form many joint correction methods[79]. (2) The AKF technique and the AR model are combined for real-time correction[80]. (3) The RLS algorithm and the AR model are integrated for real-time correction[81]. (4) On the basis of the hetero-associative technique and knowledge refinement, scholars proposed a comprehensive correction method with multiple information sources, correction contents and correction techniques by imitating the information association of neural networks in biological brains and storing all real-time and historical information as well as error correction contents and correction algorithms[33, 82]. (5) Artificial neural network (ANN) and AR model are combined for comprehensive real-time correction[82-84]. (6) The optimal error correction method of real-time correction models is post-processors in nature[29]. (7) Real-time correction and combined forecasting are integrated for correction[85].

The theories and methods of real-time correction mentioned above have been widely applied to practical flood forecasting, which have played a significant role in disaster mitigation and prevention, promoting scientific and technological progress in the hydrological industry. In fact, all real-time correction methods of flood forecasting, in essence, optimize forecast or progress variables through different algorithms (real-time correction techniques) to enhance their real-time updating capabilities, thus improving the final forecast accuracy.

2 Representative real-time correction techniques and their features

In the real-time correction methods for flood forecasting mentioned above, feedback simulation, AR algorithm, the RLS algorithm, the KF technique and the DSRC algorithm are frequently used. Feedback simulation and AR algorithm belong to TBC. The former one is the practical correction technique by manual experience, while the latter one is the fundamental correction method for dealing with time series. The RLS algorithm is a typical comprehensive correction method. It can estimate parameters for correction models of TBC and PBC methods, which can also be combined with other correction techniques for error correction. This technique is flexible with wide application. The KF technique and the DSRC algorithm belong to the PBC method, and both of them represent the latest progress.

2.1 Feedback simulation

The real-time correction of feedback simulation[7] uses valid information available to the system to correct errors of flood forecasting in real time based on the similarity of forecast errors. Its basic principle is to feed back the characteristics of the forecast flow series and the measured flow series in adjacent periods to the forecast system to regenerate the corrected flow series, so that the forecast values can approximate to the measurements.

The correlation coefficient R_c between measurement values and forecast values and their deterministic coefficient D_y are calculated by

$$D_y = R_c^2 \tag{1}$$

$$R_c = \frac{\sum_{i=1}^{N}(Q_f(i) - \bar{Q}_f)(Q_{ob}(i) - \bar{Q}_{ob})}{\sqrt{\sum_{i=1}^{N}(Q_f(i) - \bar{Q}_f)^2 \sum_{i=1}^{m}(Q_{ob}(i) - \bar{Q}_{ob})^2}} \tag{2}$$

$$\bar{Q}_{ob} = \frac{\sum_{i=1}^{m} Q_{ob}(i)}{m},\ \bar{Q}_f = \frac{\sum_{i=1}^{m} Q_f(i)}{m} \tag{3}$$

where: $Q_{ob}(i)$ is the measured flow series, $i = 1, 2, \cdots, N$; $Q_f(i)$ is the forecast flow series, $i = 1, 2, \cdots, M$; N and M are the lengths of the measured flow series and the forecast flow series, and $M > N$; $\bar{Q}_{ob}$ is the average flow of the measured flow series; $\bar{Q}_f$ is the average flow of the forecast flow series corresponding to the measured flow series.

The difference $\Delta Q_{ob}(i)$ between the measured flows and the difference $\Delta Q_f(i)$ between the forecast flows at neighboring moments are calculated by

$$\Delta Q_{ob}(i)=\begin{cases}0 & i=1\\ Q_{ob}(i)-Q_{ob}(i-1) & i=2,3,\cdots,N\end{cases}\tag{4}$$

$$\Delta Q_f(i)=\begin{cases}0 & i=1\\ Q_f(i)-Q_f(i-1) & i=2,3,\cdots,N\end{cases}\tag{5}$$

The factor is calculated by

$$A_{\mathrm{FACT}}(i)=\frac{\Delta Q_{ob}(i+1)+\Delta Q_{ob}(i)}{\Delta Q_f(i+1)+\Delta Q_f(i)}$$

$$\text{or } A_{\mathrm{FACT}}(i)=\frac{\Delta Q_{ob}(i+1)-\Delta Q_{ob}(i)}{\Delta Q_f(i+1)-\Delta Q_f(i)}\tag{6}$$

The following is calculated by

$$F(i,j)=A_{\mathrm{FACT}}(i)^{0.75j}\qquad j=1,2,\cdots,6\tag{7}$$

According to experience, the range of A_{FACT} is generally $A_{\mathrm{FACT}}\in(0.45, 2.21)$. When $j=6$, $F(i,j)$ approximates to 1.0.

Since $\Delta Q_f(i)$ 0 and $\Delta Q_f(i)<0$, the whole flooding process is divided into the water-rising process and the water-recessing process. Then the flows in these two processes are corrected.

(1) The error in the water-rising process ($\Delta Q_f(i)$ 0) is corrected by

$$Q_{ob}(i)=\begin{cases}Q_{ob}(i-1)+\Delta Q_f(i) & \\ \qquad i-(N+6) & 0, i>7\\ Q_{ob}(i-1)+\Delta Q_f(i)c & \\ \qquad i-(N+6)<0 & \end{cases}\tag{8}$$

where: c is the real-time correction coefficient, which is denoted by

$$c=\frac{F_{(i-6,6)}+F_{(i-5,5)}+\cdots+F_{(N,i-N)}}{7+N-i}\tag{9}$$

If $N=1$, the real-time corrected flow in this process by feedback simulation is

$$Q_{ob}(i)=Q_{ob}(i-1)+(Q_f(i)-Q_f(i-1))\tag{10}$$

where: $i=2,3,\cdots,K$, and K is the ordinal number corresponding to flood peaks.

(2) The error in the water-recessing process $[\Delta Q_f(i)<0]$ is corrected by

$$Q_{ob}(i)=Q_f(i)\frac{Q_{ob}(i-1)}{Q_f(i-1)}\tag{11}$$

The real-time correction technique of feedback simulation can fully take advantage of measurement and forecast information to establish empirical formulas. It can re-generate forecast flow through feedback simulation, so as to improve forecast accuracy. Feedback simulation is not related to flood forecast models, so it can be used universally. It has a simple principle and does not need to calibrate parameters. Thus, this technique is always used in automatic hydrologic telemetering systems, with strong practicability and wide application[7,26]. However, its correction effect depends on whether the trend of forecast series is accurate. When the forecast series cannot accurately grasp the flow trend in the future, it is also difficult for the corrected series to accurately forecast the future flow. Moreover, the real-time correction technique of feedback simulation will accumulate forecast errors in the alternating process of flood forecasting and error correction: when the forecast period is short, this method has good correction effects; otherwise, it performs poorly and the forecast accuracy is reduced accordingly.

2.2 AR algorithm

Assuming the forecast errors have interdependence, the correction algorithm of AR model[8] finds patterns from historical forecast error sequence, which are used to forecast future errors and thus correct original forecast results. In the forecasting, it usually constructs error-based AR models (correction models) based on errors between measurement values and forecast values in several periods before the forecasting. Then, based on this correction model, it calculates the error at the forecast moment and adds it to the forecast value, which is the corrected forecast value at that moment.

The AR estimator of errors is

$$e'_{t+L}=c_1e_t+c_2e_{t-1}+\cdots+c_pe_{t-p+1}+\xi_{t+L}\tag{12}$$

The corrector of forecast results is

$$Q_C(t+L|t)=Q_C(t+L)+e'_{t+L}\tag{13}$$

where: e'_{t+L} is the estimate of the model error at moment $(t+L)$; e_t is the calculated value of the model error at moment t, and $e_t=Q(t)-Q_C(t)$; ξ_{t+L} is the system residual at moment $(t+L)$ after correction, which is the white noise simultaneously satisfying normal distribution and independence of time series; $Q_C(t+L)$ is the calculated value of the model before correction; $Q_C(t+L|t)$ is the calculated value of the model after correction; $c_1, c_2, \cdots, c_p$ are AR coefficient series, which can be constants and also variable coefficients related to the latest feedback information; p is the regressive order of the model, which is generally two or three.

The correction method of the AR model is simple and requires less information, so it is widely applied in practice. The key lies in the determination of regression coefficients. They are generally estimated by the least squares method, the recursive least squares method or the robust recursive least squares method based on practical data[47]. However, the AR model relies on the interdependence of forecast errors: The correction has poor effects when forecast variables change significantly, such as flood rise and rapid changes in flow near peaks (inflection points of the curve), which may cause variations in error patterns. In addition, the AR correction model relies on the time-series dependence of forecast errors, so the errors accumulate rapidly during the extrapolation process. This method is not suitable for large watersheds or long forecast periods.

2.3 RLS algorithm

The RLS algorithm[50] corrects estimates of model parameters by adding corrections through new system input and output, so as to obtain new estimates of model parameters that more accurately represent the current state of the system. It is summarized as follows:

$$\theta^{s'} = \theta^{s} + \Delta\theta \tag{14}$$

where: $\theta^{s'}$ is the parameter estimate of the new model; θ^{s} is the parameter estimate of the original model; $\Delta\theta$ is the correction quantity.

According to the least squares method, the on-line estimate of the parameter can be obtained

$$\theta^{s}_{N+1} = \theta^{s}_{N} + \boldsymbol{G}_{N+1}(\boldsymbol{y}_{N+1} - \theta^{\mathrm{T}}_{N+1}\theta^{s}_{N}) \tag{15}$$

$$\boldsymbol{G}_{N+1} = \boldsymbol{P}_{N}\theta_{N+1}(1+\theta^{\mathrm{T}}_{N+1}\boldsymbol{P}_{N}\theta_{N+1})^{-1} \tag{16}$$

$$\boldsymbol{P}_{N+1} = (1-\boldsymbol{G}_{N+1}\theta^{\mathrm{T}}_{N+1})\boldsymbol{P}_{N} \tag{17}$$

where: θ^{s}_{N+1} is the parameter estimate of step $(N+1)$; θ^{s}_{N} is the parameter estimate of step N; $\theta^{\mathrm{T}}_{N+1}$ is the new input of the model; $\boldsymbol{y}_{N+1}$ is the new output of the model; $\boldsymbol{G}_{N+1}$ is the gain matrix of step $(N+1)$; $\boldsymbol{P}_{N}$ is the error covariance matrix of step N; $\boldsymbol{P}_{N+1}$ is the error covariance matrix of step $(N+1)$.

Equations (15)-(17) are also called as the basic RLS algorithm. It uses the forecast error($\boldsymbol{y}_{N+1} - \theta^{\mathrm{T}}_{N+1}\theta^{s}_{N}$), the "innovation", to correct the original parameter estimate θ^{s}_{N}, obtaining a new parameter estimate θ^{s}_{N+1}.

The RLS algorithm treats all data (historical and up-to-date data) equally in the calculation, so it is suitable for linear and constant systems. However, for hydrologic systems, which are nonlinear and time-varying, the equal operation for new and old data may be not reasonable. For time-varying systems, newer data can better reflect the current state of the system and represent the information of current parameters, so they deserve more attention. Therefore, the methods of fading memory, finite memory and self-adaptive fading memory were proposed subsequently to improve the basic RSL algorithm. The improved RLS algorithms could better track dynamic characteristics of systems and obtained more satisfactory correction effects[47-50].

2.4 KF technique

The KF correction technique[2] usually uses two equations (state equation and measurement equation) to describe the entire linear dynamic process of flood. The state equation indicates the dynamic variation of the system state vector with time, while the measurement equation describes the interdependence between the system state vector and the measurement vector.

The state equation is

$$\boldsymbol{X}_{k} = \Phi_{k|k-1}\boldsymbol{X}_{k-1} + \boldsymbol{G}_{k-1}\boldsymbol{U}_{k-1} + \Gamma_{k-1}\omega_{k-1} \tag{18}$$

The measurement equation is

$$\boldsymbol{Z}_{k} = \boldsymbol{H}_{k}\boldsymbol{X}_{k} + \nu_{k} \tag{19}$$

where: $\boldsymbol{X}_{k}$ is the system state vector at moment k; $\Phi_{k|k-1}$ is the state-transition matrix of the system from moment (k-1) to k; $\boldsymbol{X}_{k-1}$ is the system state vector at moment (k-1); $\boldsymbol{G}_{k-1}$ is the input matrix at moment (k-1); $\boldsymbol{U}_{k-1}$ is the input vector at moment (k-1); Γ_{k-1} is the distribution matrix of model noise at moment (k-1); ω_{k-1} is the model noise vector at moment (k-1); $\boldsymbol{Z}_{k}$ is the measurement vector at moment k; $\boldsymbol{H}_{k}$ is the measurement matrix at moment k; ν_{k} is the measurement noise vector at moment k.

The statistical characteristic at the initial state is set as

$$\mathrm{E}\{\boldsymbol{X}_{0}\} = \boldsymbol{U}_{0} \tag{20}$$

$$\mathrm{Var}\boldsymbol{X}_0 = E\{(\boldsymbol{X}_0 - \boldsymbol{U}_0)(\boldsymbol{X}_0 - \boldsymbol{U}_0)^{\mathrm{T}}\} = \boldsymbol{P}_0 \quad (21)$$

$$\mathrm{Cov}(\boldsymbol{X}_0, \omega_k) = 0 \quad (22)$$

$$\mathrm{Cov}(\boldsymbol{X}_0, V_k) = 0 \quad (23)$$

With the substitution of measurements $\boldsymbol{Z}_1, \boldsymbol{Z}_2, \cdots, \boldsymbol{Z}_k$, $\boldsymbol{X}_{k+i}$ is calculated according to the theory of linear unbiased minimum variance (when $i<0$, it is interpolation; when $i=0$, it is filtering; when $i>0$, it is forecasting.)

The estimate errors can be calculated by the expectation $\boldsymbol{P}_{k|k-1}$ of the forecast error of the state vector and the expectation $\boldsymbol{P}_{k|k}$ of the filtering error of the state vector, namely

$$\boldsymbol{P}_{k|k-1} = E[\hat{\boldsymbol{x}}_{k|k-1}\hat{\boldsymbol{x}}_{k|k-1}^{\mathrm{T}}] \quad (24)$$

$$\hat{\boldsymbol{x}}_{k|k-1} = \boldsymbol{x}_k - \hat{\boldsymbol{x}}_{k|k-1} \quad (25)$$

$$\boldsymbol{P}_{k|k} = E[\hat{\boldsymbol{x}}_{k|k}\hat{\boldsymbol{x}}_{k|k}^{\mathrm{T}}] \quad (26)$$

$$\hat{\boldsymbol{x}}_{k|k} = \boldsymbol{x}_k - \hat{\boldsymbol{x}}_{k|k} \quad (27)$$

where: $\boldsymbol{x}_k$ is the true value; $\hat{x}_{k|k-1}$ is the forecast value at moment k, which is calculated by the state variable at the moment $(k-1)$; $\hat{x}_{k|k}$ is the filtering value at moment k.

Breaking through the limitations of classical control theory, the KF technique is suitable for stationary or non-stationary, linear or non-linear, concentrated or distributed, multi-input or multi-output systems. Therefore, the KF correction technique is inclusive and flexible with wide application. Scholars[18, 57] combined the standard KF correction technique with hydrologic models and hydrodynamic models and obtained satisfactory error correction effects. However, KF requires accurate estimation of system models and noises in applications. Due to the complex flooding process, the models describing hydrologic systems and the distribution functions of noise are similar, resulting in limitations of the standard KF correction technique in real-time flood forecasting. Hence, many improved KF correction algorithms have been proposed such as EKF, EnKF and UKF[58-62]. These techniques all conduct non-linearization for propagation of mean values and variances to improve the simulation accuracy. However, they have different methods of non-linearization. For example, EKF directly linearizes nonlinear functions to avoid the nonlinear process, while EnKF and UKF both approximate relevant statistics based on a large number of sampling points (set)[61]. Therefore, these new filtering correction techniques are more applicable and have a wider range of applications for nonlinear systems such as flood forecasting models.

2.5 DSRC algorithm

The DSRC algorithm[67] regards the forecast model as a response system and corrects input variables by calculating system response curves corresponding to the input variables in the period. The corrected input variables are used to re-conduct flood forecasting, so the corrected flow forecasting process at sections of basin outlets can be obtained.

The flood forecasting model can be simplified to the following non-linear system:

$$Q(t) = f[X(t), \theta] \quad (28)$$

where: $Q(t)$ is the calculated flow of the model; $X(t)$ denotes the input variable or state variable of the forecast model, such as the rainfall P, runoff R and the storage S of free water in the Xinanjiang (XAJ) model; θ is the model parameter; t indicates time.

Assuming that the model parameter does vary with time, the calculated flow is only influenced by the input variable and the state variable, namely $X(t)$. Thus, Equation (28) can be simplified as

$$Q(t) = f[X(t)] \quad (29)$$

The right side of Equation (29) is expanded by the Taylor series. Ignoring all the high-order terms and remaining the first order, we have

$$\boldsymbol{Q}(X, t) = f(\boldsymbol{X}_C, t) + \boldsymbol{U}\Delta t + \varepsilon \quad (30)$$

where: $\boldsymbol{X}_C = [xc_1, xc_2, \cdots, xc_n]^{\mathrm{T}}$ is the initial variable series waiting-to-be corrected; $\Delta\boldsymbol{X} = [\Delta x_1, \Delta x_2, \cdots, \Delta x_n,]^{\mathrm{T}}$ is the estimated error of corrected variables; $f(X_C, t)$ is the initial calculated flow of the model; $\boldsymbol{Q}(X, t)$ is the measured flow; $\varepsilon = [e_1, e_2, \cdots, e_n]^{\mathrm{T}}$ is the measured error of flow; $\boldsymbol{U}$ is the response matrix of the dynamic system, which can be solved by the backward difference method.

According to the classical least squares method, we have

$$\Delta X = (\boldsymbol{U}^{\mathrm{T}}\boldsymbol{U})^{-1}\boldsymbol{U}^{\mathrm{T}}(\boldsymbol{Q}(X, t) - f(\boldsymbol{X}_C, t)) \quad (31)$$

We can obtain the corrected flow by adding the estimated error ΔX to the initial value $\boldsymbol{X}_C$ of the corrected variable and then inputting it to the model for re-calculation.

Based on systems and differential theory, DSRC corrects input variables period by period. With a strong physical basis, this method does not lose the forecast period and thus has a good correction effect. In the last decade, many scholars[65-69] have corrected process and state variables such as runoff, storage of free water, surface rainfall and soil moisture content in the Yangtze river, the Huaihe river and the Minjiang river by the DSRC method, and all achieved better correction results than AR and other correction models. The possible instable correction of DSRC in practical applications (ill-posedness of inversion) can be solved by the addition of a penalty function to formulas. The DSRC algorithm bears partial variations of correction terms with the penalty function, so as to reduce the sensitivities of correction quantities to flow variations, assuring the stability of DSRC correction[70-71]. In addition, DSRC correction is applied with an assumption that terminal errors are caused by only one (or several) sub-process (variable) in flood forecasting, while the other sub-processes or variables do not have errors. Such correction attributing all terminal errors to the error of one sub-process or variable is not consistent with the actual situation that the errors of flood forecasting exist in each sub-process, so it has limitations. Therefore, a recent study[72] proposed an extension of DSRC to correct all the sub-process errors, which could further enhance the correction effect and the forecast accuracy. The method is described with the simultaneous correction of calculation errors and model errors of areal precipitation as the example.

In a basin with many precipitation stations, the quantitative relationships among the density of the precipitation station network ρ_m, the proportion η_{P,ρ_m} ($E_{P,\rho_m}/E_{T,\rho_m}$) of the areal rainfall error to the total error and the proportion η_{M,ρ_m} ($E_{M,\rho_m}/E_{T,\rho_m}$) of the model error to the total error are constructed, and $\eta_{P,\rho_m}+\eta_{M,\rho_m}=1$. The relationships are shown in Tab. 1.

Tab. 1 Quantitative relationship among η_{P,ρ_m}, η_{M,ρ_m} and ρ_m

Density of precipitation stations	Proportion of areal rainfall error	Proportion of model error
ρ_1	$\eta_{P,\rho_1}=1-\eta_{M,\rho_1}$	$\eta_{M,\rho_1}=E_{T,\rho_n}/E_{T,\rho_1}$
⋮	⋮	⋮
ρ_m	$\eta_{P,\rho_m}=1-\eta_{M,\rho_m}$	$\eta_{M,\rho_m}=E_{T,\rho_n}/E_{T,\rho_m}$
⋮	⋮	⋮
ρ_n	$\eta_{P,\rho_n}=1-\eta_{M,\rho_n}=0$	$\eta_{M,\rho_n}=E_{T,\rho_n}/E_{T,\rho_n}=1$

According to the quantitative relationships in Tab. 1, the total flood forecasting error $E_{T,\rho}$ of the studied basin (with a density of precipitation stations of ρ) is divided into the areal rainfall error $E_{P,\rho}$ and the model error $E_{M,\rho}$ according to the distribution proportions of the errors.

$$E_{P,\rho}=\eta_{P,\rho}\times E_{T,\rho} \tag{32}$$

$$E_{M,\rho}=\eta_{M,\rho}\times E_{T,\rho} \tag{33}$$

Then, according to the system response theory of DSRC, the areal rainfall error $E_{P,\rho}$ and the model error $E_{M,\rho}$ of the studied basin are corrected at the same time. The corrected quantity series of areal rainfall ΔP_ρ and the corrected quantity series of model parameter $\Delta\theta_\rho$ can be obtained by

$$\Delta P_\rho=(\boldsymbol{A}^{\mathrm{T}}\boldsymbol{A})^{-1}\boldsymbol{A}^{\mathrm{T}}E_{P,\rho}=\eta_{P,\rho}\cdot(\boldsymbol{A}^{\mathrm{T}}\boldsymbol{A})^{-1}\boldsymbol{A}^{\mathrm{T}}E_{T,\rho} \tag{34}$$

$$\Delta\theta_\rho=(\boldsymbol{B}^{\mathrm{T}}\boldsymbol{B})^{-1}\boldsymbol{B}^{\mathrm{T}}E_{M,\rho}=\eta_{M,\rho}\cdot(\boldsymbol{B}^{\mathrm{T}}\boldsymbol{B})^{-1}\boldsymbol{B}^{\mathrm{T}}E_{T,\rho} \tag{35}$$

where: the total error sequence of flood forecasting $E_{T,\rho}$ is the difference between the measured flow series $Q(P,\theta,t)$ and the forecast flow series $f(P_c,\rho,\theta_{c,\rho},t)$; $P_{c,\rho}$ is the areal rainfall series before correction; $\theta_{c,\rho}$ is the model parameter series before correction; ΔP_ρ is the correction quantity of areal rainfall; $\boldsymbol{A}$ is the dynamic system response matrix corresponding to areal rainfall; $\Delta\theta_\rho$ is the correction quantity of the model parameter; $\boldsymbol{B}$ is the dynamic system response matrix corresponding to the model parameter.

The corrected areal rainfall series $P'_{c,\rho}$ and the corrected model parameter series $\theta'_{c,\rho}$ are

$$P'_{c,\rho}=P_{c,\rho}+\Delta P_\rho \tag{36}$$

$$\theta'_{c,\rho}=\theta_{c,\rho}+\Delta\theta_\rho \tag{37}$$

The corrected $P'_{c,\rho}$ and $\theta'_{c,\rho}$ are re-inputted to the forecast model, so the final corrected flow process can be obtained by

$$Q'_{c,\rho}(t) = f[P'_{c,\rho}, \theta'_{c,\rho}, t] \tag{38}$$

The five representative real-time correction methods have different features. Feedback simulation is a model of manual empirical correction methods, which is convenient and practical. The AR algorithm and the RLS algorithm both belong to regression models, which are mature in techniques and easy to implement. They have a wide range of applications in practice. With the theoretical advantage, the KF technique is flexible and applicable. Therefore, KF has derived many improved algorithms, but this type of filtering methods has high requirements on data. The DSRC method is the representative of the latest research, with stable performance and significant correction effect. Future hydrology will progress rapidly with the computer technology. Especially with the introduction of new generation of science and technology such as optimization algorithms, big data processing and artificial intelligence, it will enrich and promote the development and applications of these real-time correction techniques for flood forecasting.

3 Conclusions and prospects

Real-correction is an important for flood forecasting. After years of development, a number of research fruits have been witnessed from simple AR models to complex KF techniques and from experts' empirical correction to artificial intelligence based correction. The real-time correction methods of flood forecasting can be categorized as TBC and PBC. These methods have various advantages and play an important role in real-time flood forecasting. In general, the emergence of big data makes the development of real-time correction techniques of flood forecasting closely linked with the progress of mathematics and information technology. The rapid development of artificial intelligence and machine learning brings new opportunities for the advancement of real-time correction techniques of flood forecasting. The correction technique is expected to make new progress in the following aspects in the future.

(1) Real-time correction based on assimilation techniques, such as EnKF and particle swarm filtering, has shown different advantages, which can be an important research direction in the future. As the rapid development of space-sky-ground integrated monitoring network, the monitoring for water cycles will be greatly enhanced in terms of content, frequency and accuracy. The monitoring information of flood will be more detailed in temporal and spatial scales, and that of other hydrological cycle elements related to flood will be more abundant. How to make full use of multivariate/multi-source data and develop the assimilation technique of real-time correction data of flood forecasting are worthy to be studied in depth.

(2) Scientific integration of hydro-physical background analysis and mathematical descriptions of forecast errors is an effective method to improve the accuracy of TBC. TBC directly deals with terminal forecast errors, which is convenient and practical. However, most of the existing TBC methods rely only on mathematical means to establish error description equations for error correction, which hardly explore the physical generation mechanism of errors. Applications show that even for the same hydrological forecast scheme, the pattern of flood forecasting errors will be different in case of the same rainfall but different rainfall centers, stages of water rising and recessing, flood magnitudes and seasons.

(3) PBC, which considers the flood process, will be the main research direction of real-time correction for flood forecasting in the future. In essence, the terminal errors of flood forecasting are accumulated from the errors in sub-processes of flood forecasting. PBC corrects errors of sub-processes and thus reduces the final errors, which is its theoretical advantage. However, it is limited in practice as the complete intermediate monitoring data are difficult to obtain. With the help of big data, the detailed monitoring data of intermediate flood processes such as rainfall, runoff and confluence are more available, and it will further promote the development of PBC. For example, based on the system response theory, the DSRC method can be improved or extended based on the sufficient monitoring information of rainfall and runoff. When the discharge data of numerous water conservation

projects in a basin are available in real time, nodes can be set in the Muskingum matrix equation of the KF method to incorporate the influences of human activities to correction equations.

(4) The big-data-based correction model for forecast errors is expected to be a new direction of breakthrough. Although big data analysis has not achieved substantial progress in real-time correction for flood forecasting, it represents the most promising direction that will generate breakthroughs in the future. We can search the association rules between terminal errors or process errors and the data based on massive measurements and their derived data (including: rainfall, soil moisture, storage of reservoirs, base flow of river channels in the previous period; the center of rainstorm, spatial and temporal distribution, and rainfall (intensity) of the current rain, as well as the climate background and general circulation factors in the more earlier stage; rainfall and flood series observed in history; forecast results of different models, etc.). This can be achieved by machine learning algorithms such as random forest, support vector machine, convolutional neural network (CNN), recurrent neural network (RNN), long short-term memory (LSTM) networks and deep neural network (DNN). Then big-data correction models can be established for forecast errors.

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